QLib Documentation

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Contents

`Qlib` is an AI-oriented quantitative investment platform, which aims to realize the potential, empower the research, and create the value of AI technologies in quantitative investment.

CHAPTER 1

Document Structure

1.1 Qlib: Quantitative Platform

1.1.1 Introduction

Qlib is an AI-oriented quantitative investment platform, which aims to realize the potential, empower the research, and create the value of AI technologies in quantitative investment.

With Qlib, users can easily try their ideas to create better Quant investment strategies.

1.1.2 Framework

At the module level, Qlib is a platform that consists of above components. The components are designed as loose-coupled modules and each component could be used stand-alone.

This framework may be intimidating for new users to Qlib. It tries to accurately include a lot of details of Qlib's design. For users new to Qlib, you can skip it first and read it later.

Name	Description
Infrastructure layer	*Infrastructure* layer provides underlying support for Quant research. *DataServer* provides high-performance infrastructure for users to manage and retrieve raw data. *Trainer* provides flexible interface to control the training process of models which enable algorithms controlling the training process.
Learning Framework layer	The *Forecast Model* and *Trading Agent* are learnable. They are learned based on the *Learning Framework* layer and then applied to multiple scenarios in *Workflow* layer. The supported learning paradigms can be categorized into reinforcement learning and supervised learning. The learning framework leverages the *Workflow* layer as well(e.g. sharing *Information Extractor*, creating environments based on *Execution Env*).
Workflow layer	*Workflow* layer covers the whole workflow of quantitative investment. Both supervised-learning-based strategies and RL-based Strategies are supported. *Information Extractor* extracts data for models. *Forecast Model* focuses on producing all kinds of forecast signals (e.g. *alpha*, risk) for other modules. With these signals *Decision Generator* will generate the target trading decisions(i.e. portfolio, orders) If RL-based Strategies are adopted, the *Policy* is learned in a end-to-end way, the trading deicsions are generated directly. Decisions will be executed by *Execution Env* (i.e. the trading market). There may be multiple levels of *Strategy* and *Executor* (e.g. an *order executor trading strategy and intraday order executor* could behave like an interday trading loop and be nested in *daily portfolio management trading strategy and interday trading executor* trading loop)
Interface layer	*Interface* layer tries to present a user-friendly interface for the underlying system. *Analyser* module will provide users detailed analysis reports of forecasting signals, portfolios and execution results

- The modules with hand-drawn style are under development and will be released in the future.
- The modules with dashed borders are highly user-customizable and extendible.

(p.s. framework image is created with https://draw.io/)

1.2 Quick Start

1.2.1 Introduction

This `Quick Start` guide tries to demonstrate

- It's very easy to build a complete Quant research workflow and try users' ideas with `Qlib`.
- Though with public data and simple models, machine learning technologies work very well in practical Quant investment.

1.2.2 Installation

Users can easily intsall `Qlib` according to the following steps:

- Before installing `Qlib` from source, users need to install some dependencies:

- Clone the repository and install `Qlib`

To known more about *installation*, please refer to Qlib Installation.

1.2.3 Prepare Data

Load and prepare data by running the following code:

This dataset is created by public data collected by crawler scripts in `scripts/data_collector/`, which have been released in the same repository. Users could create the same dataset with it.

To known more about *prepare data*, please refer to Data Preparation.

1.2.4 Auto Quant Research Workflow

`Qlib` provides a tool named `qrun` to run the whole workflow automatically (including building dataset, training models, backtest and evaluation). Users can start an auto quant research workflow and have a graphical reports analysis according to the following steps:

- **Quant Research Workflow:**
  - Run `qrun` with a config file of the LightGBM model *workflow_config_lightgbm.yaml* as following.
  - **Workflow result** The result of `qrun` is as follows, which is also the typical result of `Forecast model(alpha)`. Please refer to Intraday Trading. for more details about the result.

```
                                                      risk
excess_return_without_cost mean               0.000605
                           std                0.005481
                           annualized_return  0.152373
                           information_ratio  1.751319
                           max_drawdown      -0.059055
excess_return_with_cost    mean               0.000410
                           std                0.005478
                           annualized_return  0.103265
                           information_ratio  1.187411
                           max_drawdown      -0.075024
```

  To know more about *workflow* and *qrun*, please refer to Workflow: Workflow Management.

- **Graphical Reports Analysis:**
  - **Run `examples/workflow_by_code.ipynb` with jupyter notebook** Users can have portfolio analysis or prediction score (model prediction) analysis by run `examples/workflow_by_code.ipynb`.
  - **Graphical Reports** Users can get graphical reports about the analysis, please refer to Analysis: Evaluation & Results Analysis for more details.

1.2.5 Custom Model Integration

`Qlib` provides a batch of models (such as `lightGBM` and `MLP` models) as examples of `Forecast Model`. In addition to the default model, users can integrate their own custom models into `Qlib`. If users are interested in the custom model, please refer to Custom Model Integration.

1.3 Installation

1.3.1 Qlib Installation

Note: *Qlib* supports both *Windows* and *Linux*. It's recommended to use *Qlib* in *Linux*. `Qlib` supports Python3, which is up to Python3.8.

Users can easily install `Qlib` by pip according to the following command:

```
pip install pyqlib
```

Also, Users can install `Qlib` by the source code according to the following steps:

- Enter the root directory of `Qlib`, in which the file `setup.py` exists.
- Then, please execute the following command to install the environment dependencies and install `Qlib`:

  ```
  $ pip install numpy
  $ pip install --upgrade cython
  $ git clone https://github.com/microsoft/qlib.git && cd qlib
  $ python setup.py install
  ```

Note: It's recommended to use anaconda/miniconda to setup the environment. `Qlib` needs lightgbm and pytorch packages, use pip to install them.

Use the following code to make sure the installation successful:

```
>>> import qlib
>>> qlib.__version__
<LATEST VERSION>
```

1.4 Qlib Initialization

1.4.1 Initialization

Please follow the steps below to initialize `Qlib`.

Download and prepare the Data: execute the following command to download stock data. Please pay *attention* that the data is collected from Yahoo Finance and the data might not be perfect. We recommend users to prepare their own data if they have high-quality datasets. Please refer to Data for more information about customized dataset.

```
python scripts/get_data.py qlib_data --target_dir ~/.qlib/qlib_data/cn_data -
↪-region cn
```

Please refer to Data Preparation for more information about *get_data.py*,

Initialize Qlib before calling other APIs: run following code in python.

```
import qlib
# region in [REG_CN, REG_US]
from qlib.constant import REG_CN
```

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```
provider_uri = "~/.qlib/qlib_data/cn_data"  # target_dir
qlib.init(provider_uri=provider_uri, region=REG_CN)
```

Note: Do not import qlib package in the repository directory of `Qlib`, otherwise, errors may occur.

Parameters

Besides *provider_uri* and *region*, *qlib.init* has other parameters. The following are several important parameters of *qlib.init* (*Qlib* has a lot of config. Only part of parameters are limited here. More detailed setting can be found here):

- ***provider_uri*** Type: str. The URI of the Qlib data. For example, it could be the location where the data loaded by `get_data.py` are stored.
- ***region***

  Type: str, optional parameter(default: *qlib.constant.REG_CN*). Currently: `qlib.constant.REG_US` ('us') and `qlib.constant.REG_CN` ('cn') is supported. Different value of *region* will result in different stock market mode. - `qlib.constant.REG_US`: US stock market. - `qlib.constant.REG_CN`: China stock market.

  Different modes will result in different trading limitations and costs. The region is just shortcuts for defining a batch of configurations, which include minimal trading order unit (`trade_unit`), trading limitation (`limit_threshold`) , etc. It is not a necessary part and users can set the key configurations manually if the existing region setting can't meet their requirements.
- ***redis_host***

  Type: str, optional parameter(default: "127.0.0.1"), host of *redis* The lock and cache mechanism relies on redis.
- ***redis_port*** Type: int, optional parameter(default: 6379), port of *redis*

  Note: The value of *region* should be aligned with the data stored in *provider_uri*. Currently, `scripts/get_data.py` only provides China stock market data. If users want to use the US stock market data, they should prepare their own US-stock data in *provider_uri* and switch to US-stock mode.

  Note: If Qlib fails to connect redis via *redis_host* and *redis_port*, cache mechanism will not be used! Please refer to Cache for details.
- ***exp_manager*** Type: dict, optional parameter, the setting of *experiment manager* to be used in qlib. Users can specify an experiment manager class, as well as the tracking URI for all the experiments. However, please be aware that we only support input of a dictionary in the following style for *exp_manager*. For more information about *exp_manager*, users can refer to Recorder: Experiment Management.

```
# For example, if you want to set your tracking_uri to a <specific folder>,␣
↪you can initialize qlib below
qlib.init(provider_uri=provider_uri, region=REG_CN, exp_manager= {
    "class": "MLflowExpManager",
    "module_path": "qlib.workflow.expm",
    "kwargs": {
        "uri": "python_execution_path/mlruns",
```

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```
        "default_exp_name": "Experiment",
    }
})
```

- ***mongo*** Type: dict, optional parameter, the setting of MongoDB which will be used in some features such as Task Management, with high performance and clustered processing. Users need to follow the steps in installation to install MongoDB firstly and then access it via a URI. Users can access mongodb with credential by setting "task_url" to a string like *"mongodb://%s:%s@%s" % (user, pwd, host + ":" + port)*.

```
# For example, you can initialize qlib below
qlib.init(provider_uri=provider_uri, region=REG_CN, mongo={
    "task_url": "mongodb://localhost:27017/",  # your mongo url
    "task_db_name": "rolling_db", # the database name of Task Management
})
```

- ***logging_level*** The logging level for the system.
- ***kernels*** The number of processes used when calculating features in Qlib's expression engine. It is very helpful to set it to 1 when you are debuggin an expression calculating exception

1.5 Data Retrieval

1.5.1 Introduction

Users can get stock data with `Qlib`. The following examples demonstrate the basic user interface.

1.5.2 Examples

`QLib` Initialization:

Note: In order to get the data, users need to initialize `Qlib` with *qlib.init* first. Please refer to initialization.

If users followed steps in initialization and downloaded the data, they should use the following code to initialize qlib

```
>> import qlib
>> qlib.init(provider_uri='~/.qlib/qlib_data/cn_data')
```

Load trading calendar with given time range and frequency:

```
>> from qlib.data import D
>> D.calendar(start_time='2010-01-01', end_time='2017-12-31', freq='day')[:2]
[Timestamp('2010-01-04 00:00:00'), Timestamp('2010-01-05 00:00:00')]
```

Parse a given market name into a stock pool config:

```
>> from qlib.data import D
>> D.instruments(market='all')
{'market': 'all', 'filter_pipe': []}
```

Load instruments of certain stock pool in the given time range:

```
>> from qlib.data import D
>> instruments = D.instruments(market='csi300')
>> D.list_instruments(instruments=instruments, start_time='2010-01-01', end_time=
↪'2017-12-31', as_list=True)[:6]
['SH600036', 'SH600110', 'SH600087', 'SH600900', 'SH600089', 'SZ000912']
```

Load dynamic instruments from a base market according to a name filter

```
>> from qlib.data import D
>> from qlib.data.filter import NameDFilter
>> nameDFilter = NameDFilter(name_rule_re='SH[0-9]{4}55')
>> instruments = D.instruments(market='csi300', filter_pipe=[nameDFilter])
>> D.list_instruments(instruments=instruments, start_time='2015-01-01', end_time=
↪'2016-02-15', as_list=True)
['SH600655', 'SH601555']
```

Load dynamic instruments from a base market according to an expression filter

```
>> from qlib.data import D
>> from qlib.data.filter import ExpressionDFilter
>> expressionDFilter = ExpressionDFilter(rule_expression='$close>2000')
>> instruments = D.instruments(market='csi300', filter_pipe=[expressionDFilter])
>> D.list_instruments(instruments=instruments, start_time='2015-01-01', end_time=
↪'2016-02-15', as_list=True)
['SZ000651', 'SZ000002', 'SH600655', 'SH600570']
```

For more details about filter, please refer Filter API.

Load features of certain instruments in a given time range:

```
>> from qlib.data import D
>> instruments = ['SH600000']
>> fields = ['$close', '$volume', 'Ref($close, 1)', 'Mean($close, 3)', '$high-$low']
>> D.features(instruments, fields, start_time='2010-01-01', end_time='2017-12-31',␣
↪freq='day').head().to_string()
'                           $close     $volume  Ref($close, 1)  Mean($close, 3)  ␣
↪$high-$low
... instrument  datetime
... SH600000    2010-01-04  86.778313  16162960.0       88.825928        88.061483    ␣
↪2.907631
...             2010-01-05  87.433578  28117442.0       86.778313        87.679273    ␣
↪3.235252
...             2010-01-06  85.713585  23632884.0       87.433578        86.641825    ␣
↪1.720009
...             2010-01-07  83.788803  20813402.0       85.713585        85.645322    ␣
↪3.030487
...             2010-01-08  84.730675  16044853.0       83.788803        84.744354    ␣
↪2.047623'
```

Load features of certain stock pool in a given time range:

Note: With cache enabled, the qlib data server will cache data all the time for the requested stock pool and fields, it may take longer to process the request for the first time than that without cache. But after the first time, requests with the same stock pool and fields will hit the cache and be processed faster even the requested time period changes.

```
>> from qlib.data import D
>> from qlib.data.filter import NameDFilter, ExpressionDFilter
>> nameDFilter = NameDFilter(name_rule_re='SH[0-9]{4}55')
>> expressionDFilter = ExpressionDFilter(rule_expression='$close>Ref($close,1)')
>> instruments = D.instruments(market='csi300', filter_pipe=[nameDFilter,␣
↪expressionDFilter])
>> fields = ['$close', '$volume', 'Ref($close, 1)', 'Mean($close, 3)', '$high-$low']
>> D.features(instruments, fields, start_time='2010-01-01', end_time='2017-12-31',␣
↪freq='day').head().to_string()
'                              $close        $volume  Ref($close, 1)  Mean($close, 3)␣
↪ $high-$low
... instrument  datetime
... SH600655    2010-01-04  2699.567383  158193.328125     2619.070312      2626.
↪097738  124.580566
...             2010-01-08  2612.359619   77501.406250     2584.567627      2623.
↪220133   83.373047
...             2010-01-11  2712.982422  160852.390625     2612.359619      2636.
↪636556  146.621582
...             2010-01-12  2788.688232  164587.937500     2712.982422      2704.
↪676758  128.413818
...             2010-01-13  2790.604004  145460.453125     2788.688232      2764.
↪091553  128.413818'
```

For more details about features, please refer Feature API.

Note: When calling *D.features()* at the client, use parameter *disk_cache=0* to skip dataset cache, use *disk_cache=1* to generate and use dataset cache. In addition, when calling at the server, users can use *disk_cache=2* to update the dataset cache.

When you are building complicated expressions, implementing all the expressions in a single string may not be easy. For example, it looks quite long and complicated:

```
>> from qlib.data import D
>> data = D.features(["sh600519"], ["(($high / $close) + ($open / $close)) * (($high /
↪ $close) + ($open / $close)) / (($high / $close) + ($open / $close))"], start_time=
↪"20200101")
```

But using string is not the only way to implement the expression. You can also implement expression by code. Here is an exmaple which does the same thing as above examples.

```
>> from qlib.data.ops import *
>> f1 = Feature("high") / Feature("close")
>> f2 = Feature("open") / Feature("close")
>> f3 = f1 + f2
>> f4 = f3 * f3 / f3

>> data = D.features(["sh600519"], [f4], start_time="20200101")
>> data.head()
```

1.5.3 API

To know more about how to use the Data, go to API Reference: Data API

1.6 Custom Model Integration

1.6.1 Introduction

`Qlib`'s *Model Zoo* includes models such as `LightGBM`, `MLP`, `LSTM`, etc.. These models are examples of `Forecast Model`. In addition to the default models `Qlib` provide, users can integrate their own custom models into `Qlib`.

Users can integrate their own custom models according to the following steps.

- Define a custom model class, which should be a subclass of the qlib.model.base.Model.
- Write a configuration file that describes the path and parameters of the custom model.
- Test the custom model.

1.6.2 Custom Model Class

The Custom models need to inherit qlib.model.base.Model and override the methods in it.

- **Override the *__init__* method**
  - `Qlib` passes the initialized parameters to the __init__ method.
  - The hyperparameters of model in the configuration must be consistent with those defined in the *__init__* method.
  - Code Example: In the following example, the hyperparameters of model in the configuration file should contain parameters such as *loss:mse*.

```
def __init__(self, loss='mse', **kwargs):
    if loss not in {'mse', 'binary'}:
        raise NotImplementedError
    self._scorer = mean_squared_error if loss == 'mse' else roc_auc_
↪score
    self._params.update(objective=loss, **kwargs)
    self._model = None
```

- **Override the *fit* method**
  - `Qlib` calls the fit method to train the model.
  - The parameters must include training feature *dataset*, which is designed in the interface.
  - The parameters could include some *optional* parameters with default values, such as *num_boost_round = 1000* for *GBDT*.
  - Code Example: In the following example, *num_boost_round = 1000* is an optional parameter.

```
def fit(self, dataset: DatasetH, num_boost_round = 1000, **kwargs):

    # prepare dataset for lgb training and evaluation
    df_train, df_valid = dataset.prepare(
        ["train", "valid"], col_set=["feature", "label"], data_
↪key=DataHandlerLP.DK_L
    )
    x_train, y_train = df_train["feature"], df_train["label"]
    x_valid, y_valid = df_valid["feature"], df_valid["label"]

    # Lightgbm need 1D array as its label
```

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```
    if y_train.values.ndim == 2 and y_train.values.shape[1] == 1:
        y_train, y_valid = np.squeeze(y_train.values), np.squeeze(y_
↪valid.values)
    else:
        raise ValueError("LightGBM doesn't support multi-label␣
↪training")

    dtrain = lgb.Dataset(x_train.values, label=y_train)
    dvalid = lgb.Dataset(x_valid.values, label=y_valid)

    # fit the model
    self.model = lgb.train(
        self.params,
        dtrain,
        num_boost_round=num_boost_round,
        valid_sets=[dtrain, dvalid],
        valid_names=["train", "valid"],
        early_stopping_rounds=early_stopping_rounds,
        verbose_eval=verbose_eval,
        evals_result=evals_result,
        **kwargs
    )
```

- **Override the *predict* method**
  - The parameters must include the parameter *dataset*, which will be userd to get the test dataset.
  - Return the *prediction score*.
  - Please refer to Model API for the parameter types of the fit method.
  - Code Example: In the following example, users need to use *LightGBM* to predict the label(such as *preds*) of test data *x_test* and return it.

```
def predict(self, dataset: DatasetH, **kwargs)-> pandas.Series:
    if self.model is None:
        raise ValueError("model is not fitted yet!")
    x_test = dataset.prepare("test", col_set="feature", data_
↪key=DataHandlerLP.DK_I)
    return pd.Series(self.model.predict(x_test.values), index=x_
↪test.index)
```

- **Override the *finetune* method (Optional)**
  - This method is optional to the users. When users want to use this method on their own models, they should inherit the `ModelFT` base class, which includes the interface of *finetune*.
  - The parameters must include the parameter *dataset*.
  - Code Example: In the following example, users will use *LightGBM* as the model and finetune it.

```
def finetune(self, dataset: DatasetH, num_boost_round=10, verbose_
↪eval=20):
    # Based on existing model and finetune by train more rounds
    dtrain, _ = self._prepare_data(dataset)
    self.model = lgb.train(
        self.params,
        dtrain,
        num_boost_round=num_boost_round,
```

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```
        init_model=self.model,
        valid_sets=[dtrain],
        valid_names=["train"],
        verbose_eval=verbose_eval,
    )
```

1.6.3 Configuration File

The configuration file is described in detail in the Workflow document. In order to integrate the custom model into `Qlib`, users need to modify the "model" field in the configuration file. The configuration describes which models to use and how we can initialize it.

- Example: The following example describes the *model* field of configuration file about the custom lightgbm model mentioned above, where *module_path* is the module path, *class* is the class name, and *args* is the hyper-parameter passed into the __init__ method. All parameters in the field is passed to *self._params* by ***kwargs* in *__init__* except *loss = mse*.

```yaml
model:
    class: LGBModel
    module_path: qlib.contrib.model.gbdt
    args:
        loss: mse
        colsample_bytree: 0.8879
        learning_rate: 0.0421
        subsample: 0.8789
        lambda_l1: 205.6999
        lambda_l2: 580.9768
        max_depth: 8
        num_leaves: 210
        num_threads: 20
```

Users could find configuration file of the baselines of the `Model` in `examples/benchmarks`. All the configurations of different models are listed under the corresponding model folder.

1.6.4 Model Testing

Assuming that the configuration file is `examples/benchmarks/LightGBM/workflow_config_lightgbm.yaml`, users can run the following command to test the custom model:

```
cd examples  # Avoid running program under the directory contains `qlib`
qrun benchmarks/LightGBM/workflow_config_lightgbm.yaml
```

Note: `qrun` is a built-in command of `Qlib`.

Also, `Model` can also be tested as a single module. An example has been given in `examples/workflow_by_code.ipynb`.

1.6.5 Reference

To know more about `Forecast Model`, please refer to Forecast Model: Model Training & Prediction and Model API.

1.7 Workflow: Workflow Management

1.7.1 Introduction

The components in Qlib Framework are designed in a loosely-coupled way. Users could build their own Quant research workflow with these components like Example.

Besides, `Qlib` provides more user-friendly interfaces named `qrun` to automatically run the whole workflow defined by configuration. Running the whole workflow is called an *execution*. With `qrun`, user can easily start an *execution*, which includes the following steps:

- **Data**
  - Loading
  - Processing
  - Slicing
- **Model**
  - Training and inference
  - Saving & loading
- **Evaluation**
  - Forecast signal analysis
  - Backtest

For each *execution*, `Qlib` has a complete system to tracking all the information as well as artifacts generated during training, inference and evaluation phase. For more information about how `Qlib` handles this, please refer to the related document: Recorder: Experiment Management.

1.7.2 Complete Example

Before getting into details, here is a complete example of `qrun`, which defines the workflow in typical Quant research. Below is a typical config file of `qrun`.

```yaml
qlib_init:
    provider_uri: "~/.qlib/qlib_data/cn_data"
    region: cn
market: &market csi300
benchmark: &benchmark SH000300
data_handler_config: &data_handler_config
    start_time: 2008-01-01
    end_time: 2020-08-01
    fit_start_time: 2008-01-01
    fit_end_time: 2014-12-31
    instruments: *market
port_analysis_config: &port_analysis_config
    strategy:
        class: TopkDropoutStrategy
        module_path: qlib.contrib.strategy.strategy
        kwargs:
            topk: 50
            n_drop: 5
            signal:
```

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```yaml
                - <MODEL>
                - <DATASET>
    backtest:
        limit_threshold: 0.095
        account: 100000000
        benchmark: *benchmark
        deal_price: close
        open_cost: 0.0005
        close_cost: 0.0015
        min_cost: 5
task:
    model:
        class: LGBModel
        module_path: qlib.contrib.model.gbdt
        kwargs:
            loss: mse
            colsample_bytree: 0.8879
            learning_rate: 0.0421
            subsample: 0.8789
            lambda_l1: 205.6999
            lambda_l2: 580.9768
            max_depth: 8
            num_leaves: 210
            num_threads: 20
    dataset:
        class: DatasetH
        module_path: qlib.data.dataset
        kwargs:
            handler:
                class: Alpha158
                module_path: qlib.contrib.data.handler
                kwargs: *data_handler_config
            segments:
                train: [2008-01-01, 2014-12-31]
                valid: [2015-01-01, 2016-12-31]
                test: [2017-01-01, 2020-08-01]
    record:
        - class: SignalRecord
          module_path: qlib.workflow.record_temp
          kwargs: {}
        - class: PortAnaRecord
          module_path: qlib.workflow.record_temp
          kwargs:
              config: *port_analysis_config
```

After saving the config into *configuration.yaml*, users could start the workflow and test their ideas with a single command below.

```
qrun configuration.yaml
```

If users want to use `qrun` under debug mode, please use the following command:

```
python -m pdb qlib/workflow/cli.py examples/benchmarks/LightGBM/workflow_config_
↪lightgbm_Alpha158.yaml
```

Note: *qrun* will be placed in your $PATH directory when installing `Qlib`.

Note: The symbol *&* in *yaml* file stands for an anchor of a field, which is useful when another fields include this parameter as part of the value. Taking the configuration file above as an example, users can directly change the value of *market* and *benchmark* without traversing the entire configuration file.

1.7.3 Configuration File

Let's get into details of `qrun` in this section. Before using `qrun`, users need to prepare a configuration file. The following content shows how to prepare each part of the configuration file.

The design logic of the configuration file is very simple. It predefines fixed workflows and provide this yaml interface to users to define how to initialize each component. It follow the design of init_instance_by_config . It defines the initialization of each component of Qlib, which typically include the class and the initialization arguments.

For example, the following yaml and code are equivalent.

```yaml
model:
    class: LGBModel
    module_path: qlib.contrib.model.gbdt
    kwargs:
        loss: mse
        colsample_bytree: 0.8879
        learning_rate: 0.0421
        subsample: 0.8789
        lambda_l1: 205.6999
        lambda_l2: 580.9768
        max_depth: 8
        num_leaves: 210
        num_threads: 20
```

```python
from qlib.contrib.model.gbdt import LGBModel
kwargs = {
    "loss": "mse" ,
    "colsample_bytree": 0.8879,
    "learning_rate": 0.0421,
    "subsample": 0.8789,
    "lambda_l1": 205.6999,
    "lambda_l2": 580.9768,
    "max_depth": 8,
    "num_leaves": 210,
    "num_threads": 20,
}
LGBModel(kwargs)
```

Qlib Init Section

At first, the configuration file needs to contain several basic parameters which will be used for qlib initialization.

```yaml
provider_uri: "~/.qlib/qlib_data/cn_data"
region: cn
```

The meaning of each field is as follows:

- ***provider_uri*** Type: str. The URI of the Qlib data. For example, it could be the location where the data loaded by `get_data.py` are stored.
- ***region***
  - If *region* == "us", `Qlib` will be initialized in US-stock mode.
  - If *region* == "cn", `Qlib` will be initialized in China-stock mode.

  Note: The value of *region* should be aligned with the data stored in *provider_uri*.

Task Section

The *task* field in the configuration corresponds to a *task*, which contains the parameters of three different subsections: *Model*, *Dataset* and *Record*.

Model Section

In the *task* field, the *model* section describes the parameters of the model to be used for training and inference. For more information about the base `Model` class, please refer to Qlib Model.

```yaml
model:
    class: LGBModel
    module_path: qlib.contrib.model.gbdt
    kwargs:
        loss: mse
        colsample_bytree: 0.8879
        learning_rate: 0.0421
        subsample: 0.8789
        lambda_l1: 205.6999
        lambda_l2: 580.9768
        max_depth: 8
        num_leaves: 210
        num_threads: 20
```

The meaning of each field is as follows:

- ***class*** Type: str. The name for the model class.
- ***module_path*** Type: str. The path for the model in qlib.
- ***kwargs*** The keywords arguments for the model. Please refer to the specific model implementation for more information: models.

Note: `Qlib` provides a util named: `init_instance_by_config` to initialize any class inside `Qlib` with the configuration includes the fields: *class*, *module_path* and *kwargs*.

Dataset Section

The *dataset* field describes the parameters for the `Dataset` module in `Qlib` as well those for the module `DataHandler`. For more information about the `Dataset` module, please refer to Qlib Data.

The keywords arguments configuration of the `DataHandler` is as follows:

```
data_handler_config: &data_handler_config
    start_time: 2008-01-01
    end_time: 2020-08-01
    fit_start_time: 2008-01-01
    fit_end_time: 2014-12-31
    instruments: *market
```

Users can refer to the document of DataHandler for more information about the meaning of each field in the configuration.

Here is the configuration for the `Dataset` module which will take care of data preprocessing and slicing during the training and testing phase.

```
dataset:
    class: DatasetH
    module_path: qlib.data.dataset
    kwargs:
        handler:
            class: Alpha158
            module_path: qlib.contrib.data.handler
            kwargs: *data_handler_config
        segments:
            train: [2008-01-01, 2014-12-31]
            valid: [2015-01-01, 2016-12-31]
            test: [2017-01-01, 2020-08-01]
```

Record Section

The *record* field is about the parameters the `Record` module in `Qlib. Record` is responsible for tracking training process and results such as *information Coefficient (IC)* and *backtest* in a standard format.

The following script is the configuration of *backtest* and the *strategy* used in *backtest*:

```
port_analysis_config: &port_analysis_config
    strategy:
        class: TopkDropoutStrategy
        module_path: qlib.contrib.strategy.strategy
        kwargs:
            topk: 50
            n_drop: 5
            signal:
                - <MODEL>
                - <DATASET>
    backtest:
        limit_threshold: 0.095
        account: 100000000
        benchmark: *benchmark
        deal_price: close
        open_cost: 0.0005
        close_cost: 0.0015
        min_cost: 5
```

For more information about the meaning of each field in configuration of *strategy* and *backtest*, users can look up the documents: Strategy and Backtest.

Here is the configuration details of different *Record Template* such as `SignalRecord` and `PortAnaRecord`:

```yaml
record:
    - class: SignalRecord
      module_path: qlib.workflow.record_temp
      kwargs: {}
    - class: PortAnaRecord
      module_path: qlib.workflow.record_temp
      kwargs:
        config: *port_analysis_config
```

For more information about the `Record` module in `Qlib`, user can refer to the related document: Record.

1.8 Data Layer: Data Framework & Usage

1.8.1 Introduction

`Data Layer` provides user-friendly APIs to manage and retrieve data. It provides high-performance data infrastructure.

It is designed for quantitative investment. For example, users could build formulaic alphas with `Data Layer` easily. Please refer to Building Formulaic Alphas for more details.

The introduction of `Data Layer` includes the following parts.

- Data Preparation
- Data API
- Data Loader
- Data Handler
- Dataset
- Cache
- Data and Cache File Structure

Here is a typical example of Qlib data workflow

- Users download data and converting data into Qlib format(with filename suffix *.bin*). In this step, typically only some basic data are stored on disk(such as OHLCV).
- Creating some basic features based on Qlib's expression Engine(e.g. "Ref($close, 60) / $close", the return of last 60 trading days). Supported operators in the expression engine can be found here. This step is typically implemented in Qlib's Data Loader which is a component of Data Handler .
- If users require more complicated data processing (e.g. data normalization), Data Handler support user-customized processors to process data(some predefined processors can be found here). The processors are different from operators in expression engine. It is designed for some complicated data processing methods which is hard to supported in operators in expression engine.
- At last, Dataset is responsible to prepare model-specific dataset from the processed data of Data Handler

1.8.2 Data Preparation

Qlib Format Data

We've specially designed a data structure to manage financial data, please refer to the File storage design section in Qlib paper for detailed information. Such data will be stored with filename suffix *.bin* (We'll call them *.bin* file, *.bin* format, or qlib format). *.bin* file is designed for scientific computing on finance data.

`Qlib` provides two different off-the-shelf datasets, which can be accessed through this link:

Dataset	US Market	China Market
Alpha360		
Alpha158		

Also, `Qlib` provides a high-frequency dataset. Users can run a high-frequency dataset example through this link.

Qlib Format Dataset

`Qlib` has provided an off-the-shelf dataset in *.bin* format, users could use the script `scripts/get_data.py` to download the China-Stock dataset as follows. User can also use numpy to load *.bin* file to validate data. The price volume data look different from the actual dealling price because of they are **adjusted** (adjusted price). And then you may find that the adjusted price may be different from different data sources. This is because different data sources may vary in the way of adjusting prices. Qlib normalize the price on first trading day of each stock to 1 when adjusting them. Users can leverage *$factor* to get the original trading price (e.g. *$close / $factor* to get the original close price).

Here are some discussions about the price adjusting of Qlib.

- https://github.com/microsoft/qlib/issues/991#issuecomment-1075252402

```
# download 1d
python scripts/get_data.py qlib_data --target_dir ~/.qlib/qlib_data/cn_data --region␣
↪cn

# download 1min
python scripts/get_data.py qlib_data --target_dir ~/.qlib/qlib_data/qlib_cn_1min --
↪region cn --interval 1min
```

In addition to China-Stock data, `Qlib` also includes a US-Stock dataset, which can be downloaded with the following command:

```
python scripts/get_data.py qlib_data --target_dir ~/.qlib/qlib_data/us_data --region␣
↪us
```

After running the above command, users can find china-stock and us-stock data in `Qlib` format in the `~/.qlib/qlib_data/cn_data` directory and `~/.qlib/qlib_data/us_data` directory respectively.

`Qlib` also provides the scripts in `scripts/data_collector` to help users crawl the latest data on the Internet and convert it to qlib format.

When `Qlib` is initialized with this dataset, users could build and evaluate their own models with it. Please refer to Initialization for more details.

Automatic update of daily frequency data

> **It is recommended that users update the data manually once (–trading_date 2021-05-25) and then set it to update automatically.**
>
> For more information refer to: yahoo collector

- **Automatic update of data to the "qlib" directory each trading day(Linux)**
  - use *crontab*: *crontab -e*
  - set up timed tasks:

```
* * * * 1-5 python <script path> update_data_to_bin --qlib_data_1d_
↪dir <user data dir>
```

    * **script path**: *scripts/data_collector/yahoo/collector.py*
- Manual update of data

```
python scripts/data_collector/yahoo/collector.py update_data_to_
↪bin --qlib_data_1d_dir <user data dir> --trading_date <start␣
↪date> --end_date <end date>
```

  - *trading_date*: start of trading day
  - *end_date*: end of trading day(not included)

Converting CSV Format into Qlib Format

`Qlib` has provided the script `scripts/dump_bin.py` to convert **any** data in CSV format into *.bin* files (`Qlib` format) as long as they are in the correct format.

Besides downloading the prepared demo data, users could download demo data directly from the Collector as follows for reference to the CSV format. Here are some example:

for daily data:

```
python scripts/get_data.py csv_data_cn --target_dir ~/.qlib/csv_data/cn_data
```

for 1min data:

```
python scripts/data_collector/yahoo/collector.py download_data --source_dir ~/.
↪qlib/stock_data/source/cn_1min --region CN --start 2021-05-20 --end 2021-05-23 -
↪-delay 0.1 --interval 1min --limit_nums 10
```

Users can also provide their own data in CSV format. However, the CSV data **must satisfies** following criterions:

- CSV file is named after a specific stock *or* the CSV file includes a column of the stock name
  - Name the CSV file after a stock: *SH600000.csv*, *AAPL.csv* (not case sensitive).
  - CSV file includes a column of the stock name. User **must** specify the column name when dumping the data. Here is an example:

```
python scripts/dump_bin.py dump_all ... --symbol_field_name symbol
```

    where the data are in the following format:
- CSV file **must** includes a column for the date, and when dumping the data, user must specify the date column name. Here is an example:

```
python scripts/dump_bin.py dump_all ... --date_field_name date
```

  where the data are in the following format:

Supposed that users prepare their CSV format data in the directory `~/.qlib/csv_data/my_data`, they can run the following command to start the conversion.

```
python scripts/dump_bin.py dump_all --csv_path  ~/.qlib/csv_data/my_data --qlib_dir ~/
↪.qlib/qlib_data/my_data --include_fields open,close,high,low,volume,factor
```

For other supported parameters when dumping the data into *.bin* file, users can refer to the information by running the following commands:

```
python dump_bin.py dump_all --help
```

After conversion, users can find their Qlib format data in the directory *~/.qlib/qlib_data/my_data*.

Note: The arguments of *–include_fields* should correspond with the column names of CSV files. The columns names of dataset provided by `Qlib` should include open, close, high, low, volume and factor at least.

- ***open*** The adjusted opening price
- ***close*** The adjusted closing price
- ***high*** The adjusted highest price
- ***low*** The adjusted lowest price
- ***volume*** The adjusted trading volume
- ***factor*** The Restoration factor. Normally, `factor = adjusted_price / original_price`, *adjusted price* reference: split adjusted

In the convention of *Qlib* data processing, *open, close, high, low, volume, money and factor* will be set to NaN if the stock is suspended. If you want to use your own alpha-factor which can't be calculate by OCHLV, like PE, EPS and so on, you could add it to the CSV files with OHCLV together and then dump it to the Qlib format data.

Stock Pool (Market)

`Qlib` defines stock pool as stock list and their date ranges. Predefined stock pools (e.g. csi300) may be imported as follows.

```
python collector.py --index_name CSI300 --qlib_dir <user qlib data dir> --method␣
↪parse_instruments
```

Multiple Stock Modes

`Qlib` now provides two different stock modes for users: China-Stock Mode & US-Stock Mode. Here are some different settings of these two modes:

Region	Trade Unit	Limit Threshold
China	100	0.099
US	1	None

The *trade unit* defines the unit number of stocks can be used in a trade, and the *limit threshold* defines the bound set to the percentage of ups and downs of a stock.

- **If users use `Qlib` in china-stock mode, china-stock data is required. Users can use `Qlib` in china-stock mode according t**
    - Download china-stock in qlib format, please refer to section *Qlib Format Dataset*.

- **Initialize `Qlib` in china-stock mode** Supposed that users download their Qlib format data in the directory `~/.qlib/qlib_data/cn_data`. Users only need to initialize `Qlib` as follows.

```
from qlib.constant import REG_CN
qlib.init(provider_uri='~/.qlib/qlib_data/cn_data', region=REG_CN)
```

- **If users use `Qlib` in US-stock mode, US-stock data is required. `Qlib` also provides a script to download US-stock data. U**

  - Download us-stock in qlib format, please refer to section *Qlib Format Dataset*.
  - **Initialize `Qlib` in US-stock mode** Supposed that users prepare their Qlib format data in the directory `~/.qlib/qlib_data/us_data`. Users only need to initialize `Qlib` as follows.

```
from qlib.config import REG_US
qlib.init(provider_uri='~/.qlib/qlib_data/us_data', region=REG_US)
```

Note: PRs for new data source are highly welcome! Users could commit the code to crawl data as a PR like the examples here. And then we will use the code to create data cache on our server which other users could use directly.

1.8.3 Data API

Data Retrieval

Users can use APIs in `qlib.data` to retrieve data, please refer to Data Retrieval.

Feature

`Qlib` provides *Feature* and *ExpressionOps* to fetch the features according to users' needs.

- ***Feature*** Load data from the data provider. User can get the features like *$high*, *$low*, *$open*, *$close*, .etc, which should correspond with the arguments of *–include_fields*, please refer to section *Converting CSV Format into Qlib Format*.
- ***ExpressionOps*** *ExpressionOps* will use operator for feature construction. To know more about `Operator`, please refer to Operator API. Also, `Qlib` supports users to define their own custom `Operator`, an example has been given in `tests/test_register_ops.py`.

To know more about `Feature`, please refer to Feature API.

Filter

`Qlib` provides *NameDFilter* and *ExpressionDFilter* to filter the instruments according to users' needs.

- ***NameDFilter*** Name dynamic instrument filter. Filter the instruments based on a regulated name format. A name rule regular expression is required.
- ***ExpressionDFilter*** Expression dynamic instrument filter. Filter the instruments based on a certain expression. An expression rule indicating a certain feature field is required.
  - *basic features filter*: rule_expression = '$close/$open>5'
  - *cross-sectional features filter* : rule_expression = '$rank($close)<10'
  - *time-sequence features filter*: rule_expression = '$Ref($close, 3)>100'

Here is a simple example showing how to use filter in a basic `Qlib` workflow configuration file:

```
filter: &filter
    filter_type: ExpressionDFilter
    rule_expression: "Ref($close, -2) / Ref($close, -1) > 1"
    filter_start_time: 2010-01-01
    filter_end_time: 2010-01-07
    keep: False

data_handler_config: &data_handler_config
    start_time: 2010-01-01
    end_time: 2021-01-22
    fit_start_time: 2010-01-01
    fit_end_time: 2015-12-31
    instruments: *market
    filter_pipe: [*filter]
```

To know more about `Filter`, please refer to Filter API.

Reference

To know more about `Data API`, please refer to Data API.

1.8.4 Data Loader

`Data Loader` in `Qlib` is designed to load raw data from the original data source. It will be loaded and used in the `Data Handler` module.

QlibDataLoader

The `QlibDataLoader` class in `Qlib` is such an interface that allows users to load raw data from the `Qlib` data source.

StaticDataLoader

The `StaticDataLoader` class in `Qlib` is such an interface that allows users to load raw data from file or as provided.

Interface

Here are some interfaces of the `QlibDataLoader` class:

class qlib.data.dataset.loader.**DataLoader**

DataLoader is designed for loading raw data from original data source.

load(*instruments*, *start_time=None*, *end_time=None*) → pandas.core.frame.DataFrame

load the data as pd.DataFrame.

Example of the data (The multi-index of the columns is optional.):

```
                         feature                                              ␣
↪                       label
                         $close     $volume     Ref($close, 1)  Mean(
↪$close, 3)  $high-$low  LABEL0
datetime    instrument
2010-01-04  SH600000    81.807068  17145150.0       83.737389               ␣
↪83.016739    2.741058  0.0032
            SH600004    13.313329  11800983.0       13.313329               ␣
↪13.317701    0.183632  0.0042
            SH600005    37.796539  12231662.0       38.258602               ␣
↪37.919757    0.970325  0.0289
```

Parameters

- **instruments** (*str or dict*) – it can either be the market name or the config file of instruments generated by InstrumentProvider.
- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.

Returns data load from the under layer source

Return type pd.DataFrame

API

To know more about `Data Loader`, please refer to Data Loader API.

1.8.5 Data Handler

The `Data Handler` module in `Qlib` is designed to handler those common data processing methods which will be used by most of the models.

Users can use `Data Handler` in an automatic workflow by `qrun`, refer to Workflow: Workflow Management for more details.

DataHandlerLP

In addition to use `Data Handler` in an automatic workflow with `qrun`, `Data Handler` can be used as an independent module, by which users can easily preprocess data (standardization, remove NaN, etc.) and build datasets.

In order to achieve so, `Qlib` provides a base class qlib.data.dataset.DataHandlerLP. The core idea of this class is that: we will have some learnable `Processors` which can learn the parameters of data processing(e.g., parameters for zscore normalization). When new data comes in, these *trained* `Processors` can then process the new data and thus processing real-time data in an efficient way becomes possible. More information about `Processors` will be listed in the next subsection.

Interface

Here are some important interfaces that `DataHandlerLP` provides:

class qlib.data.dataset.handler.**DataHandlerLP**(*instruments=None*, *start_time=None*, *end_time=None*, *data_loader: Union[dict, str, qlib.data.dataset.loader.DataLoader] = None*, *infer_processors: List[T] = []*, *learn_processors: List[T] = []*, *shared_processors: List[T] = []*, *process_type='append'*, *drop_raw=False*, ***kwargs*)

DataHandler with **(L)earnable (P)rocessor**

This handler will produce three pieces of data in pd.DataFrame format.

- DK_R / self._data: the raw data loaded from the loader
- DK_I / self._infer: the data processed for inference
- DK_L / self._learn: the data processed for learning model.

The motivation of using different processor workflows for learning and inference Here are some examples.

- The instrument universe for learning and inference may be different.
- The processing of some samples may rely on label (for example, some samples hit the limit may need extra processing or be dropped).
  - These processors only apply to the learning phase.

Tips to improve the performance of data handler

- To reduce the memory cost
  - *drop_raw=True*: this will modify the data inplace on raw data;

__init__(*instruments=None*, *start_time=None*, *end_time=None*, *data_loader: Union[dict, str, qlib.data.dataset.loader.DataLoader] = None*, *infer_processors: List[T] = []*, *learn_processors: List[T] = []*, *shared_processors: List[T] = []*, *process_type='append'*, *drop_raw=False*, ***kwargs*)

Parameters

- **infer_processors** (*list*) –
  - list of <description info> of processors to generate data for inference
  - example of <description info>:
- **learn_processors** (*list*) – similar to infer_processors, but for generating data for learning models
- **process_type** (*str*) – PTYPE_I = 'independent'
  - self._infer will be processed by infer_processors
  - self._learn will be processed by learn_processors

  PTYPE_A = 'append'
  - self._infer will be processed by infer_processors
  - self._learn will be processed by infer_processors + learn_processors
    - (e.g. self._infer processed by learn_processors)
- **drop_raw** (*bool*) – Whether to drop the raw data

fit()
fit data without processing the data

fit_process_data()
fit and process data

The input of the *fit* will be the output of the previous processor

process_data(*with_fit: bool = False*)
process_data data. Fun *processor.fit* if necessary

Notation: (data) [processor]

data processing flow of self.process_type == DataHandlerLP.PTYPE_I

```
(self._data)-[shared_processors]-(_shared_df)-[learn_processors]-(_learn_df)
                                              \
                                               -[infer_processors]-(_infer_df)
```

data processing flow of self.process_type == DataHandlerLP.PTYPE_A

```
(self._data)-[shared_processors]-(_shared_df)-[infer_processors]-(_infer_df)-
↪[learn_processors]-(_learn_df)
```

Parameters **with_fit** (*bool*) – The input of the *fit* will be the output of the previous processor

config(*processor_kwargs: dict = None*, ***kwargs*)
configuration of data. # what data to be loaded from data source

This method will be used when loading pickled handler from dataset. The data will be initialized with different time range.

setup_data(*init_type: str = 'fit_seq'*, ***kwargs*)
Set up the data in case of running initialization for multiple time

Parameters

- **init_type** (*str*) – The type *IT_** listed above.
- **enable_cache** (*bool*) – default value is false:
  - if *enable_cache* == True:

    the processed data will be saved on disk, and handler will load the cached data from the disk directly when we call *init* next time

fetch(*selector: Union[pandas._libs.tslibs.timestamps.Timestamp, slice, str] = slice(None, None, None)*, *level: Union[str, int] = 'datetime'*, *col_set='__all'*, *data_key: str = 'infer'*, *squeeze: bool = False*, *proc_func: Callable = None*) → pandas.core.frame.DataFrame
fetch data from underlying data source

Parameters

- **selector** (*Union[pd.Timestamp, slice, str]*) – describe how to select data by index.
- **level** (*Union[str, int]*) – which index level to select the data.
- **col_set** (*str*) – select a set of meaningful columns.(e.g. features, columns).
- **data_key** (*str*) – the data to fetch: DK_*.
- **proc_func** (*Callable*) – please refer to the doc of DataHandler.fetch

Returns

Return type pd.DataFrame

get_cols (*col_set='__all', data_key: str = 'infer'*) → list
get the column names

Parameters

- **col_set** (*str*) – select a set of meaningful columns.(e.g. features, columns).
- **data_key** (*str*) – the data to fetch: DK_*.

Returns list of column names

Return type list

classmethod cast (*handler: qlib.data.dataset.handler.DataHandlerLP*) → qlib.data.dataset.handler.DataHandlerLP
Motivation

- A user creates a datahandler in his customized package. Then he wants to share the processed handler to other users without introduce the package dependency and complicated data processing logic.
- This class make it possible by casting the class to DataHandlerLP and only keep the processed data

Parameters **handler** (`DataHandlerLP`) – A subclass of DataHandlerLP

Returns the converted processed data

Return type *DataHandlerLP*

If users want to load features and labels by config, users can define a new handler and call the static method *parse_config_to_fields* of `qlib.contrib.data.handler.Alpha158`.

Also, users can pass `qlib.contrib.data.processor.ConfigSectionProcessor` that provides some preprocess methods for features defined by config into the new handler.

Processor

The `Processor` module in `Qlib` is designed to be learnable and it is responsible for handling data processing such as *normalization* and *drop none/nan features/labels*.

`Qlib` provides the following `Processors`:

- `DropnaProcessor`: *processor* that drops N/A features.
- `DropnaLabel`: *processor* that drops N/A labels.
- `TanhProcess`: *processor* that uses *tanh* to process noise data.
- `ProcessInf`: *processor* that handles infinity values, it will be replaces by the mean of the column.
- `Fillna`: *processor* that handles N/A values, which will fill the N/A value by 0 or other given number.
- `MinMaxNorm`: *processor* that applies min-max normalization.
- `ZscoreNorm`: *processor* that applies z-score normalization.
- `RobustZScoreNorm`: *processor* that applies robust z-score normalization.
- `CSZScoreNorm`: *processor* that applies cross sectional z-score normalization.
- `CSRankNorm`: *processor* that applies cross sectional rank normalization.

- `CSZFillna`: *processor* that fills N/A values in a cross sectional way by the mean of the column.

Users can also create their own *processor* by inheriting the base class of `Processor`. Please refer to the implementation of all the processors for more information (Processor Link).

To know more about `Processor`, please refer to Processor API.

Example

`Data Handler` can be run with `qrun` by modifying the configuration file, and can also be used as a single module.

Know more about how to run `Data Handler` with `qrun`, please refer to Workflow: Workflow Management

Qlib provides implemented data handler *Alpha158*. The following example shows how to run *Alpha158* as a single module.

Note: Users need to initialize `Qlib` with *qlib.init* first, please refer to initialization.

```
import qlib
from qlib.contrib.data.handler import Alpha158

data_handler_config = {
    "start_time": "2008-01-01",
    "end_time": "2020-08-01",
    "fit_start_time": "2008-01-01",
    "fit_end_time": "2014-12-31",
    "instruments": "csi300",
}

if __name__ == "__main__":
    qlib.init()
    h = Alpha158(**data_handler_config)

    # get all the columns of the data
    print(h.get_cols())

    # fetch all the labels
    print(h.fetch(col_set="label"))

    # fetch all the features
    print(h.fetch(col_set="feature"))
```

Note: In the `Alpha158`, `Qlib` uses the label *Ref($close, -2)/Ref($close, -1) - 1* that means the change from T+1 to T+2, rather than *Ref($close, -1)/$close - 1*, of which the reason is that when getting the T day close price of a china stock, the stock can be bought on T+1 day and sold on T+2 day.

API

To know more about `Data Handler`, please refer to Data Handler API.

1.8.6 Dataset

The `Dataset` module in `Qlib` aims to prepare data for model training and inferencing.

The motivation of this module is that we want to maximize the flexibility of different models to handle data that are suitable for themselves. This module gives the model the flexibility to process their data in an unique way. For instance, models such as `GBDT` may work well on data that contains *nan* or *None* value, while neural networks such as `MLP` will break down on such data.

If user's model need process its data in a different way, user could implement his own `Dataset` class. If the model's data processing is not special, `DatasetH` can be used directly.

The `DatasetH` class is the *dataset* with *Data Handler*. Here is the most important interface of the class:

class qlib.data.dataset.__init__.**DatasetH**(*handler: Union[Dict[KT, VT], qlib.data.dataset.handler.DataHandler], segments: Dict[str, Tuple], fetch_kwargs: Dict[KT, VT] = {}, **kwargs*)

Dataset with Data(H)andler

User should try to put the data preprocessing functions into handler. Only following data processing functions should be placed in Dataset:

- The processing is related to specific model.
- The processing is related to data split.

__init__(*handler: Union[Dict[KT, VT], qlib.data.dataset.handler.DataHandler], segments: Dict[str, Tuple], fetch_kwargs: Dict[KT, VT] = {}, **kwargs*)

Setup the underlying data.

Parameters

- **handler** (*Union[dict, DataHandler]*) – handler could be:
  - instance of *DataHandler*
  - config of *DataHandler*. Please refer to *DataHandler*
- **segments** (*dict*) – Describe the options to segment the data. Here are some examples:

config(*handler_kwargs: dict = None*, ***kwargs*)

Initialize the DatasetH

Parameters

- **handler_kwargs** (*dict*) – Config of DataHandler, which could include the following arguments:
  - arguments of DataHandler.conf_data, such as 'instruments', 'start_time' and 'end_time'.
- **kwargs** (*dict*) – Config of DatasetH, such as
  - **segments** [dict] Config of segments which is same as 'segments' in self.__init__

setup_data(*handler_kwargs: dict = None*, ***kwargs*)

Setup the Data

Parameters **handler_kwargs** (*dict*) – init arguments of DataHandler, which could include the following arguments:

- init_type : Init Type of Handler
- enable_cache : whether to enable cache

prepare(*segments: Union[List[str], Tuple[str], str, slice, pandas.core.indexes.base.Index], col_set='__all', data_key='infer', **kwargs*) → Union[List[pandas.core.frame.DataFrame], pandas.core.frame.DataFrame]

Prepare the data for learning and inference.

Parameters

- **segments** (*Union[List[Text], Tuple[Text], Text, slice]*) – Describe the scope of the data to be prepared Here are some examples:
  - 'train'
  - ['train', 'valid']
- **col_set** (*str*) – The col_set will be passed to self.handler when fetching data. TODO: make it automatic:
  - select DK_I for test data
  - select DK_L for training data.
- **data_key** (*str*) – The data to fetch: DK_* Default is DK_I, which indicate fetching data for **inference**.
- **kwargs** –

  The parameters that kwargs may contain:

  flt_col [str] It only exists in TSDatasetH, can be used to add a column of data(True or False) to filter data. This parameter is only supported when it is an instance of TSDatasetH.

Returns

Return type Union[List[pd.DataFrame], pd.DataFrame]

Raises NotImplementedError:

API

To know more about `Dataset`, please refer to Dataset API.

1.8.7 Cache

`Cache` is an optional module that helps accelerate providing data by saving some frequently-used data as cache file. `Qlib` provides a *Memcache* class to cache the most-frequently-used data in memory, an inheritable *ExpressionCache* class, and an inheritable *DatasetCache* class.

Global Memory Cache

Memcache is a global memory cache mechanism that composes of three *MemCacheUnit* instances to cache **Calendar**, **Instruments**, and **Features**. The *MemCache* is defined globally in *cache.py* as *H*. Users can use *H['c'], H['i'], H['f']* to get/set *memcache*.

class `qlib.data.cache.`**MemCacheUnit**(**args, **kwargs*)

Memory Cache Unit.

__init__(**args, **kwargs*)

Initialize self. See help(type(self)) for accurate signature.

limited
whether memory cache is limited

class qlib.data.cache.**MemCache**(*mem_cache_size_limit=None*, *limit_type='length'*)
Memory cache.

__init__(*mem_cache_size_limit=None*, *limit_type='length'*)

Parameters

- **mem_cache_size_limit** – cache max size.
- **limit_type** – length or sizeof; length(call fun: len), size(call fun: sys.getsizeof).

ExpressionCache

ExpressionCache is a cache mechanism that saves expressions such as **Mean($close, 5)**. Users can inherit this base class to define their own cache mechanism that saves expressions according to the following steps.

- Override *self._uri* method to define how the cache file path is generated
- Override *self._expression* method to define what data will be cached and how to cache it.

The following shows the details about the interfaces:

class qlib.data.cache.**ExpressionCache**(*provider*)
Expression cache mechanism base class.

This class is used to wrap expression provider with self-defined expression cache mechanism.

Note: Override the *_uri* and *_expression* method to create your own expression cache mechanism.

expression(*instrument*, *field*, *start_time*, *end_time*, *freq*)
Get expression data.

Note: Same interface as *expression* method in expression provider

update(*cache_uri: Union[str, pathlib.Path], freq: str = 'day'*)
Update expression cache to latest calendar.

Override this method to define how to update expression cache corresponding to users' own cache mechanism.

Parameters

- **cache_uri** (`str or Path`) – the complete uri of expression cache file (include dir path).
- **freq** (`str`) –

Returns 0(successful update)/ 1(no need to update)/ 2(update failure).

Return type int

`Qlib` has currently provided implemented disk cache *DiskExpressionCache* which inherits from *ExpressionCache* . The expressions data will be stored in the disk.

DatasetCache

DatasetCache is a cache mechanism that saves datasets. A certain dataset is regulated by a stock pool configuration (or a series of instruments, though not recommended), a list of expressions or static feature fields, the start time, and end time for the collected features and the frequency. Users can inherit this base class to define their own cache mechanism that saves datasets according to the following steps.

- Override *self._uri* method to define how their cache file path is generated
- Override *self._expression* method to define what data will be cached and how to cache it.

The following shows the details about the interfaces:

class qlib.data.cache.**DatasetCache**(*provider*)

Dataset cache mechanism base class.

This class is used to wrap dataset provider with self-defined dataset cache mechanism.

Note: Override the *_uri* and *_dataset* method to create your own dataset cache mechanism.

dataset(*instruments*, *fields*, *start_time=None*, *end_time=None*, *freq='day'*, *disk_cache=1*, *inst_processors=[]*)

Get feature dataset.

Note: Same interface as *dataset* method in dataset provider

Note: The server use redis_lock to make sure read-write conflicts will not be triggered but client readers are not considered.

update(*cache_uri: Union[str, pathlib.Path], freq: str = 'day'*)

Update dataset cache to latest calendar.

Override this method to define how to update dataset cache corresponding to users' own cache mechanism.

Parameters

- **cache_uri** (`str or Path`) – the complete uri of dataset cache file (include dir path).
- **freq** (`str`) –

Returns 0(successful update)/ 1(no need to update)/ 2(update failure)

Return type int

static cache_to_origin_data(*data*, *fields*)

cache data to origin data

Parameters

- **data** – pd.DataFrame, cache data.
- **fields** – feature fields.

Returns pd.DataFrame.

static normalize_uri_args(*instruments*, *fields*, *freq*)

normalize uri args

`Qlib` has currently provided implemented disk cache *DiskDatasetCache* which inherits from *DatasetCache* . The datasets' data will be stored in the disk.

1.8.8 Data and Cache File Structure

We've specially designed a file structure to manage data and cache, please refer to the File storage design section in Qlib paper for detailed information. The file structure of data and cache is listed as follows.

1.9 Forecast Model: Model Training & Prediction

1.9.1 Introduction

`Forecast Model` is designed to make the *prediction score* about stocks. Users can use the `Forecast Model` in an automatic workflow by `qrun`, please refer to Workflow: Workflow Management.

Because the components in `Qlib` are designed in a loosely-coupled way, `Forecast Model` can be used as an independent module also.

1.9.2 Base Class & Interface

`Qlib` provides a base class qlib.model.base.Model from which all models should inherit.

The base class provides the following interfaces:

class qlib.model.base.**Model**

Learnable Models

fit (*dataset: qlib.data.dataset.Dataset*, *reweighter: qlib.data.dataset.weight.Reweighter*)

Learn model from the base model

Note: The attribute names of learned model should *not* start with '_'. So that the model could be dumped to disk.

The following code example shows how to retrieve *x_train*, *y_train* and *w_train* from the *dataset*:

```
# get features and labels
df_train, df_valid = dataset.prepare(
    ["train", "valid"], col_set=["feature", "label"], data_
↪key=DataHandlerLP.DK_L
)
x_train, y_train = df_train["feature"], df_train["label"]
x_valid, y_valid = df_valid["feature"], df_valid["label"]

# get weights
try:
    wdf_train, wdf_valid = dataset.prepare(["train", "valid"], col_
↪set=["weight"],
                                           data_key=DataHandlerLP.DK_
↪L)
    w_train, w_valid = wdf_train["weight"], wdf_valid["weight"]
except KeyError as e:
```

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```
    w_train = pd.DataFrame(np.ones_like(y_train.values), index=y_
↪train.index)
    w_valid = pd.DataFrame(np.ones_like(y_valid.values), index=y_
↪valid.index)
```

Parameters **dataset** (Dataset) – dataset will generate the processed data from model training.

predict (*dataset: qlib.data.dataset.Dataset*, *segment: Union[str, slice] = 'test'*) → object
give prediction given Dataset

Parameters

- **dataset** (Dataset) – dataset will generate the processed dataset from model training.
- **segment** (*Text or slice*) – dataset will use this segment to prepare data. (default=test)

Returns

Return type Prediction results with certain type such as *pandas.Series*.

`Qlib` also provides a base class qlib.model.base.ModelFT, which includes the method for finetuning the model.

For other interfaces such as *finetune*, please refer to Model API.

1.9.3 Example

`Qlib`'s *Model Zoo* includes models such as `LightGBM`, `MLP`, `LSTM`, etc.. These models are treated as the baselines of `Forecast Model`. The following steps show how to run`` LightGBM`` as an independent module.

- Initialize `Qlib` with *qlib.init* first, please refer to Initialization.
- **Run the following code to get the *prediction score pred_score***

```
from qlib.contrib.model.gbdt import LGBModel
from qlib.contrib.data.handler import Alpha158
from qlib.utils import init_instance_by_config, flatten_dict
from qlib.workflow import R
from qlib.workflow.record_temp import SignalRecord, PortAnaRecord

market = "csi300"
benchmark = "SH000300"

data_handler_config = {
    "start_time": "2008-01-01",
    "end_time": "2020-08-01",
    "fit_start_time": "2008-01-01",
    "fit_end_time": "2014-12-31",
    "instruments": market,
}

task = {
    "model": {
        "class": "LGBModel",
        "module_path": "qlib.contrib.model.gbdt",
        "kwargs": {
```

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```
                "loss": "mse",
                "colsample_bytree": 0.8879,
                "learning_rate": 0.0421,
                "subsample": 0.8789,
                "lambda_l1": 205.6999,
                "lambda_l2": 580.9768,
                "max_depth": 8,
                "num_leaves": 210,
                "num_threads": 20,
            },
        },
        "dataset": {
            "class": "DatasetH",
            "module_path": "qlib.data.dataset",
            "kwargs": {
                "handler": {
                    "class": "Alpha158",
                    "module_path": "qlib.contrib.data.handler",
                    "kwargs": data_handler_config,
                },
                "segments": {
                    "train": ("2008-01-01", "2014-12-31"),
                    "valid": ("2015-01-01", "2016-12-31"),
                    "test": ("2017-01-01", "2020-08-01"),
                },
            },
        },
}

# model initiaiton
model = init_instance_by_config(task["model"])
dataset = init_instance_by_config(task["dataset"])

# start exp
with R.start(experiment_name="workflow"):
    # train
    R.log_params(**flatten_dict(task))
    model.fit(dataset)

    # prediction
    recorder = R.get_recorder()
    sr = SignalRecord(model, dataset, recorder)
    sr.generate()
```

Note: *Alpha158* is the data handler provided by `Qlib`, please refer to Data Handler. *SignalRecord* is the *Record Template* in `Qlib`, please refer to Workflow.

Also, the above example has been given in `examples/train_backtest_analyze.ipynb`. Technically, the meaning of the model prediction depends on the label setting designed by user. By default, the meaning of the score is normally the rating of the instruments by the forecasting model. The higher the score, the more profit the instruments.

1.9.4 Custom Model

Qlib supports custom models. If users are interested in customizing their own models and integrating the models into `Qlib`, please refer to Custom Model Integration.

1.9.5 API

Please refer to Model API.

1.10 Portfolio Strategy: Portfolio Management

1.10.1 Introduction

`Portfolio Strategy` is designed to adopt different portfolio strategies, which means that users can adopt different algorithms to generate investment portfolios based on the prediction scores of the `Forecast Model`. Users can use the `Portfolio Strategy` in an automatic workflow by `Workflow` module, please refer to Workflow: Workflow Management.

Because the components in `Qlib` are designed in a loosely-coupled way, `Portfolio Strategy` can be used as an independent module also.

`Qlib` provides several implemented portfolio strategies. Also, `Qlib` supports custom strategy, users can customize strategies according to their own requirements.

After users specifying the models(forecasting signals) and strategies, running backtest will help users to check the performance of a custom model(forecasting signals)/strategy.

1.10.2 Base Class & Interface

BaseStrategy

Qlib provides a base class `qlib.strategy.base.BaseStrategy`. All strategy classes need to inherit the base class and implement its interface.

- ***generate_trade_decision*** generate_trade_decision is a key interface that generates trade decisions in each trading bar. The frequency to call this method depends on the executor frequency("time_per_step"="day" by default). But the trading frequency can be decided by users' implementation. For example, if the user wants to trading in weekly while the *time_per_step* is "day" in executor, user can return non-empty TradeDecision weekly(otherwise return empty like this).

Users can inherit *BaseStrategy* to customize their strategy class.

WeightStrategyBase

Qlib also provides a class `qlib.contrib.strategy.WeightStrategyBase` that is a subclass of *BaseStrategy*.

WeightStrategyBase only focuses on the target positions, and automatically generates an order list based on positions. It provides the *generate_target_weight_position* interface.

- ***generate_target_weight_position***

- According to the current position and trading date to generate the target position. The cash is not considered in the output weight distribution.
- Return the target position.

Note: Here the *target position* means the target percentage of total assets.

WeightStrategyBase implements the interface *generate_order_list*, whose processions is as follows.

- Call *generate_target_weight_position* method to generate the target position.
- Generate the target amount of stocks from the target position.
- Generate the order list from the target amount

Users can inherit *WeightStrategyBase* and implement the interface *generate_target_weight_position* to customize their strategy class, which only focuses on the target positions.

1.10.3 Implemented Strategy

Qlib provides a implemented strategy classes named *TopkDropoutStrategy*.

TopkDropoutStrategy

TopkDropoutStrategy is a subclass of *BaseStrategy* and implement the interface *generate_order_list* whose process is as follows.

- Adopt the `Topk-Drop` algorithm to calculate the target amount of each stock

Note: There are two parameters for the `Topk-Drop` algorithm:

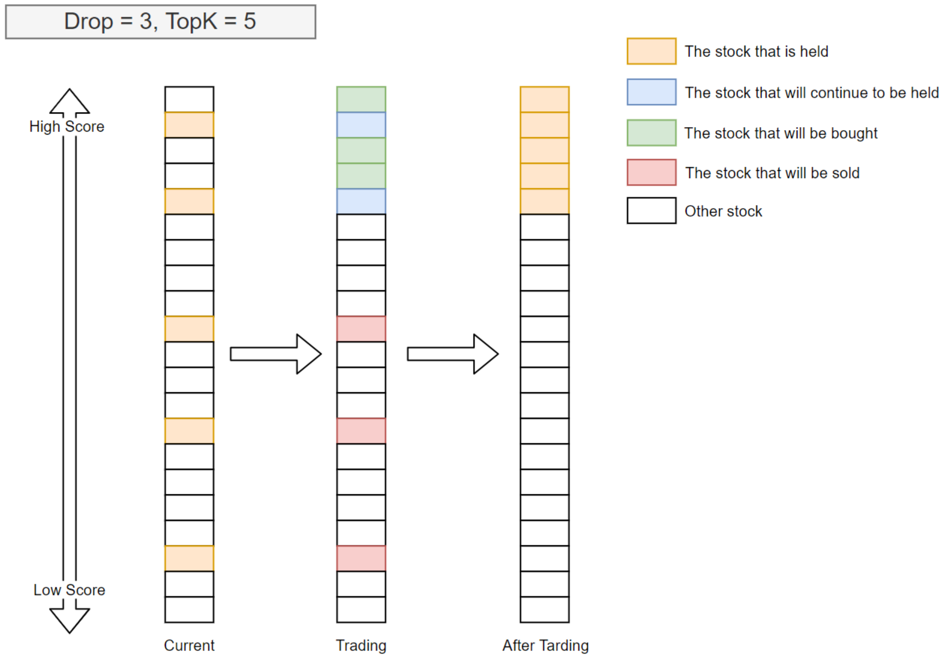
- *Topk*: The number of stocks held
- *Drop*: The number of stocks sold on each trading day

In general, the number of stocks currently held is *Topk*, with the exception of being zero at the beginning period of trading. For each trading day, let d be the number of the instruments currently held and with a rank $gt K$ when ranked by the prediction scores from high to low. Then *d* number of stocks currently held with the worst *prediction score* will be sold, and the same number of unheld stocks with the best *prediction score* will be bought.

In general, $d=$‘Drop‘, especially when the pool of the candidate instruments is large, K is large, and *Drop* is small.

In most cases, `TopkDrop` algorithm sells and buys *Drop* stocks every trading day, which yields a turnover rate of 2$times$‘Drop‘/K.

The following images illustrate a typical scenario.



- Generate the order list from the target amount

EnhancedIndexingStrategy

EnhancedIndexingStrategy Enhanced indexing combines the arts of active management and passive management, with the aim of outperforming a benchmark index (e.g., S&P 500) in terms of portfolio return while controlling the risk exposure (a.k.a. tracking error).

For more information, please refer to *qlib.contrib.strategy.signal_strategy.EnhancedIndexingStrategy* and *qlib.contrib.strategy.optimizer.enhanced_indexing.EnhancedIndexingOptimizer*.

1.10.4 Usage & Example

First, user can create a model to get trading signals(the variable name is `pred_score` in following cases).

Prediction Score

The *prediction score* is a pandas DataFrame. Its index is <datetime(pd.Timestamp), instrument(str)> and it must contains a *score* column.

A prediction sample is shown as follows.

```
  datetime instrument     score
2019-01-04   SH600000 -0.505488
2019-01-04   SZ002531 -0.320391
2019-01-04   SZ000999  0.583808
2019-01-04   SZ300569  0.819628
2019-01-04   SZ001696 -0.137140
             ...            ...
```

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```
2019-04-30   SZ000996 -1.027618
2019-04-30   SH603127  0.225677
2019-04-30   SH603126  0.462443
2019-04-30   SH603133 -0.302460
2019-04-30   SZ300760 -0.126383
```

`Forecast Model` module can make predictions, please refer to Forecast Model: Model Training & Prediction.

Normally, the prediction score is the output of the models. But some models are learned from a label with a different scale. So the scale of the prediction score may be different from your expectation(e.g. the return of instruments).

Qlib didn't add a step to scale the prediction score to a unified scale due to the following reasons. - Because not every trading strategy cares about the scale(e.g. TopkDropoutStrategy only cares about the order). So the strategy is responsible for rescaling the prediction score(e.g. some portfolio-optimization-based strategies may require a meaningful scale). - The model has the flexibility to define the target, loss, and data processing. So we don't think there is a silver bullet to rescale it back directly barely based on the model's outputs. If you want to scale it back to some meaningful values(e.g. stock returns.), an intuitive solution is to create a regression model for the model's recent outputs and your recent target values.

Running backtest

- In most cases, users could backtest their portfolio management strategy with `backtest_daily`.

```python
from pprint import pprint

import qlib
import pandas as pd
from qlib.utils.time import Freq
from qlib.utils import flatten_dict
from qlib.contrib.evaluate import backtest_daily
from qlib.contrib.evaluate import risk_analysis
from qlib.contrib.strategy import TopkDropoutStrategy

# init qlib
qlib.init(provider_uri=<qlib data dir>)

CSI300_BENCH = "SH000300"
STRATEGY_CONFIG = {
    "topk": 50,
    "n_drop": 5,
    # pred_score, pd.Series
    "signal": pred_score,
}


strategy_obj = TopkDropoutStrategy(**STRATEGY_CONFIG)
report_normal, positions_normal = backtest_daily(
    start_time="2017-01-01", end_time="2020-08-01", strategy=strategy_obj
)
analysis = dict()
# default frequency will be daily (i.e. "day")
analysis["excess_return_without_cost"] = risk_analysis(report_normal[
↪"return"] - report_normal["bench"])
analysis["excess_return_with_cost"] = risk_analysis(report_normal["return
↪"] - report_normal["bench"] - report_normal["cost"])
```

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```
analysis_df = pd.concat(analysis)  # type: pd.DataFrame
pprint(analysis_df)
```

- If users would like to control their strategies in a more detailed(e.g. users have a more advanced version of executor), user could follow this example.

```
from pprint import pprint

import qlib
import pandas as pd
from qlib.utils.time import Freq
from qlib.utils import flatten_dict
from qlib.backtest import backtest, executor
from qlib.contrib.evaluate import risk_analysis
from qlib.contrib.strategy import TopkDropoutStrategy

# init qlib
qlib.init(provider_uri=<qlib data dir>)

CSI300_BENCH = "SH000300"
# Benchmark is for calculating the excess return of your strategy.
# Its data format will be like **ONE normal instrument**.
# For example, you can query its data with the code below
# `D.features(["SH000300"], ["$close"], start_time='2010-01-01', end_
↪time='2017-12-31', freq='day')`
# It is different from the argument `market`, which indicates a universe␣
↪of stocks (e.g. **A SET** of stocks like csi300)
# For example, you can query all data from a stock market with the code␣
↪below.
# ` D.features(D.instruments(market='csi300'), ["$close"], start_time=
↪'2010-01-01', end_time='2017-12-31', freq='day')`

FREQ = "day"
STRATEGY_CONFIG = {
    "topk": 50,
    "n_drop": 5,
    # pred_score, pd.Series
    "signal": pred_score,
}

EXECUTOR_CONFIG = {
    "time_per_step": "day",
    "generate_portfolio_metrics": True,
}

backtest_config = {
    "start_time": "2017-01-01",
    "end_time": "2020-08-01",
    "account": 100000000,
    "benchmark": CSI300_BENCH,
    "exchange_kwargs": {
        "freq": FREQ,
        "limit_threshold": 0.095,
        "deal_price": "close",
        "open_cost": 0.0005,
        "close_cost": 0.0015,
```

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```
        "min_cost": 5,
    },
}

# strategy object
strategy_obj = TopkDropoutStrategy(**STRATEGY_CONFIG)
# executor object
executor_obj = executor.SimulatorExecutor(**EXECUTOR_CONFIG)
# backtest
portfolio_metric_dict, indicator_dict = backtest(executor=executor_obj,␣
↪strategy=strategy_obj, **backtest_config)
analysis_freq = "{0}{1}".format(*Freq.parse(FREQ))
# backtest info
report_normal, positions_normal = portfolio_metric_dict.get(analysis_
↪freq)

# analysis
analysis = dict()
analysis["excess_return_without_cost"] = risk_analysis(
    report_normal["return"] - report_normal["bench"], freq=analysis_freq
)
analysis["excess_return_with_cost"] = risk_analysis(
    report_normal["return"] - report_normal["bench"] - report_normal[
↪"cost"], freq=analysis_freq
)

analysis_df = pd.concat(analysis)  # type: pd.DataFrame
# log metrics
analysis_dict = flatten_dict(analysis_df["risk"].unstack().T.to_dict())
# print out results
pprint(f"The following are analysis results of benchmark return(
↪{analysis_freq}).")
pprint(risk_analysis(report_normal["bench"], freq=analysis_freq))
pprint(f"The following are analysis results of the excess return without␣
↪cost({analysis_freq}).")
pprint(analysis["excess_return_without_cost"])
pprint(f"The following are analysis results of the excess return with␣
↪cost({analysis_freq}).")
pprint(analysis["excess_return_with_cost"])
```

Result

The backtest results are in the following form:

```
                                                  risk
excess_return_without_cost mean               0.000605
                           std                0.005481
                           annualized_return  0.152373
                           information_ratio  1.751319
                           max_drawdown      -0.059055
excess_return_with_cost    mean               0.000410
                           std                0.005478
                           annualized_return  0.103265
                           information_ratio  1.187411
                           max_drawdown      -0.075024
```

- ***excess_return_without_cost***
  - ***mean*** Mean value of the *CAR* (cumulative abnormal return) without cost
  - ***std*** The *Standard Deviation* of *CAR* (cumulative abnormal return) without cost.
  - ***annualized_return*** The *Annualized Rate* of *CAR* (cumulative abnormal return) without cost.
  - ***information_ratio*** The *Information Ratio* without cost. please refer to Information Ratio – IR.
  - ***max_drawdown*** The *Maximum Drawdown* of *CAR* (cumulative abnormal return) without cost, please refer to Maximum Drawdown (MDD).
- ***excess_return_with_cost***
  - ***mean*** Mean value of the *CAR* (cumulative abnormal return) series with cost
  - ***std*** The *Standard Deviation* of *CAR* (cumulative abnormal return) series with cost.
  - ***annualized_return*** The *Annualized Rate* of *CAR* (cumulative abnormal return) with cost.
  - ***information_ratio*** The *Information Ratio* with cost. please refer to Information Ratio – IR.
  - ***max_drawdown*** The *Maximum Drawdown* of *CAR* (cumulative abnormal return) with cost, please refer to Maximum Drawdown (MDD).

1.10.5 Reference

To know more about the *prediction score pred_score* output by `Forecast Model`, please refer to Forecast Model: Model Training & Prediction.

1.11 Design of Nested Decision Execution Framework for High-Frequency Trading

1.11.1 Introduction

Daily trading (e.g. portfolio management) and intraday trading (e.g. orders execution) are two hot topics in Quant investment and are usually studied separately.

To get the join trading performance of daily and intraday trading, they must interact with each other and run backtest jointly. In order to support the joint backtest strategies at multiple levels, a corresponding framework is required. None of the publicly available high-frequency trading frameworks considers multi-level joint trading, which makes the backtesting aforementioned inaccurate.

Besides backtesting, the optimization of strategies from different levels is not standalone and can be affected by each other. For example, the best portfolio management strategy may change with the performance of order executions(e.g. a portfolio with higher turnover may become a better choice when we improve the order execution strategies). To achieve overall good performance, it is necessary to consider the interaction of strategies at a different levels.

Therefore, building a new framework for trading on multiple levels becomes necessary to solve the various problems mentioned above, for which we designed a nested decision execution framework that considers the interaction of strategies.

The design of the framework is shown in the yellow part in the middle of the figure above. Each level consists of `Trading Agent` and `Execution Env`. `Trading Agent` has its own data processing module (`Information Extractor`), forecasting module (`Forecast Model`) and decision generator (`Decision Generator`). The trading algorithm generates the decisions by the `Decision Generator` based on the forecast signals output by the `Forecast Module`, and the decisions generated by the trading algorithm are passed to the `Execution Env`, which returns the execution results.

The frequency of the trading algorithm, decision content and execution environment can be customized by users (e.g. intraday trading, daily-frequency trading, weekly-frequency trading), and the execution environment can be nested with finer-grained trading algorithm and execution environment inside (i.e. sub-workflow in the figure, e.g. daily-frequency orders can be turned into finer-grained decisions by splitting orders within the day). The flexibility of the nested decision execution framework makes it easy for users to explore the effects of combining different levels of trading strategies and break down the optimization barriers between different levels of the trading algorithm.

The optimization for the nested decision execution framework can be implemented with the support of QlibRL. To know more about how to use the QlibRL, go to API Reference: RL API.

1.11.2 Example

An example of a nested decision execution framework for high-frequency can be found here.

Besides, the above examples, here are some other related works about high-frequency trading in Qlib.

- Prediction with high-frequency data
- Examples to extract features from high-frequency data without fixed frequency.
- A paper for high-frequency trading.

1.12 Meta Controller: Meta-Task & Meta-Dataset & Meta-Model

1.12.1 Introduction

`Meta Controller` provides guidance to `Forecast Model`, which aims to learn regular patterns among a series of forecasting tasks and use learned patterns to guide forthcoming forecasting tasks. Users can implement their own meta-model instance based on `Meta Controller` module.

1.12.2 Meta Task

A *Meta Task* instance is the basic element in the meta-learning framework. It saves the data that can be used for the *Meta Model*. Multiple *Meta Task* instances may share the same *Data Handler*, controlled by *Meta Dataset*. Users should use *prepare_task_data()* to obtain the data that can be directly fed into the *Meta Model*.

class `qlib.model.meta.task.`**`MetaTask`**(*task: dict*, *meta_info: object*, *mode: str = 'full'*)

A single meta-task, a meta-dataset contains a list of them. It serves as a component as in MetaDatasetDS

The data processing is different

- the processed input may be different between training and testing
  - When training, the X, y, X_test, y_test in training tasks are necessary (# PROC_MODE_FULL #) but not necessary in test tasks. (# PROC_MODE_TEST #)
  - When the meta model can be transferred into other dataset, only meta_info is necessary (# PROC_MODE_TRANSFER #)

`__init__`(*task: dict*, *meta_info: object*, *mode: str = 'full'*)

The *__init__* func is responsible for

- store the task

- store the origin input data for
- process the input data for meta data

Parameters

- **task** (*dict*) – the task to be enhanced by meta model
- **meta_info** (*object*) – the input for meta model

get_meta_input() → object

Return the **processed** meta_info

1.12.3 Meta Dataset

Meta Dataset controls the meta-information generating process. It is on the duty of providing data for training the *Meta Model*. Users should use *prepare_tasks* to retrieve a list of *Meta Task* instances.

class qlib.model.meta.dataset.**MetaTaskDataset**(*segments: Union[Dict[str, Tuple], float], *args, **kwargs*)

A dataset fetching the data in a meta-level.

A Meta Dataset is responsible for

- input tasks(e.g. Qlib tasks) and prepare meta tasks
  - meta task contains more information than normal tasks (e.g. input data for meta model)

The learnt pattern could transfer to other meta dataset. The following cases should be supported

- A meta-model trained on meta-dataset A and then applied to meta-dataset B
  - Some pattern are shared between meta-dataset A and B, so meta-input on meta-dataset A are used when meta model are applied on meta-dataset-B

__init__(*segments: Union[Dict[str, Tuple], float], *args, **kwargs*)

The meta-dataset maintains a list of meta-tasks when it is initialized.

The segments indicates the way to divide the data

The duty of the *__init__* function of MetaTaskDataset - initialize the tasks

prepare_tasks(*segments: Union[List[str], str], *args, **kwargs*) → List[qlib.model.meta.task.MetaTask]

Prepare the data in each meta-task and ready for training.

The following code example shows how to retrieve a list of meta-tasks from the *meta_dataset*:

```
# get the train segment and the test segment, both of them are lists
train_meta_tasks, test_meta_tasks = meta_dataset.prepare_tasks([
↪"train", "test"])
```

Parameters **segments** (*Union[List[Text], Tuple[Text], Text]*) – the info to select data

Returns A list of the prepared data of each meta-task for training the meta-model. For multiple segments [seg1, seg2, ... , segN], the returned list will be [[tasks in seg1], [tasks in seg2], ... , [tasks in segN]]. Each task is a meta task

Return type list

1.12.4 Meta Model

General Meta Model

Meta Model instance is the part that controls the workflow. The usage of the *Meta Model* includes: 1. Users train their *Meta Model* with the *fit* function. 2. The *Meta Model* instance guides the workflow by giving useful information via the *inference* function.

class `qlib.model.meta.model.`**`MetaModel`**

The meta-model guiding the model learning.

The word *Guiding* can be categorized into two types based on the stage of model learning - The definition of learning tasks: Please refer to docs of *MetaTaskModel* - Controlling the learning process of models: Please refer to the docs of *MetaGuideModel*

`fit`(**args*, ***kwargs*)

The training process of the meta-model.

`inference`(**args*, ***kwargs*) → object

The inference process of the meta-model.

Returns Some information to guide the model learning

Return type object

Meta Task Model

This type of meta-model may interact with task definitions directly. Then, the *Meta Task Model* is the class for them to inherit from. They guide the base tasks by modifying the base task definitions. The function *prepare_tasks* can be used to obtain the modified base task definitions.

class `qlib.model.meta.model.`**`MetaTaskModel`**

This type of meta-model deals with base task definitions. The meta-model creates tasks for training new base forecasting models after it is trained. *prepare_tasks* directly modifies the task definitions.

`fit`(*meta_dataset: qlib.model.meta.dataset.MetaTaskDataset*)

The MetaTaskModel is expected to get prepared MetaTask from meta_dataset. And then it will learn knowledge from the meta tasks

`inference`(*meta_dataset: qlib.model.meta.dataset.MetaTaskDataset*) → List[dict]

MetaTaskModel will make inference on the meta_dataset The MetaTaskModel is expected to get prepared MetaTask from meta_dataset. Then it will create modified task with Qlib format which can be executed by Qlib trainer.

Returns A list of modified task definitions.

Return type List[dict]

Meta Guide Model

This type of meta-model participates in the training process of the base forecasting model. The meta-model may guide the base forecasting models during their training to improve their performances.

class `qlib.model.meta.model.`**`MetaGuideModel`**

This type of meta-model aims to guide the training process of the base model. The meta-model interacts with the base forecasting models during their training process.

`fit`(**args*, ***kwargs*)

The training process of the meta-model.

inference (**args*, ***kwargs*)
The inference process of the meta-model.

Returns Some information to guide the model learning

Return type object

1.12.5 Example

`Qlib` provides an implementation of `Meta Model` module, `DDG-DA`, which adapts to the market dynamics.

`DDG-DA` includes four steps:

1. Calculate meta-information and encapsulate it into `Meta Task` instances. All the meta-tasks form a `Meta Dataset` instance.
2. Train `DDG-DA` based on the training data of the meta-dataset.
3. Do the inference of the `DDG-DA` to get guide information.
4. Apply guide information to the forecasting models to improve their performances.

The above example can be found in `examples/benchmarks_dynamic/DDG-DA/workflow.py`.

1.13 Qlib Recorder: Experiment Management

1.13.1 Introduction

`Qlib` contains an experiment management system named `QlibRecorder`, which is designed to help users handle experiment and analyse results in an efficient way.

There are three components of the system:

- ***ExperimentManager*** a class that manages experiments.
- ***Experiment*** a class of experiment, and each instance of it is responsible for a single experiment.
- ***Recorder*** a class of recorder, and each instance of it is responsible for a single run.

Here is a general view of the structure of the system:

This experiment management system defines a set of interface and provided a concrete implementation `MLflowExpManager`, which is based on the machine learning platform: `MLFlow` (link).

If users set the implementation of `ExpManager` to be `MLflowExpManager`, they can use the command *mlflow ui* to visualize and check the experiment results. For more information, please refer to the related documents here.

1.13.2 Qlib Recorder

`QlibRecorder` provides a high level API for users to use the experiment management system. The interfaces are wrapped in the variable `R` in `Qlib`, and users can directly use `R` to interact with the system. The following command shows how to import `R` in Python:

```
from qlib.workflow import R
```

`QlibRecorder` includes several common API for managing *experiments* and *recorders* within a workflow. For more available APIs, please refer to the following section about *Experiment Manager*, *Experiment* and *Recorder*.

Here are the available interfaces of `QlibRecorder`:

class qlib.workflow.__init__.**QlibRecorder**(*exp_manager: qlib.workflow.expm.ExpManager*)

A global system that helps to manage the experiments.

__init__(*exp_manager: qlib.workflow.expm.ExpManager*)

Initialize self. See help(type(self)) for accurate signature.

start(**, experiment_id: Optional[str] = None, experiment_name: Optional[str] = None, recorder_id: Optional[str] = None, recorder_name: Optional[str] = None, uri: Optional[str] = None, resume: bool = False*)

Method to start an experiment. This method can only be called within a Python's *with* statement. Here is the example code:

```
# start new experiment and recorder
with R.start(experiment_name='test', recorder_name='recorder_1'):
    model.fit(dataset)
    R.log...
    ... # further operations

# resume previous experiment and recorder
with R.start(experiment_name='test', recorder_name='recorder_1',␣
↪resume=True): # if users want to resume recorder, they have to specify the␣
↪exact same name for experiment and recorder.
    ... # further operations
```

Parameters

- **experiment_id** (*str*) – id of the experiment one wants to start.
- **experiment_name** (*str*) – name of the experiment one wants to start.
- **recorder_id** (*str*) – id of the recorder under the experiment one wants to start.
- **recorder_name** (*str*) – name of the recorder under the experiment one wants to start.
- **uri** (*str*) – The tracking uri of the experiment, where all the artifacts/metrics etc. will be stored. The default uri is set in the qlib.config. Note that this uri argument will not change the one defined in the config file. Therefore, the next time when users call this function in the same experiment, they have to also specify this argument with the same value. Otherwise, inconsistent uri may occur.
- **resume** (*bool*) – whether to resume the specific recorder with given name under the given experiment.

start_exp(**, experiment_id=None, experiment_name=None, recorder_id=None, recorder_name=None, uri=None, resume=False*)

Lower level method for starting an experiment. When use this method, one should end the experiment manually and the status of the recorder may not be handled properly. Here is the example code:

```
R.start_exp(experiment_name='test', recorder_name='recorder_1')
... # further operations
R.end_exp('FINISHED') or R.end_exp(Recorder.STATUS_S)
```

Parameters

- **experiment_id** (*str*) – id of the experiment one wants to start.
- **experiment_name** (*str*) – the name of the experiment to be started
- **recorder_id** (*str*) – id of the recorder under the experiment one wants to start.

- **recorder_name** (*str*) – name of the recorder under the experiment one wants to start.
- **uri** (*str*) – the tracking uri of the experiment, where all the artifacts/metrics etc. will be stored. The default uri are set in the qlib.config.
- **resume** (*bool*) – whether to resume the specific recorder with given name under the given experiment.

Returns

Return type An experiment instance being started.

end_exp (*recorder_status='FINISHED'*)
Method for ending an experiment manually. It will end the current active experiment, as well as its active recorder with the specified *status* type. Here is the example code of the method:

```
R.start_exp(experiment_name='test')
... # further operations
R.end_exp('FINISHED') or R.end_exp(Recorder.STATUS_S)
```

Parameters **status** (*str*) – The status of a recorder, which can be SCHEDULED, RUNNING, FINISHED, FAILED.

search_records (*experiment_ids*, ***kwargs*)
Get a pandas DataFrame of records that fit the search criteria.

The arguments of this function are not set to be rigid, and they will be different with different implementation of `ExpManager` in `Qlib`. `Qlib` now provides an implementation of `ExpManager` with mlflow, and here is the example code of the this method with the `MLflowExpManager`:

```
R.log_metrics(m=2.50, step=0)
records = R.search_records([experiment_id], order_by=["metrics.m DESC"])
```

Parameters

- **experiment_ids** (*list*) – list of experiment IDs.
- **filter_string** (*str*) – filter query string, defaults to searching all runs.
- **run_view_type** (*int*) – one of enum values ACTIVE_ONLY, DELETED_ONLY, or ALL (e.g. in mlflow.entities.ViewType).
- **max_results** (*int*) – the maximum number of runs to put in the dataframe.
- **order_by** (*list*) – list of columns to order by (e.g., "metrics.rmse").

Returns

- *A pandas.DataFrame of records, where each metric, parameter, and tag*
- *are expanded into their own columns named metrics.*, params.*, and tags.**
- *respectively. For records that don't have a particular metric, parameter, or tag, their*
- *value will be (NumPy) Nan, None, or None respectively.*

list_experiments ()
Method for listing all the existing experiments (except for those being deleted.)

```
exps = R.list_experiments()
```

Returns

Return type A dictionary (name -> experiment) of experiments information that being stored.

list_recorders(*experiment_id=None*, *experiment_name=None*)

Method for listing all the recorders of experiment with given id or name.

If user doesn't provide the id or name of the experiment, this method will try to retrieve the default experiment and list all the recorders of the default experiment. If the default experiment doesn't exist, the method will first create the default experiment, and then create a new recorder under it. (More information about the default experiment can be found here).

Here is the example code:

```
recorders = R.list_recorders(experiment_name='test')
```

Parameters

- **experiment_id** (*str*) – id of the experiment.
- **experiment_name** (*str*) – name of the experiment.

Returns

Return type A dictionary (id -> recorder) of recorder information that being stored.

get_exp(*, *experiment_id=None*, *experiment_name=None*, *create: bool = True*, *start: bool = False*) → qlib.workflow.exp.Experiment

Method for retrieving an experiment with given id or name. Once the *create* argument is set to True, if no valid experiment is found, this method will create one for you. Otherwise, it will only retrieve a specific experiment or raise an Error.

- If '*create*' is True:
  - If *active experiment* exists:
    - no id or name specified, return the active experiment.
    - if id or name is specified, return the specified experiment. If no such exp found, create a new experiment with given id or name.
  - If *active experiment* not exists:
    - no id or name specified, create a default experiment, and the experiment is set to be active.
    - if id or name is specified, return the specified experiment. If no such exp found, create a new experiment with given name or the default experiment.
- Else If '*create*' is False:
  - If *active experiment* exists:
    - no id or name specified, return the active experiment.
    - if id or name is specified, return the specified experiment. If no such exp found, raise Error.
  - If *active experiment* not exists:
    - no id or name specified. If the default experiment exists, return it, otherwise, raise Error.
    - if id or name is specified, return the specified experiment. If no such exp found, raise Error.

Here are some use cases:

```
# Case 1
with R.start('test'):
    exp = R.get_exp()
    recorders = exp.list_recorders()

# Case 2
with R.start('test'):
    exp = R.get_exp(experiment_name='test1')

# Case 3
exp = R.get_exp() -> a default experiment.

# Case 4
exp = R.get_exp(experiment_name='test')

# Case 5
exp = R.get_exp(create=False) -> the default experiment if exists.
```

Parameters

- **experiment_id** (*str*) – id of the experiment.
- **experiment_name** (*str*) – name of the experiment.
- **create** (*boolean*) – an argument determines whether the method will automatically create a new experiment according to user's specification if the experiment hasn't been created before.
- **start** (*bool*) – when start is True, if the experiment has not started(not activated), it will start It is designed for R.log_params to auto start experiments

Returns

Return type An experiment instance with given id or name.

delete_exp(*experiment_id=None*, *experiment_name=None*)

Method for deleting the experiment with given id or name. At least one of id or name must be given, otherwise, error will occur.

Here is the example code:

```
R.delete_exp(experiment_name='test')
```

Parameters

- **experiment_id** (*str*) – id of the experiment.
- **experiment_name** (*str*) – name of the experiment.

get_uri()

Method for retrieving the uri of current experiment manager.

Here is the example code:

```
uri = R.get_uri()
```

Returns

Return type The uri of current experiment manager.

set_uri (*uri: Optional[str]*)
Method to reset the **default** uri of current experiment manager.

NOTE:

- When the uri is refer to a file path, please using the absolute path instead of strings like "~/mlruns/" The backend don't support strings like this.

uri_context (*uri: str*)
Temporarily set the exp_manager's **default_uri** to uri

NOTE: - Please refer to the NOTE in the *set_uri*

Parameters uri (*Text*) – the temporal uri

get_recorder (**, recorder_id=None, recorder_name=None, experiment_id=None, experiment_name=None*) → qlib.workflow.recorder.Recorder
Method for retrieving a recorder.

- If *active recorder* exists:
  - no id or name specified, return the active recorder.
  - if id or name is specified, return the specified recorder.
- If *active recorder* not exists:
  - no id or name specified, raise Error.
  - if id or name is specified, and the corresponding experiment_name must be given, return the specified recorder. Otherwise, raise Error.

The recorder can be used for further process such as *save_object*, *load_object*, *log_params*, *log_metrics*, etc.

Here are some use cases:

```
# Case 1
with R.start(experiment_name='test'):
    recorder = R.get_recorder()

# Case 2
with R.start(experiment_name='test'):
    recorder = R.get_recorder(recorder_id='2e7a4efd66574fa49039e00ffaefa99d')

# Case 3
recorder = R.get_recorder() -> Error

# Case 4
recorder = R.get_recorder(recorder_id='2e7a4efd66574fa49039e00ffaefa99d') ->␣
↪Error

# Case 5
recorder = R.get_recorder(recorder_id='2e7a4efd66574fa49039e00ffaefa99d',␣
↪experiment_name='test')
```

Here are some things users may concern - Q: What recorder will it return if multiple recorder meets the query (e.g. query with experiment_name) - A: If mlflow backend is used, then the recorder with the latest *start_time* will be returned. Because MLflow's *search_runs* function guarantee it

Parameters

- **recorder_id** (*str*) – id of the recorder.
- **recorder_name** (*str*) – name of the recorder.
- **experiment_name** (*str*) – name of the experiment.

Returns

Return type A recorder instance.

delete_recorder (*recorder_id=None*, *recorder_name=None*)

Method for deleting the recorders with given id or name. At least one of id or name must be given, otherwise, error will occur.

Here is the example code:

```
R.delete_recorder(recorder_id='2e7a4efd66574fa49039e00ffaefa99d')
```

Parameters

- **recorder_id** (*str*) – id of the experiment.
- **recorder_name** (*str*) – name of the experiment.

save_objects (*local_path=None*, *artifact_path=None*, ***kwargs*)

Method for saving objects as artifacts in the experiment to the uri. It supports either saving from a local file/directory, or directly saving objects. User can use valid python's keywords arguments to specify the object to be saved as well as its name (name: value).

In summary, this API is designs for saving **objects** to **the experiments management backend path**, 1. Qlib provide two methods to specify **objects** - Passing in the object directly by passing with ***kwargs* (e.g. R.save_objects(trained_model=model)) - Passing in the local path to the object, i.e. *local_path* parameter. 2. *artifact_path* represents the **the experiments management backend path**

- If *active recorder* exists: it will save the objects through the active recorder.
- If *active recorder* not exists: the system will create a default experiment, and a new recorder and save objects under it.

Note: If one wants to save objects with a specific recorder. It is recommended to first get the specific recorder through *get_recorder* API and use the recorder the save objects. The supported arguments are the same as this method.

Here are some use cases:

```
# Case 1
with R.start(experiment_name='test'):
    pred = model.predict(dataset)
    R.save_objects(**{"pred.pkl": pred}, artifact_path='prediction')
    rid = R.get_recorder().id
...
R.get_recorder(recorder_id=rid).load_object("prediction/pred.pkl")   #  after␣
↪saving objects, you can load the previous object with this api

# Case 2
with R.start(experiment_name='test'):
    R.save_objects(local_path='results/pred.pkl', artifact_path="prediction")
    rid = R.get_recorder().id
```

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```
...
R.get_recorder(recorder_id=rid).load_object("prediction/pred.pkl")  # after␣
↪saving objects, you can load the previous object with this api
```

Parameters

- **local_path** (*str*) – if provided, them save the file or directory to the artifact URI.
- **artifact_path** (*str*) – the relative path for the artifact to be stored in the URI.
- ****kwargs** (*Dict[Text, Any]*) – the object to be saved. For example, *{"pred.pkl": pred}*

load_object (*name: str*)
Method for loading an object from artifacts in the experiment in the uri.

log_params (***kwargs*)
Method for logging parameters during an experiment. In addition to using `R`, one can also log to a specific recorder after getting it with *get_recorder* API.

- If *active recorder* exists: it will log parameters through the active recorder.
- If *active recorder* not exists: the system will create a default experiment as well as a new recorder, and log parameters under it.

Here are some use cases:

```
# Case 1
with R.start('test'):
    R.log_params(learning_rate=0.01)

# Case 2
R.log_params(learning_rate=0.01)
```

Parameters argument (*keyword*) – name1=value1, name2=value2, . . .

log_metrics (*step=None*, ***kwargs*)
Method for logging metrics during an experiment. In addition to using `R`, one can also log to a specific recorder after getting it with *get_recorder* API.

- If *active recorder* exists: it will log metrics through the active recorder.
- If *active recorder* not exists: the system will create a default experiment as well as a new recorder, and log metrics under it.

Here are some use cases:

```
# Case 1
with R.start('test'):
    R.log_metrics(train_loss=0.33, step=1)

# Case 2
R.log_metrics(train_loss=0.33, step=1)
```

Parameters argument (*keyword*) – name1=value1, name2=value2, . . .

log_artifact (*local_path: str*, *artifact_path: Optional[str] = None*)
Log a local file or directory as an artifact of the currently active run

- If *active recorder* exists: it will set tags through the active recorder.
- If *active recorder* not exists: the system will create a default experiment as well as a new recorder, and set the tags under it.

Parameters

- **local_path** (*str*) – Path to the file to write.
- **artifact_path** (*Optional[str]*) – If provided, the directory in `artifact_uri` to write to.

download_artifact(*path: str*, *dst_path: Optional[str] = None*) → str

Download an artifact file or directory from a run to a local directory if applicable, and return a local path for it.

Parameters

- **path** (*str*) – Relative source path to the desired artifact.
- **dst_path** (*Optional[str]*) – Absolute path of the local filesystem destination directory to which to download the specified artifacts. This directory must already exist. If unspecified, the artifacts will either be downloaded to a new uniquely-named directory on the local filesystem.

Returns Local path of desired artifact.

Return type str

set_tags(***kwargs*)

Method for setting tags for a recorder. In addition to using `R`, one can also set the tag to a specific recorder after getting it with *get_recorder* API.

- If *active recorder* exists: it will set tags through the active recorder.
- If *active recorder* not exists: the system will create a default experiment as well as a new recorder, and set the tags under it.

Here are some use cases:

```
# Case 1
with R.start('test'):
    R.set_tags(release_version="2.2.0")

# Case 2
R.set_tags(release_version="2.2.0")
```

Parameters **argument** (*keyword*) – name1=value1, name2=value2, . . .

1.13.3 Experiment Manager

The `ExpManager` module in `Qlib` is responsible for managing different experiments. Most of the APIs of `ExpManager` are similar to `QlibRecorder`, and the most important API will be the `get_exp` method. User can directly refer to the documents above for some detailed information about how to use the `get_exp` method.

class qlib.workflow.expm.**ExpManager**(*uri: str*, *default_exp_name: Optional[str]*)

This is the *ExpManager* class for managing experiments. The API is designed similar to mlflow. (The link: https://mlflow.org/docs/latest/python_api/mlflow.html)

The *ExpManager* is expected to be a singleton (btw, we can have multiple *Experiment's with different uri. user can get different experiments from different uri, and then compare records of them). Global Config (i.e. 'C*) is also a singleton.

So we try to align them together. They share the same variable, which is called **default uri**. Please refer to *ExpManager.default_uri* for details of variable sharing.

When the user starts an experiment, the user may want to set the uri to a specific uri (it will override **default uri** during this period), and then unset the **specific uri** and fallback to the **default uri**. *ExpManager._active_exp_uri* is that **specific uri**.

`__init__`(*uri: str, default_exp_name: Optional[str]*)
Initialize self. See help(type(self)) for accurate signature.

`start_exp`(**, experiment_id: Optional[str] = None, experiment_name: Optional[str] = None, recorder_id: Optional[str] = None, recorder_name: Optional[str] = None, uri: Optional[str] = None, resume: bool = False, **kwargs*) → qlib.workflow.exp.Experiment
Start an experiment. This method includes first get_or_create an experiment, and then set it to be active.

Maintaining *_active_exp_uri* is included in start_exp, remaining implementation should be included in _end_exp in subclass

Parameters

- **`experiment_id`** (*str*) – id of the active experiment.
- **`experiment_name`** (*str*) – name of the active experiment.
- **`recorder_id`** (*str*) – id of the recorder to be started.
- **`recorder_name`** (*str*) – name of the recorder to be started.
- **`uri`** (*str*) – the current tracking URI.
- **`resume`** (*boolean*) – whether to resume the experiment and recorder.

Returns

Return type An active experiment.

`end_exp`(*recorder_status: str = 'SCHEDULED', **kwargs*)
End an active experiment.

Maintaining *_active_exp_uri* is included in end_exp, remaining implementation should be included in _end_exp in subclass

Parameters

- **`experiment_name`** (*str*) – name of the active experiment.
- **`recorder_status`** (*str*) – the status of the active recorder of the experiment.

`create_exp`(*experiment_name: Optional[str] = None*)
Create an experiment.

Parameters **`experiment_name`** (*str*) – the experiment name, which must be unique.

Returns

- *An experiment object.*
- *Raise*
- *–*
- *ExpAlreadyExistError*

search_records (*experiment_ids=None*, ***kwargs*)

Get a pandas DataFrame of records that fit the search criteria of the experiment. Inputs are the search criteria user want to apply.

Returns

- *A pandas.DataFrame of records, where each metric, parameter, and tag*
- *are expanded into their own columns named metrics.*, params.*, and tags.**
- *respectively. For records that don't have a particular metric, parameter, or tag, their*
- *value will be (NumPy) Nan, None, or None respectively.*

get_exp (***, *experiment_id=None*, *experiment_name=None*, *create: bool = True*, *start: bool = False*)

Retrieve an experiment. This method includes getting an active experiment, and get_or_create a specific experiment.

When user specify experiment id and name, the method will try to return the specific experiment. When user does not provide recorder id or name, the method will try to return the current active experiment. The *create* argument determines whether the method will automatically create a new experiment according to user's specification if the experiment hasn't been created before.

- If *create* is True:
  - If *active experiment* exists:
    - no id or name specified, return the active experiment.
    - if id or name is specified, return the specified experiment. If no such exp found, create a new experiment with given id or name. If *start* is set to be True, the experiment is set to be active.
  - If *active experiment* not exists:
    - no id or name specified, create a default experiment.
    - if id or name is specified, return the specified experiment. If no such exp found, create a new experiment with given id or name. If *start* is set to be True, the experiment is set to be active.
- Else If *create* is False:
  - If *active experiment* exists:
    - no id or name specified, return the active experiment.
    - if id or name is specified, return the specified experiment. If no such exp found, raise Error.
  - If *active experiment* not exists:
    - no id or name specified. If the default experiment exists, return it, otherwise, raise Error.
    - if id or name is specified, return the specified experiment. If no such exp found, raise Error.

Parameters

- **experiment_id** (*str*) – id of the experiment to return.
- **experiment_name** (*str*) – name of the experiment to return.
- **create** (*boolean*) – create the experiment it if hasn't been created before.
- **start** (*boolean*) – start the new experiment if one is created.

Returns

Return type An experiment object.

delete_exp(*experiment_id=None*, *experiment_name=None*)
Delete an experiment.

Parameters

- **experiment_id** (*str*) – the experiment id.
- **experiment_name** (*str*) – the experiment name.

default_uri
Get the default tracking URI from qlib.config.C

uri
Get the default tracking URI or current URI.

Returns

Return type The tracking URI string.

list_experiments()
List all the existing experiments.

Returns

Return type A dictionary (name -> experiment) of experiments information that being stored.

For other interfaces such as *create_exp*, *delete_exp*, please refer to Experiment Manager API.

1.13.4 Experiment

The `Experiment` class is solely responsible for a single experiment, and it will handle any operations that are related to an experiment. Basic methods such as *start*, *end* an experiment are included. Besides, methods related to *recorders* are also available: such methods include *get_recorder* and *list_recorders*.

class qlib.workflow.exp.**Experiment**(*id*, *name*)
This is the *Experiment* class for each experiment being run. The API is designed similar to mlflow. (The link: https://mlflow.org/docs/latest/python_api/mlflow.html)

__init__(*id*, *name*)
Initialize self. See help(type(self)) for accurate signature.

start(*, *recorder_id=None*, *recorder_name=None*, *resume=False*)
Start the experiment and set it to be active. This method will also start a new recorder.

Parameters

- **recorder_id** (*str*) – the id of the recorder to be created.
- **recorder_name** (*str*) – the name of the recorder to be created.
- **resume** (*bool*) – whether to resume the first recorder

Returns

Return type An active recorder.

end(*recorder_status='SCHEDULED'*)
End the experiment.

Parameters **recorder_status** (*str*) – the status the recorder to be set with when ending (SCHEDULED, RUNNING, FINISHED, FAILED).

create_recorder(*recorder_name=None*)
Create a recorder for each experiment.

Parameters **recorder_name** (*str*) – the name of the recorder to be created.

Returns

Return type A recorder object.

search_records(***kwargs*)
Get a pandas DataFrame of records that fit the search criteria of the experiment. Inputs are the search criteria user want to apply.

Returns

- *A pandas.DataFrame of records, where each metric, parameter, and tag*
- *are expanded into their own columns named metrics.*, params.*, and tags.**
- *respectively. For records that don't have a particular metric, parameter, or tag, their*
- *value will be (NumPy) Nan, None, or None respectively.*

delete_recorder(*recorder_id*)
Create a recorder for each experiment.

Parameters **recorder_id** (*str*) – the id of the recorder to be deleted.

get_recorder(*recorder_id=None, recorder_name=None, create: bool = True, start: bool = False*) → qlib.workflow.recorder.Recorder
Retrieve a Recorder for user. When user specify recorder id and name, the method will try to return the specific recorder. When user does not provide recorder id or name, the method will try to return the current active recorder. The *create* argument determines whether the method will automatically create a new recorder according to user's specification if the recorder hasn't been created before.

- If *create* is True:
  - If *active recorder* exists:
    * no id or name specified, return the active recorder.
    * if id or name is specified, return the specified recorder. If no such exp found, create a new recorder with given id or name. If *start* is set to be True, the recorder is set to be active.
  - If *active recorder* not exists:
    * no id or name specified, create a new recorder.
    * if id or name is specified, return the specified experiment. If no such exp found, create a new recorder with given id or name. If *start* is set to be True, the recorder is set to be active.
- Else If *create* is False:
  - If *active recorder* exists:
    * no id or name specified, return the active recorder.
    * if id or name is specified, return the specified recorder. If no such exp found, raise Error.
  - If *active recorder* not exists:
    * no id or name specified, raise Error.
    * if id or name is specified, return the specified recorder. If no such exp found, raise Error.

Parameters

- **recorder_id** (*str*) – the id of the recorder to be deleted.

- **recorder_name** (*str*) – the name of the recorder to be deleted.
- **create** (*boolean*) – create the recorder if it hasn't been created before.
- **start** (*boolean*) – start the new recorder if one is **created**.

Returns

Return type A recorder object.

list_recorders(*rtype: typing_extensions.Literal['dict', 'list'][dict, list] = 'dict', **flt_kwargs*) → Union[List[qlib.workflow.recorder.Recorder], Dict[str, qlib.workflow.recorder.Recorder]]

List all the existing recorders of this experiment. Please first get the experiment instance before calling this method. If user want to use the method *R.list_recorders()*, please refer to the related API document in *QlibRecorder*.

flt_kwargs [dict] filter recorders by conditions e.g. list_recorders(status=Recorder.STATUS_FI)

Returns

if *rtype* == "dict": A dictionary (id -> recorder) of recorder information that being stored.

elif *rtype* == "list": A list of Recorder.

Return type The return type depends on *rtype*

For other interfaces such as *search_records*, *delete_recorder*, please refer to Experiment API.

`Qlib` also provides a default `Experiment`, which will be created and used under certain situations when users use the APIs such as *log_metrics* or *get_exp*. If the default `Experiment` is used, there will be related logged information when running `Qlib`. Users are able to change the name of the default `Experiment` in the config file of `Qlib` or during `Qlib`'s initialization, which is set to be '*Experiment*'.

1.13.5 Recorder

The `Recorder` class is responsible for a single recorder. It will handle some detailed operations such as `log_metrics`, `log_params` of a single run. It is designed to help user to easily track results and things being generated during a run.

Here are some important APIs that are not included in the `QlibRecorder`:

class qlib.workflow.recorder.**Recorder**(*experiment_id*, *name*)

This is the *Recorder* class for logging the experiments. The API is designed similar to mlflow. (The link: https://mlflow.org/docs/latest/python_api/mlflow.html)

The status of the recorder can be SCHEDULED, RUNNING, FINISHED, FAILED.

__init__(*experiment_id*, *name*)

Initialize self. See help(type(self)) for accurate signature.

save_objects(*local_path=None*, *artifact_path=None*, ***kwargs*)

Save objects such as prediction file or model checkpoints to the artifact URI. User can save object through keywords arguments (name:value).

Please refer to the docs of qlib.workflow:R.save_objects

Parameters

- **local_path** (*str*) – if provided, them save the file or directory to the artifact URI.
- **artifact_path=None** (*str*) – the relative path for the artifact to be stored in the URI.

load_object(*name*)
Load objects such as prediction file or model checkpoints.

Parameters **name** (*str*) – name of the file to be loaded.

Returns

Return type The saved object.

start_run()
Start running or resuming the Recorder. The return value can be used as a context manager within a *with* block; otherwise, you must call end_run() to terminate the current run. (See *ActiveRun* class in mlflow)

Returns

Return type An active running object (e.g. mlflow.ActiveRun object)

end_run()
End an active Recorder.

log_params(***kwargs*)
Log a batch of params for the current run.

Parameters **arguments** (*keyword*) – key, value pair to be logged as parameters.

log_metrics(*step=None*, ***kwargs*)
Log multiple metrics for the current run.

Parameters **arguments** (*keyword*) – key, value pair to be logged as metrics.

log_artifact(*local_path: str*, *artifact_path: Optional[str] = None*)
Log a local file or directory as an artifact of the currently active run.

Parameters

- **local_path** (*str*) – Path to the file to write.
- **artifact_path** (*Optional[str]*) – If provided, the directory in `artifact_uri` to write to.

set_tags(***kwargs*)
Log a batch of tags for the current run.

Parameters **arguments** (*keyword*) – key, value pair to be logged as tags.

delete_tags(**keys*)
Delete some tags from a run.

Parameters **keys** (*series of strs of the keys*) – all the name of the tag to be deleted.

list_artifacts(*artifact_path: str = None*)
List all the artifacts of a recorder.

Parameters **artifact_path** (*str*) – the relative path for the artifact to be stored in the URI.

Returns

Return type A list of artifacts information (name, path, etc.) that being stored.

download_artifact(*path: str*, *dst_path: Optional[str] = None*) → str
Download an artifact file or directory from a run to a local directory if applicable, and return a local path for it.

Parameters

- **path** (*str*) – Relative source path to the desired artifact.
- **dst_path** (*Optional[str]*) – Absolute path of the local filesystem destination directory to which to download the specified artifacts. This directory must already exist. If unspecified, the artifacts will either be downloaded to a new uniquely-named directory on the local filesystem.

Returns Local path of desired artifact.

Return type str

list_metrics()
List all the metrics of a recorder.

Returns

Return type A dictionary of metrics that being stored.

list_params()
List all the params of a recorder.

Returns

Return type A dictionary of params that being stored.

list_tags()
List all the tags of a recorder.

Returns

Return type A dictionary of tags that being stored.

For other interfaces such as *save_objects*, *load_object*, please refer to Recorder API.

1.13.6 Record Template

The `RecordTemp` class is a class that enables generate experiment results such as IC and backtest in a certain format. We have provided three different *Record Template* class:

- `SignalRecord`: This class generates the *prediction* results of the model.
- `SigAnaRecord`: This class generates the *IC*, *ICIR*, *Rank IC* and *Rank ICIR* of the model.

Here is a simple example of what is done in `SigAnaRecord`, which users can refer to if they want to calculate IC, Rank IC, Long-Short Return with their own prediction and label.

```
from qlib.contrib.eva.alpha import calc_ic, calc_long_short_return

ic, ric = calc_ic(pred.iloc[:, 0], label.iloc[:, 0])
long_short_r, long_avg_r = calc_long_short_return(pred.iloc[:, 0], label.iloc[:, 0])
```

- `PortAnaRecord`: This class generates the results of *backtest*. The detailed information about *backtest* as well as the available *strategy*, users can refer to Strategy and Backtest.

Here is a simple example of what is done in `PortAnaRecord`, which users can refer to if they want to do backtest based on their own prediction and label.

```
from qlib.contrib.strategy.strategy import TopkDropoutStrategy
from qlib.contrib.evaluate import (
    backtest as normal_backtest,
    risk_analysis,
)
```

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```
# backtest
STRATEGY_CONFIG = {
    "topk": 50,
    "n_drop": 5,
}
BACKTEST_CONFIG = {
    "limit_threshold": 0.095,
    "account": 100000000,
    "benchmark": BENCHMARK,
    "deal_price": "close",
    "open_cost": 0.0005,
    "close_cost": 0.0015,
    "min_cost": 5,
}

strategy = TopkDropoutStrategy(**STRATEGY_CONFIG)
report_normal, positions_normal = normal_backtest(pred_score, strategy=strategy,␣
↪**BACKTEST_CONFIG)

# analysis
analysis = dict()
analysis["excess_return_without_cost"] = risk_analysis(report_normal["return"] -␣
↪report_normal["bench"])
analysis["excess_return_with_cost"] = risk_analysis(report_normal["return"] - report_
↪normal["bench"] - report_normal["cost"])
analysis_df = pd.concat(analysis)  # type: pd.DataFrame
print(analysis_df)
```

For more information about the APIs, please refer to Record Template API.

1.13.7 Known Limitations

- The Python objects are saved based on pickle, which may results in issues when the environment dumping objects and loading objects are different.

1.14 Analysis: Evaluation & Results Analysis

1.14.1 Introduction

`Analysis` is designed to show the graphical reports of `Intraday Trading`, which helps users to evaluate and analyse investment portfolios visually. The following are some graphics to view:

- **analysis_position**
  - report_graph
  - score_ic_graph
  - cumulative_return_graph
  - risk_analysis_graph
  - rank_label_graph
- **analysis_model**

– model_performance_graph

All of the accumulated profit metrics(e.g. return, max drawdown) in Qlib are calculated by summation. This avoids the metrics or the plots being skewed exponentially over time.

1.14.2 Graphical Reports

Users can run the following code to get all supported reports.

```
>> import qlib.contrib.report as qcr
>> print(qcr.GRAPH_NAME_LIST)
['analysis_position.report_graph', 'analysis_position.score_ic_graph', 'analysis_
↪position.cumulative_return_graph', 'analysis_position.risk_analysis_graph',
↪'analysis_position.rank_label_graph', 'analysis_model.model_performance_graph']
```

Note: For more details, please refer to the function document: similar to `help(qcr.analysis_position.report_graph)`

1.14.3 Usage & Example

Usage of *analysis_position.report*

API

`qlib.contrib.report.analysis_position.report.`**`report_graph`**(*report_df: pandas.core.frame.DataFrame*, *show_notebook: bool = True*) → [<class 'list'>, <class 'tuple'>]

display backtest report

Example:

```
import qlib
import pandas as pd
from qlib.utils.time import Freq
from qlib.utils import flatten_dict
from qlib.backtest import backtest, executor
from qlib.contrib.evaluate import risk_analysis
from qlib.contrib.strategy import TopkDropoutStrategy

# init qlib
qlib.init(provider_uri=<qlib data dir>)

CSI300_BENCH = "SH000300"
FREQ = "day"
STRATEGY_CONFIG = {
    "topk": 50,
    "n_drop": 5,
    # pred_score, pd.Series
    "signal": pred_score,
}
```

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```
EXECUTOR_CONFIG = {
    "time_per_step": "day",
    "generate_portfolio_metrics": True,
}

backtest_config = {
    "start_time": "2017-01-01",
    "end_time": "2020-08-01",
    "account": 100000000,
    "benchmark": CSI300_BENCH,
    "exchange_kwargs": {
        "freq": FREQ,
        "limit_threshold": 0.095,
        "deal_price": "close",
        "open_cost": 0.0005,
        "close_cost": 0.0015,
        "min_cost": 5,
    },
}

# strategy object
strategy_obj = TopkDropoutStrategy(**STRATEGY_CONFIG)
# executor object
executor_obj = executor.SimulatorExecutor(**EXECUTOR_CONFIG)
# backtest
portfolio_metric_dict, indicator_dict = 
↪backtest(executor=executor_obj, strategy=strategy_obj, 
↪**backtest_config)
analysis_freq = "{0}{1}".format(*Freq.parse(FREQ))
# backtest info
report_normal_df, positions_normal = portfolio_metric_dict.
↪get(analysis_freq)

qcr.analysis_position.report_graph(report_normal_df)
```

Parameters

- **report_df** – **df.index.name** must be **date**, **df.columns** must contain **return**, **turnover**, **cost**, **bench**.

```
            return      cost        bench       turnover
date
2017-01-04  0.003421    0.000864    0.011693    0.576325
2017-01-05  0.000508    0.000447    0.000721    0.227882
2017-01-06  -0.003321   0.000212    -0.004322   0.102765
2017-01-09  0.006753    0.000212    0.006874    0.105864
2017-01-10  -0.000416   0.000440    -0.003350   0.208396
```

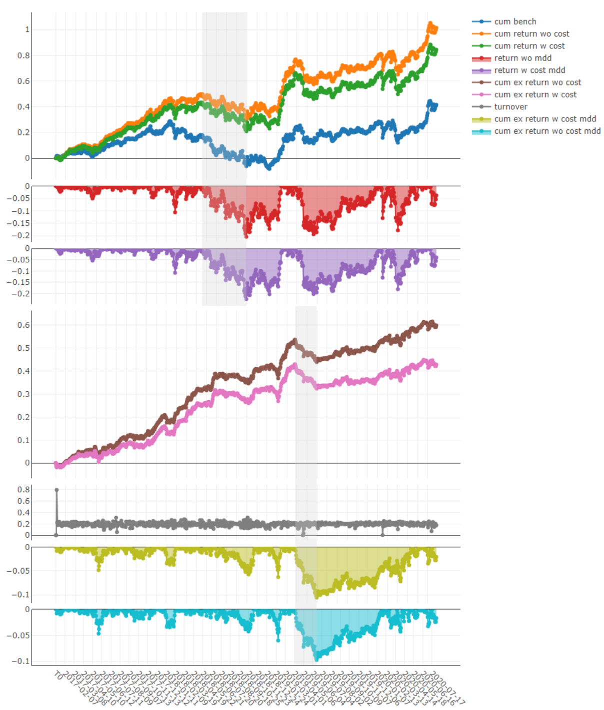
- **show_notebook** – whether to display graphics in notebook, the default is **True**.

Returns if show_notebook is True, display in notebook; else return **plotly.graph_objs.Figure** list.

Graphical Result

Note:

- Axis X: Trading day
- **Axis Y:**
  - ***cum bench*** Cumulative returns series of benchmark
  - ***cum return wo cost*** Cumulative returns series of portfolio without cost
  - ***cum return w cost*** Cumulative returns series of portfolio with cost
  - ***return wo mdd*** Maximum drawdown series of cumulative return without cost
  - ***return w cost mdd*:** Maximum drawdown series of cumulative return with cost
  - ***cum ex return wo cost*** The *CAR* (cumulative abnormal return) series of the portfolio compared to the benchmark without cost.
  - ***cum ex return w cost*** The *CAR* (cumulative abnormal return) series of the portfolio compared to the benchmark with cost.
  - ***turnover*** Turnover rate series
  - ***cum ex return wo cost mdd*** Drawdown series of *CAR* (cumulative abnormal return) without cost
  - ***cum ex return w cost mdd*** Drawdown series of *CAR* (cumulative abnormal return) with cost
- The shaded part above: Maximum drawdown corresponding to *cum return wo cost*
- The shaded part below: Maximum drawdown corresponding to *cum ex return wo cost*



Usage of *analysis_position.score_ic*

API

`qlib.contrib.report.analysis_position.score_ic.`**`score_ic_graph`**(*pred_label: pandas.core.frame.DataFrame*, *show_notebook: bool = True*) → [<class 'list'>, <class 'tuple'>]

score IC

Example:

```
from qlib.data import D
from qlib.contrib.report import analysis_position
pred_df_dates = pred_df.index.get_level_values(level='datetime')
features_df = D.features(D.instruments('csi500'), ['Ref($close, -2)/Ref($close, -1)-1'], pred_df_dates.min(), pred_df_dates.max())
features_df.columns = ['label']
pred_label = pd.concat([features_df, pred], axis=1, sort=True).reindex(features_df.index)
analysis_position.score_ic_graph(pred_label)
```

Parameters

- **`pred_label`** – index is **pd.MultiIndex**, index name is **[instrument, datetime]**; columns names is **[score, label]**.

```
instrument  datetime        score         label
SH600004  2017-12-11     -0.013502       -0.013502
            2017-12-12   -0.072367       -0.072367
            2017-12-13   -0.068605       -0.068605
            2017-12-14    0.012440        0.012440
            2017-12-15   -0.102778       -0.102778
```

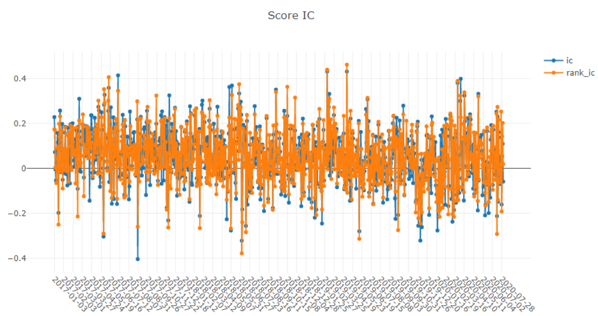
- **`show_notebook`** – whether to display graphics in notebook, the default is **True**.

Returns if show_notebook is True, display in notebook; else return **plotly.graph_objs.Figure** list.

Graphical Result

Note:

- Axis X: Trading day
- **Axis Y:**
  - ***ic*** The *Pearson correlation coefficient* series between *label* and *prediction score*. In the above example, the *label* is formulated as *Ref($close, -2)/Ref($close, -1)-1*. Please refer to Data Feature for more details.
  - ***rank_ic*** The *Spearman's rank correlation coefficient* series between *label* and *prediction score*.



Usage of *analysis_position.risk_analysis*

API

qlib.contrib.report.analysis_position.risk_analysis.**risk_analysis_graph**(*analysis_df: pandas.core.frame.DataFrame = None, report_normal_df: pandas.core.frame.DataFrame = None, report_long_short_df: pandas.core.frame.DataFrame = None, show_notebook: bool = True*) → Iterable[plotly.graph_objs._figu

Generate analysis graph and monthly analysis

Example:

```
import qlib
import pandas as pd
from qlib.utils.time import Freq
from qlib.utils import flatten_dict
from qlib.backtest import backtest, executor
from qlib.contrib.evaluate import risk_analysis
from qlib.contrib.strategy import TopkDropoutStrategy

# init qlib
qlib.init(provider_uri=<qlib data dir>)
```

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```
CSI300_BENCH = "SH000300"
FREQ = "day"
STRATEGY_CONFIG = {
    "topk": 50,
    "n_drop": 5,
    # pred_score, pd.Series
    "signal": pred_score,
}

EXECUTOR_CONFIG = {
    "time_per_step": "day",
    "generate_portfolio_metrics": True,
}

backtest_config = {
    "start_time": "2017-01-01",
    "end_time": "2020-08-01",
    "account": 100000000,
    "benchmark": CSI300_BENCH,
    "exchange_kwargs": {
        "freq": FREQ,
        "limit_threshold": 0.095,
        "deal_price": "close",
        "open_cost": 0.0005,
        "close_cost": 0.0015,
        "min_cost": 5,
    },
}

# strategy object
strategy_obj = TopkDropoutStrategy(**STRATEGY_CONFIG)
# executor object
executor_obj = executor.SimulatorExecutor(**EXECUTOR_CONFIG)
# backtest
portfolio_metric_dict, indicator_dict = 
↪backtest(executor=executor_obj, strategy=strategy_obj, 
↪**backtest_config)
analysis_freq = "{0}{1}".format(*Freq.parse(FREQ))
# backtest info
report_normal_df, positions_normal = portfolio_metric_dict.
↪get(analysis_freq)
analysis = dict()
analysis["excess_return_without_cost"] = risk_analysis(
    report_normal_df["return"] - report_normal_df["bench"], 
↪freq=analysis_freq
)
analysis["excess_return_with_cost"] = risk_analysis(
    report_normal_df["return"] - report_normal_df["bench"] - 
↪report_normal_df["cost"], freq=analysis_freq
)

analysis_df = pd.concat(analysis)  # type: pd.DataFrame
analysis_position.risk_analysis_graph(analysis_df, report_
↪normal_df)
```

Parameters

- **`analysis_df`** – analysis data, index is **pd.MultiIndex**; columns names is **[risk]**.

```
                                                  risk
excess_return_without_cost mean               0.000692
                           std                0.005374
                           annualized_return  0.174495
                           information_ratio  2.045576
                           max_drawdown      -0.079103
excess_return_with_cost    mean               0.000499
                           std                0.005372
                           annualized_return  0.125625
                           information_ratio  1.473152
                           max_drawdown      -0.088263
```

- **`report_normal_df`** – **df.index.name** must be **date**, df.columns must contain **return**, **turnover**, **cost**, **bench**.

```
            return      cost        bench       turnover
date
2017-01-04  0.003421    0.000864    0.011693    0.576325
2017-01-05  0.000508    0.000447    0.000721    0.227882
2017-01-06  -0.003321   0.000212    -0.004322   0.102765
2017-01-09  0.006753    0.000212    0.006874    0.105864
2017-01-10  -0.000416   0.000440    -0.003350   0.208396
```

- **`report_long_short_df`** – **df.index.name** must be **date**, df.columns contain **long**, **short**, **long_short**.

```
            long        short       long_short
date
2017-01-04  -0.001360   0.001394    0.000034
2017-01-05  0.002456    0.000058    0.002514
2017-01-06  0.000120    0.002739    0.002859
2017-01-09  0.001436    0.001838    0.003273
2017-01-10  0.000824    -0.001944   -0.001120
```

- **`show_notebook`** – Whether to display graphics in a notebook, default **True**. If True, show graph in notebook If False, return graph figure

Returns

Graphical Result

Note:

- **general graphics**
  - ***std***
    - ***excess_return_without_cost*** The *Standard Deviation* of *CAR* (cumulative abnormal return) without cost.
    - ***excess_return_with_cost*** The *Standard Deviation* of *CAR* (cumulative abnormal return) with cost.
  - ***annualized_return***

    * ***excess_return_without_cost*** The *Annualized Rate* of *CAR* (cumulative abnormal return) without cost.
    * ***excess_return_with_cost*** The *Annualized Rate* of *CAR* (cumulative abnormal return) with cost.

- ***information_ratio***
    * ***excess_return_without_cost*** The *Information Ratio* without cost.
    * ***excess_return_with_cost*** The *Information Ratio* with cost.

  To know more about *Information Ratio*, please refer to Information Ratio – IR.

- ***max_drawdown***
    * ***excess_return_without_cost*** The *Maximum Drawdown* of *CAR* (cumulative abnormal return) without cost.
    * ***excess_return_with_cost*** The *Maximum Drawdown* of *CAR* (cumulative abnormal return) with cost.

Note:

- **annualized_return/max_drawdown/information_ratio/std graphics**
    - Axis X: Trading days grouped by month
    - **Axis Y:**
        * **annualized_return graphics**
            · ***excess_return_without_cost_annualized_return*** The *Annualized Rate* series of monthly *CAR* (cumulative abnormal return) without cost.
            · ***excess_return_with_cost_annualized_return*** The *Annualized Rate* series of monthly *CAR* (cumulative abnormal return) with cost.
        * **max_drawdown graphics**
            · ***excess_return_without_cost_max_drawdown*** The *Maximum Drawdown* series of monthly *CAR* (cumulative abnormal return) without cost.
            · ***excess_return_with_cost_max_drawdown*** The *Maximum Drawdown* series of monthly *CAR* (cumulative abnormal return) with cost.
        * **information_ratio graphics**
            · ***excess_return_without_cost_information_ratio*** The *Information Ratio* series of monthly *CAR* (cumulative abnormal return) without cost.
            · ***excess_return_with_cost_information_ratio*** The *Information Ratio* series of monthly *CAR* (cumulative abnormal return) with cost.

- **std graphics**
  - ***excess_return_without_cost_max_drawdown*** The *Standard Deviation* series of monthly *CAR* (cumulative abnormal return) without cost.
  - ***excess_return_with_cost_max_drawdown*** The *Standard Deviation* series of monthly *CAR* (cumulative abnormal return) with cost.

Usage of *analysis_model.analysis_model_performance*

API

qlib.contrib.report.analysis_model.analysis_model_performance.**ic_figure**(*ic_df: pandas.core.frame.DataFrame*, *show_nature_day=True*, ***kwargs*) → plotly.graph_objs._figure.Fi

IC figure

Parameters

- **ic_df** – ic DataFrame
- **show_nature_day** – whether to display the abscissa of non-trading day

Returns plotly.graph_objs.Figure

qlib.contrib.report.analysis_model.analysis_model_performance.**model_performance_graph**(*pred_l pandas.co lag: int = 1, N: int = 5, reverse= rank= graph_ list = ['grou 'pred_ 'pred_ show_ bool = True, show_*) → [<class 'list'>, <class 'tuple'>]

Model performance

Parameters

- **pred_label** – index is **pd.MultiIndex**, index name is **[instrument, datetime]**; columns names is **[score, label]**. It is usually same as the label of model training(e.g. "Ref($close, -2)/Ref($close, -1) - 1").

```
instrument  datetime        score       label
SH600004    2017-12-11  -0.013502       -0.013502
                2017-12-12  -0.072367       -0.072367
                2017-12-13  -0.068605       -0.068605
                2017-12-14  0.012440        0.012440
                2017-12-15  -0.102778       -0.102778
```

- **lag** – *pred.groupby(level='instrument')['score'].shift(lag)*. It will be only used in the auto-correlation computing.
- **N** – group number, default 5.
- **reverse** – if *True*, *pred['score'] *= -1*.
- **rank** – if **True**, calculate rank ic.
- **graph_names** – graph names; default ['cumulative_return', 'pred_ic', 'pred_autocorr', 'pred_turnover'].
- **show_notebook** – whether to display graphics in notebook, the default is *True*.
- **show_nature_day** – whether to display the abscissa of non-trading day.

Returns if show_notebook is True, display in notebook; else return *plotly.graph_objs.Figure* list.

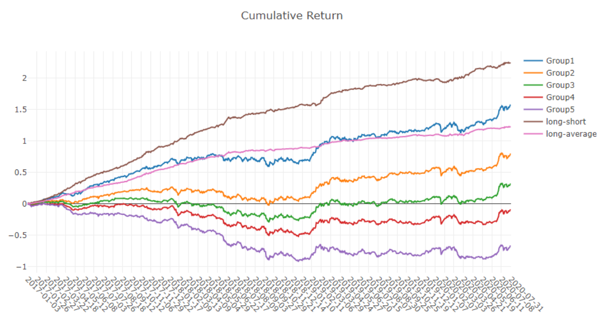
Graphical Results

Note:

- **cumulative return graphics**
  - ***Group1*:** The *Cumulative Return* series of stocks group with (*ranking ratio* of label <= 20%)
  - ***Group2*:** The *Cumulative Return* series of stocks group with (20% < *ranking ratio* of label <= 40%)
  - ***Group3*:** The *Cumulative Return* series of stocks group with (40% < *ranking ratio* of label <= 60%)
  - ***Group4*:** The *Cumulative Return* series of stocks group with (60% < *ranking ratio* of label <= 80%)
  - ***Group5*:** The *Cumulative Return* series of stocks group with (80% < *ranking ratio* of label)
  - ***long-short*:** The Difference series between *Cumulative Return* of *Group1* and of *Group5*
  - ***long-average*** The Difference series between *Cumulative Return* of *Group1* and average *Cumulative Return* for all stocks.

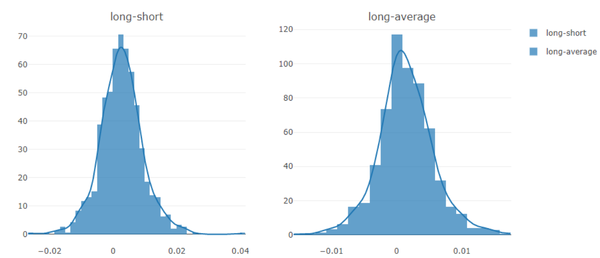
The *ranking ratio* can be formulated as follows.

$$ranking\ ratio = \frac{Ascending\ Ranking\ of\ label}{Number\ of\ Stocks\ in\ the\ Portfolio}$$



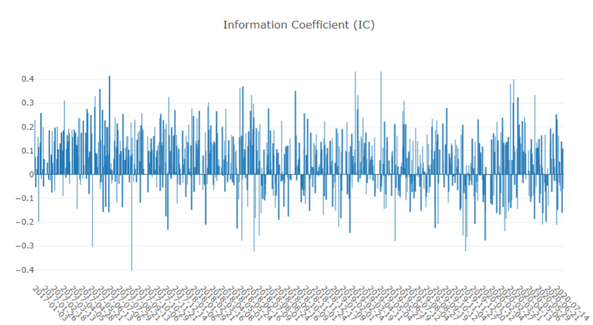
Note:

- **long-short/long-average** The distribution of long-short/long-average returns on each trading day



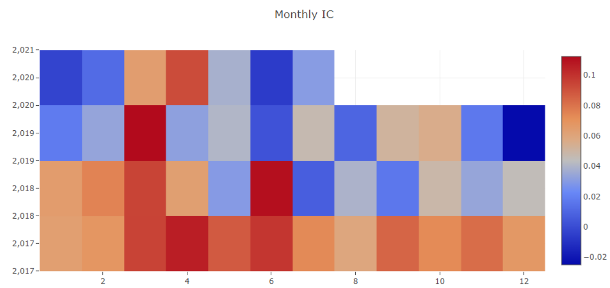
Note:

- **Information Coefficient**
  - The *Pearson correlation coefficient* series between *labels* and *prediction scores* of stocks in portfolio.
  - The graphics reports can be used to evaluate the *prediction scores*.



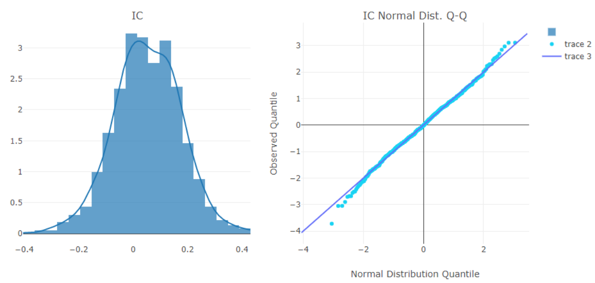
Note:

- **Monthly IC** Monthly average of the *Information Coefficient*



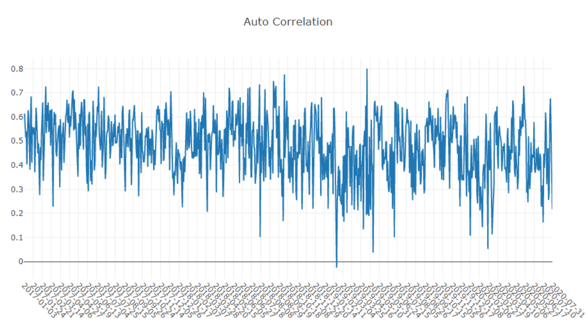
Note:

- **IC** The distribution of the *Information Coefficient* on each trading day.
- **IC Normal Dist. Q-Q** The *Quantile-Quantile Plot* is used for the normal distribution of *Information Coefficient* on each trading day.



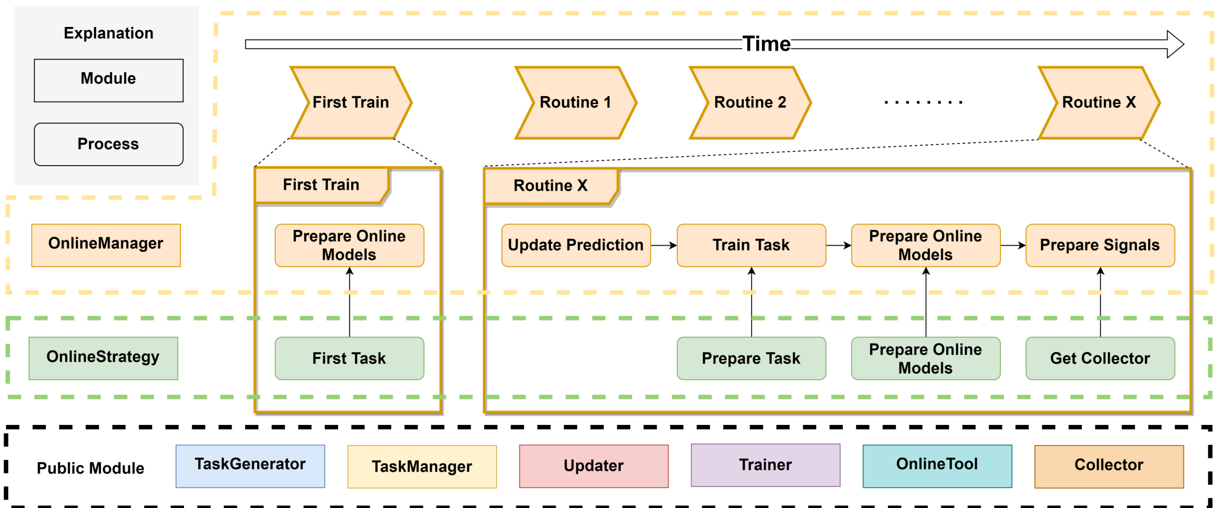
Note:

- **Auto Correlation**
  - The *Pearson correlation coefficient* series between the latest *prediction scores* and the *prediction scores lag* days ago of stocks in portfolio on each trading day.
  - The graphics reports can be used to estimate the turnover rate.



1.15 Online Serving

1.15.1 Introduction



In addition to backtesting, one way to test a model is effective is to make predictions in real market conditions or even do real trading based on those predictions. `Online Serving` is a set of modules for online models using the latest data, which including *Online Manager*, *Online Strategy*, *Online Tool*, *Updater*.

Here are several examples for reference, which demonstrate different features of `Online Serving`. If you have many models or *task* needs to be managed, please consider Task Management. The examples are based on some components in Task Management such as `TrainerRM` or `Collector`.

NOTE: User should keep his data source updated to support online serving. For example, Qlib provides a batch of scripts to help users update Yahoo daily data.

Known limitations currently - Currently, the daily updating prediction for the next trading day is supported. But generating orders for the next trading day is not supported due to the *limitations of public data <https://github.com/microsoft/qlib/issues/215#issuecomment-766293563>*_

1.15.2 Online Manager

OnlineManager can manage a set of *Online Strategy* and run them dynamically.

With the change of time, the decisive models will be also changed. In this module, we call those contributing models *online* models. In every routine(such as every day or every minute), the *online* models may be changed and the prediction of them needs to be updated. So this module provides a series of methods to control this process.

This module also provides a method to simulate *Online Strategy* in history. Which means you can verify your strategy or find a better one.

There are 4 total situations for using different trainers in different situations:

Situations	Description
Online + Trainer	When you want to do a REAL routine, the Trainer will help you train the models. It will train models task by task and strategy by strategy.
Online + DelayTrainer	DelayTrainer will skip concrete training until all tasks have been prepared by different strategies. It makes users can parallelly train all tasks at the end of *routine* or *first_train*. Otherwise, these functions will get stuck when each strategy prepare tasks.
Simulation + Trainer	It will behave in the same way as *Online + Trainer*. The only difference is that it is for simulation/backtesting instead of online trading
Simulation + DelayTrainer	When your models don't have any temporal dependence, you can use DelayTrainer for the ability to multitasking. It means all tasks in all routines can be REAL trained at the end of simulating. The signals will be prepared well at different time segments (based on whether or not any new model is online).

Here is some pseudo code that demonstrate the workflow of each situation

For simplicity

- Only one strategy is used in the strategy
- *update_online_pred* is only called in the online mode and is ignored

1) *Online + Trainer*

```
tasks = first_train()
models = trainer.train(tasks)
trainer.end_train(models)
for day in online_trading_days:
    # OnlineManager.routine
    models = trainer.train(strategy.prepare_tasks())  # for each strategy
    strategy.prepare_online_models(models)  # for each strategy

    trainer.end_train(models)
    prepare_signals()  # prepare trading signals daily
```

Online + DelayTrainer: the workflow is the same as *Online + Trainer*.

2) *Simulation + DelayTrainer*

```
# simulate
tasks = first_train()
models = trainer.train(tasks)
for day in historical_calendars:
    # OnlineManager.routine
    models = trainer.train(strategy.prepare_tasks())  # for each strategy
    strategy.prepare_online_models(models)  # for each strategy
# delay_prepare()
# FIXME: Currently the delay_prepare is not implemented in a proper way.
trainer.end_train(<for all previous models>)
prepare_signals()
```

Can we simplify current workflow?

- Can reduce the number of state of tasks?
    - For each task, we have three phases (i.e. task, partly trained task, final trained task)

class qlib.workflow.online.manager.**OnlineManager**(*strategies: Union[qlib.workflow.online.strategy.OnlineStrategy, List[qlib.workflow.online.strategy.OnlineStrategy]], trainer: qlib.model.trainer.Trainer = None, begin_time: Union[str, pandas._libs.tslibs.timestamps.Timestamp] = None, freq='day'*)

OnlineManager can manage online models with *Online Strategy*. It also provides a history recording of which models are online at what time.

__init__(*strategies: Union[qlib.workflow.online.strategy.OnlineStrategy, List[qlib.workflow.online.strategy.OnlineStrategy]], trainer: qlib.model.trainer.Trainer = None, begin_time: Union[str, pandas._libs.tslibs.timestamps.Timestamp] = None, freq='day'*)

Init OnlineManager. One OnlineManager must have at least one OnlineStrategy.

Parameters

- **strategies** (*Union[OnlineStrategy, List[OnlineStrategy]]*) – an instance of OnlineStrategy or a list of OnlineStrategy
- **begin_time** (*Union[str,pd.Timestamp], optional*) – the OnlineManager will begin at this time. Defaults to None for using the latest date.
- **trainer** (qlib.model.trainer.Trainer) – the trainer to train task. None for using TrainerR.
- **freq** (*str, optional*) – data frequency. Defaults to "day".

first_train(*strategies: List[qlib.workflow.online.strategy.OnlineStrategy] = None, model_kwargs: dict = {}*)

Get tasks from every strategy's first_tasks method and train them. If using DelayTrainer, it can finish training all together after every strategy's first_tasks.

Parameters

- **strategies** (*List[OnlineStrategy]*) – the strategies list (need this param when adding strategies). None for use default strategies.
- **model_kwargs** (*dict*) – the params for *prepare_online_models*

routine(*cur_time: Union[str, pandas._libs.tslibs.timestamps.Timestamp] = None, task_kwargs: dict = {}, model_kwargs: dict = {}, signal_kwargs: dict = {}*)

Typical update process for every strategy and record the online history.

The typical update process after a routine, such as day by day or month by month. The process is: Update predictions -> Prepare tasks -> Prepare online models -> Prepare signals.

If using DelayTrainer, it can finish training all together after every strategy's prepare_tasks.

Parameters

- **cur_time** (*Union[str,pd.Timestamp], optional*) – run routine method in this time. Defaults to None.
- **task_kwargs** (*dict*) – the params for *prepare_tasks*
- **model_kwargs** (*dict*) – the params for *prepare_online_models*
- **signal_kwargs** (*dict*) – the params for *prepare_signals*

get_collector(***kwargs*) → qlib.workflow.task.collect.MergeCollector

Get the instance of Collector to collect results from every strategy. This collector can be a basis as the signals preparation.

Parameters **`**kwargs`** – the params for get_collector.

Returns the collector to merge other collectors.

Return type *MergeCollector*

`add_strategy`(*strategies: Union[qlib.workflow.online.strategy.OnlineStrategy, List[qlib.workflow.online.strategy.OnlineStrategy]]*)

Add some new strategies to OnlineManager.

Parameters **`strategy`** (*`Union[OnlineStrategy, List[OnlineStrategy]]`*) – a list of OnlineStrategy

`prepare_signals`(*prepare_func: Callable = <qlib.model.ens.ensemble.AverageEnsemble object>, over_write=False*)

After preparing the data of the last routine (a box in box-plot) which means the end of the routine, we can prepare trading signals for the next routine.

NOTE: Given a set prediction, all signals before these prediction end times will be prepared well.

Even if the latest signal already exists, the latest calculation result will be overwritten.

Note: Given a prediction of a certain time, all signals before this time will be prepared well.

Parameters

- **`prepare_func`** (*`Callable, optional`*) – Get signals from a dict after collecting. Defaults to AverageEnsemble(), the results collected by MergeCollector must be {xxx:pred}.
- **`over_write`** (*`bool, optional`*) – If True, the new signals will overwrite. If False, the new signals will append to the end of signals. Defaults to False.

Returns the signals.

Return type pd.DataFrame

`get_signals`() → Union[pandas.core.series.Series, pandas.core.frame.DataFrame]

Get prepared online signals.

Returns pd.Series for only one signals every datetime. pd.DataFrame for multiple signals, for example, buy and sell operations use different trading signals.

Return type Union[pd.Series, pd.DataFrame]

`simulate`(*end_time=None*, *frequency='day'*, *task_kwargs={}*, *model_kwargs={}*, *signal_kwargs={}*) → Union[pandas.core.series.Series, pandas.core.frame.DataFrame]

Starting from the current time, this method will simulate every routine in OnlineManager until the end time.

Considering the parallel training, the models and signals can be prepared after all routine simulating.

The delay training way can be `DelayTrainer` and the delay preparing signals way can be `delay_prepare`.

Parameters

- **`end_time`** – the time the simulation will end
- **`frequency`** – the calendar frequency
- **`task_kwargs`** (*`dict`*) – the params for *prepare_tasks*
- **`model_kwargs`** (*`dict`*) – the params for *prepare_online_models*

- **signal_kwargs** (*dict*) – the params for *prepare_signals*

Returns pd.Series for only one signals every datetime. pd.DataFrame for multiple signals, for example, buy and sell operations use different trading signals.

Return type Union[pd.Series, pd.DataFrame]

delay_prepare (*model_kwargs={}*, *signal_kwargs={}*)
Prepare all models and signals if something is waiting for preparation.

Parameters

- **model_kwargs** – the params for *end_train*
- **signal_kwargs** – the params for *prepare_signals*

1.15.3 Online Strategy

OnlineStrategy module is an element of online serving.

class qlib.workflow.online.strategy.**OnlineStrategy** (*name_id: str*)
OnlineStrategy is working with *Online Manager*, responding to how the tasks are generated, the models are updated and signals are prepared.

__init__ (*name_id: str*)
Init OnlineStrategy. This module **MUST** use Trainer to finishing model training.

Parameters

- **name_id** (*str*) – a unique name or id.
- **trainer** (qlib.model.trainer.Trainer, *optional*) – a instance of Trainer. Defaults to None.

prepare_tasks (*cur_time*, ***kwargs*) → List[dict]
After the end of a routine, check whether we need to prepare and train some new tasks based on cur_time (None for latest).. Return the new tasks waiting for training.

You can find the last online models by OnlineTool.online_models.

prepare_online_models (*trained_models*, *cur_time=None*) → List[object]
Select some models from trained models and set them to online models. This is a typical implementation to online all trained models, you can override it to implement the complex method. You can find the last online models by OnlineTool.online_models if you still need them.

NOTE: Reset all online models to trained models. If there are no trained models, then do nothing.

NOTE: Current implementation is very naive. Here is a more complex situation which is more closer to the practical scenarios. 1. Train new models at the day before *test_start* (at time stamp *T*) 2. Switch models at the *test_start* (at time timestamp *T + 1* typically)

Parameters

- **models** (*list*) – a list of models.
- **cur_time** (*pd.Dataframe*) – current time from OnlineManger. None for the latest.

Returns a list of online models.

Return type List[object]

first_tasks () → List[dict]
Generate a series of tasks firstly and return them.

get_collector() → qlib.workflow.task.collect.Collector
Get the instance of Collector to collect different results of this strategy.

For example:

1) collect predictions in Recorder
2) collect signals in a txt file

Returns Collector

class qlib.workflow.online.strategy.**RollingStrategy**(*name_id: str, task_template: Union[dict, List[dict]], rolling_gen: qlib.workflow.task.gen.RollingGen*)
This example strategy always uses the latest rolling model sas online models.

__init__(*name_id: str, task_template: Union[dict, List[dict]], rolling_gen: qlib.workflow.task.gen.RollingGen*)
Init RollingStrategy.

Assumption: the str of name_id, the experiment name, and the trainer's experiment name are the same.

Parameters

- **name_id** (*str*) – a unique name or id. Will be also the name of the Experiment.
- **task_template** (*Union[dict, List[dict]]*) – a list of task_template or a single template, which will be used to generate many tasks using rolling_gen.
- **rolling_gen** (RollingGen) – an instance of RollingGen

get_collector(*process_list=[<qlib.model.ens.group.RollingGroup object>], rec_key_func=None, rec_filter_func=None, artifacts_key=None*)
Get the instance of Collector to collect results. The returned collector must distinguish results in different models.

Assumption: the models can be distinguished based on the model name and rolling test segments. If you do not want this assumption, please implement your method or use another rec_key_func.

Parameters

- **rec_key_func** (*Callable*) – a function to get the key of a recorder. If None, use recorder id.
- **rec_filter_func** (*Callable, optional*) – filter the recorder by return True or False. Defaults to None.
- **artifacts_key** (*List[str], optional*) – the artifacts key you want to get. If None, get all artifacts.

first_tasks() → List[dict]
Use rolling_gen to generate different tasks based on task_template.

Returns a list of tasks

Return type List[dict]

prepare_tasks(*cur_time*) → List[dict]
Prepare new tasks based on cur_time (None for the latest).

You can find the last online models by OnlineToolR.online_models.

Returns a list of new tasks.

Return type List[dict]

1.15.4 Online Tool

OnlineTool is a module to set and unset a series of *online* models. The *online* models are some decisive models in some time points, which can be changed with the change of time. This allows us to use efficient submodels as the market-style changing.

class `qlib.workflow.online.utils.`**`OnlineTool`**

OnlineTool will manage *online* models in an experiment that includes the model recorders.

`__init__`()

Init OnlineTool.

`set_online_tag`(*tag, recorder: Union[list, object]*)

Set *tag* to the model to sign whether online.

Parameters

- **tag** (*str*) – the tags in *ONLINE_TAG*, *OFFLINE_TAG*
- **recorder** (*Union[list, object]*) – the model's recorder

`get_online_tag`(*recorder: object*) → str

Given a model recorder and return its online tag.

Parameters **recorder** (*Object*) – the model's recorder

Returns the online tag

Return type str

`reset_online_tag`(*recorder: Union[list, object]*)

Offline all models and set the recorders to 'online'.

Parameters **recorder** (*Union[list, object]*) – the recorder you want to reset to 'online'.

`online_models`() → list

Get current *online* models

Returns a list of *online* models.

Return type list

`update_online_pred`(*to_date=None*)

Update the predictions of *online* models to to_date.

Parameters **to_date** (*pd.Timestamp*) – the pred before this date will be updated. None for updating to the latest.

class `qlib.workflow.online.utils.`**`OnlineToolR`**(*default_exp_name: str = None*)

The implementation of OnlineTool based on (R)ecorder.

`__init__`(*default_exp_name: str = None*)

Init OnlineToolR.

Parameters **default_exp_name** (*str*) – the default experiment name.

`set_online_tag`(*tag, recorder: Union[qlib.workflow.recorder.Recorder, List[T]]*)

Set *tag* to the model's recorder to sign whether online.

Parameters

- **tag** (*str*) – the tags in *ONLINE_TAG*, *NEXT_ONLINE_TAG*, *OFFLINE_TAG*
- **recorder** (*Union[Recorder, List]*) – a list of Recorder or an instance of Recorder

get_online_tag(*recorder: qlib.workflow.recorder.Recorder*) → str
Given a model recorder and return its online tag.

Parameters **recorder** (Recorder) – an instance of recorder

Returns the online tag

Return type str

reset_online_tag(*recorder: Union[qlib.workflow.recorder.Recorder, List[T]], exp_name: str = None*)
Offline all models and set the recorders to 'online'.

Parameters

- **recorder** (*Union[Recorder, List]*) – the recorder you want to reset to 'online'.
- **exp_name** (*str*) – the experiment name. If None, then use default_exp_name.

online_models(*exp_name: str = None*) → list
Get current *online* models

Parameters **exp_name** (*str*) – the experiment name. If None, then use default_exp_name.

Returns a list of *online* models.

Return type list

update_online_pred(*to_date=None*, *from_date=None*, *exp_name: str = None*)
Update the predictions of online models to to_date.

Parameters

- **to_date** (*pd.Timestamp*) – the pred before this date will be updated. None for updating to latest time in Calendar.
- **exp_name** (*str*) – the experiment name. If None, then use default_exp_name.

1.15.5 Updater

Updater is a module to update artifacts such as predictions when the stock data is updating.

class qlib.workflow.online.update.**RMDLoader**(*rec: qlib.workflow.recorder.Recorder*)
Recorder Model Dataset Loader

__init__(*rec: qlib.workflow.recorder.Recorder*)
Initialize self. See help(type(self)) for accurate signature.

get_dataset(*start_time*, *end_time*, *segments=None*, *unprepared_dataset: Optional[qlib.data.dataset.DatasetH] = None*) → qlib.data.dataset.DatasetH
Load, config and setup dataset.

This dataset is for inference.

Parameters

- **start_time** – the start_time of underlying data
- **end_time** – the end_time of underlying data
- **segments** – dict the segments config for dataset Due to the time series dataset (TSDatasetH), the test segments maybe different from start_time and end_time

- **unprepared_dataset** – Optional[DatasetH] if user don't want to load dataset from recorder, please specify user's dataset

Returns the instance of DatasetH

Return type *DatasetH*

class qlib.workflow.online.update.**RecordUpdater**(*record: qlib.workflow.recorder.Recorder*, **args*, ***kwargs*)

Update a specific recorders

__init__(*record: qlib.workflow.recorder.Recorder*, **args*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

update(**args*, ***kwargs*)

Update info for specific recorder

class qlib.workflow.online.update.**DSBasedUpdater**(*record: qlib.workflow.recorder.Recorder*, *to_date=None*, *from_date=None*, *hist_ref: Optional[int] = None*, *freq='day'*, *fname='pred.pkl'*, *loader_cls: type = <class 'qlib.workflow.online.update.RMDLoader'>*)

Dataset-Based Updater

- Providing updating feature for Updating data based on Qlib Dataset

Assumption

- Based on Qlib dataset
- The data to be updated is a multi-level index pd.DataFrame. For example label, prediction.

__init__(*record: qlib.workflow.recorder.Recorder*, *to_date=None*, *from_date=None*, *hist_ref: Optional[int] = None*, *freq='day'*, *fname='pred.pkl'*, *loader_cls: type = <class 'qlib.workflow.online.update.RMDLoader'>*)

Init PredUpdater.

Expected behavior in following cases:

- if *to_date* is greater than the max date in the calendar, the data will be updated to the latest date
- if there are data before *from_date* or after *to_date*, only the data between *from_date* and *to_date* are affected.

Parameters

- **record** – Recorder
- **to_date** – update to prediction to the *to_date*

  if to_date is None:

  data will updated to the latest date.
- **from_date** – the update will start from *from_date*

  if from_date is None:

  the updating will occur on the next tick after the latest data in historical data

- **hist_ref** – int Sometimes, the dataset will have historical depends. Leave the problem to users to set the length of historical dependency If user doesn't specify this parameter, Updater will try to load dataset to automatically determine the hist_ref

  Note: the start_time is not included in the *hist_ref*; So the *hist_ref* will be *step_len - 1* in most cases

- **loader_cls** – type the class to load the model and dataset

prepare_data(*unprepared_dataset: Optional[qlib.data.dataset.DatasetH] = None*) → qlib.data.dataset.DatasetH

Load dataset - if unprepared_dataset is specified, then prepare the dataset directly - Otherwise,

Separating this function will make it easier to reuse the dataset

Returns the instance of DatasetH

Return type *DatasetH*

update(*dataset: qlib.data.dataset.DatasetH = None*, *write: bool = True*, *ret_new: bool = False*) → Optional[object]

Parameters

- **dataset** (DatasetH) – DatasetH: the instance of DatasetH. None for prepare it again.
- **write** (*bool*) – will the the write action be executed
- **ret_new** (*bool*) – will the updated data be returned

Returns the updated dataset

Return type Optional[object]

get_update_data(*dataset: qlib.data.dataset.Dataset*) → pandas.core.frame.DataFrame

return the updated data based on the given dataset

The difference between *get_update_data* and *update* - *update_date* only include some data specific feature - *update* include some general routine steps(e.g. prepare dataset, checking)

class qlib.workflow.online.update.**PredUpdater**(*record: qlib.workflow.recorder.Recorder*, *to_date=None*, *from_date=None*, *hist_ref: Optional[int] = None*, *freq='day'*, *fname='pred.pkl'*, *loader_cls: type = <class 'qlib.workflow.online.update.RMDLoader'>*)

Update the prediction in the Recorder

get_update_data(*dataset: qlib.data.dataset.Dataset*) → pandas.core.frame.DataFrame

return the updated data based on the given dataset

The difference between *get_update_data* and *update* - *update_date* only include some data specific feature - *update* include some general routine steps(e.g. prepare dataset, checking)

class qlib.workflow.online.update.**LabelUpdater**(*record: qlib.workflow.recorder.Recorder*, *to_date=None*, ***kwargs*)

Update the label in the recorder

Assumption - The label is generated from record_temp.SignalRecord.

`__init__`(*record: qlib.workflow.recorder.Recorder*, *to_date=None*, ***kwargs*)
Init PredUpdater.

Expected behavior in following cases:

- if *to_date* is greater than the max date in the calendar, the data will be updated to the latest date
- if there are data before *from_date* or after *to_date*, only the data between *from_date* and *to_date* are affected.

Parameters

- **`record`** – Recorder
- **`to_date`** – update to prediction to the *to_date*

  if to_date is None:

  data will updated to the latest date.
- **`from_date`** – the update will start from *from_date*

  if from_date is None:

  the updating will occur on the next tick after the latest data in historical data
- **`hist_ref`** – int Sometimes, the dataset will have historical depends. Leave the problem to users to set the length of historical dependency If user doesn't specify this parameter, Updater will try to load dataset to automatically determine the hist_ref

  Note: the start_time is not included in the *hist_ref*; So the *hist_ref* will be *step_len - 1* in most cases
- **`loader_cls`** – type the class to load the model and dataset

`get_update_data`(*dataset: qlib.data.dataset.Dataset*) → pandas.core.frame.DataFrame
return the updated data based on the given dataset

The difference between *get_update_data* and *update* - *update_date* only include some data specific feature - *update* include some general routine steps(e.g. prepare dataset, checking)

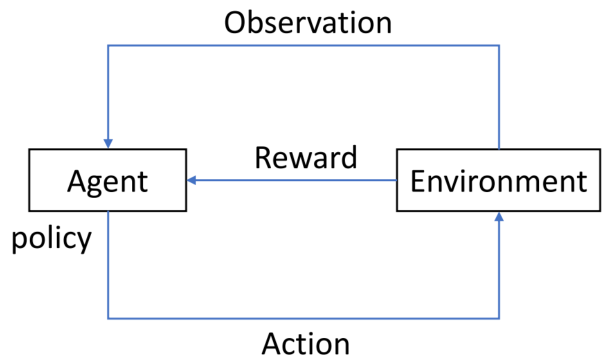
1.16 Reinforcement Learning in Quantitative Trading

1.16.1 Reinforcement Learning in Quantitative Trading

Reinforcement Learning

Different from supervised learning tasks such as classification tasks and regression tasks. Another important paradigm in machine learning is Reinforcement Learning, which attempts to optimize an accumulative numerical reward signal by directly interacting with the environment under a few assumptions such as Markov Decision Process(MDP).

As demonstrated in the following figure, an RL system consists of four elements, 1)the agent 2) the environment the agent interacts with 3) the policy that the agent follows to take actions on the environment and 4)the reward signal from the environment to the agent. In general, the agent can perceive and interpret its environment, take actions and learn through reward, to seek long-term and maximum overall reward to achieve an optimal solution.



RL attempts to learn to produce actions by trial and error. By sampling actions and then observing which one leads to our desired outcome, a policy is obtained to generate optimal actions. In contrast to supervised learning, RL learns this not from a label but from a time-delayed label called a reward. This scalar value lets us know whether the current outcome is good or bad. In a word, the target of RL is to take actions to maximize reward.

The Qlib Reinforcement Learning toolkit (QlibRL) is an RL platform for quantitative investment, which provides support to implement the RL algorithms in Qlib.

Potential Application Scenarios in Quantitative Trading

RL methods have already achieved outstanding achievement in many applications, such as game playing, resource allocating, recommendation, marketing and advertising, etc. Investment is always a continuous process, taking the stock market as an example, investors need to control their positions and stock holdings by one or more buying and selling behaviors, to maximize the investment returns. Besides, each buy and sell decision is made by investors after fully considering the overall market information and stock information. From the view of an investor, the process could be described as a continuous decision-making process generated according to interaction with the market, such problems could be solved by the RL algorithms. Following are some scenarios where RL can potentially be used in quantitative investment.

Portfolio Construction

Portfolio construction is a process of selecting securities optimally by taking a minimum risk to achieve maximum returns. With an RL-based solution, an agent allocates stocks at every time step by obtaining information for each stock and the market. The key is to develop of policy for building a portfolio and make the policy able to pick the optimal portfolio.

Order Execution

As a fundamental problem in algorithmic trading, order execution aims at fulfilling a specific trading order, either liquidation or acquirement, for a given instrument. Essentially, the goal of order execution is twofold: it not only requires to fulfill the whole order but also targets a more economical execution with maximizing profit gain (or minimizing capital loss). The order execution with only one order of liquidation or acquirement is called single-asset order execution.

Considering stock investment always aim to pursue long-term maximized profits, it usually manifests as a sequential process of continuously adjusting the asset portfolios, execution for multiple orders, including order of liquidation and acquirement, brings more constraints and makes the sequence of execution for different orders should be considered, e.g. before executing an order to buy some stocks, we have to sell at least one stock. The order execution with multiple assets is called multi-asset order execution.

According to the order execution's trait of sequential decision-making, an RL-based solution could be applied to solve the order execution. With an RL-based solution, an agent optimizes execution strategy by interacting with the market environment.

With QlibRL, the RL algorithm in the above scenarios can be easily implemented.

Nested Portfolio Construction and Order Executor

QlibRL makes it possible to jointly optimize different levels of strategies/models/agents. Take Nested Decision Execution Framework as an example, the optimization of order execution strategy and portfolio management strategies can interact with each other to maximize returns.

1.16.2 Quick Start

QlibRL provides an example of an implementation of a single asset order execution task and the following is an example of the config file to train with QlibRL.

```yaml
simulator:
    # Each step contains 30mins
    time_per_step: 30
    # Upper bound of volume, should be null or a float between 0 and 1, if it is a␣
↪float, represent upper bound is calculated by the percentage of the market volume
    vol_limit: null
env:
    # Concurrent environment workers.
    concurrency: 1
    # dummy or subproc or shmem. Corresponding to `parallelism in tianshou <https://
↪tianshou.readthedocs.io/en/master/api/tianshou.env.html#vectorenv>`_.
    parallel_mode: dummy
action_interpreter:
    class: CategoricalActionInterpreter
    kwargs:
        # Candidate actions, it can be a list with length L: [a_1, a_2,..., a_L] or␣
↪an integer n, in which case the list of length n+1 is auto-generated, i.e., [0, 1/n,
↪ 2/n,..., n/n].
        values: 14
        # Total number of steps (an upper-bound estimation)
        max_step: 8
    module_path: qlib.rl.order_execution.interpreter
state_interpreter:
    class: FullHistoryStateInterpreter
    kwargs:
        # Number of dimensions in data.
        data_dim: 6
        # Equal to the total number of records. For example, in SAOE per minute, data_
↪ticks is the length of the day in minutes.
        data_ticks: 240
        # The total number of steps (an upper-bound estimation). For example, 390min /
↪ 30min-per-step = 13 steps.
        max_step: 8
        # Provider of the processed data.
        processed_data_provider:
            class: PickleProcessedDataProvider
            module_path: qlib.rl.data.pickle_styled
            kwargs:
```

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```
                data_dir: ./data/pickle_dataframe/feature
    module_path: qlib.rl.order_execution.interpreter
reward:
    class: PAPenaltyReward
    kwargs:
        # The penalty for a large volume in a short time.
        penalty: 100.0
    module_path: qlib.rl.order_execution.reward
data:
    source:
        order_dir: ./data/training_order_split
        data_dir: ./data/pickle_dataframe/backtest
        # number of time indexes
        total_time: 240
        # start time index
        default_start_time: 0
        # end time index
        default_end_time: 240
        proc_data_dim: 6
    num_workers: 0
    queue_size: 20
network:
    class: Recurrent
    module_path: qlib.rl.order_execution.network
policy:
    class: PPO
    kwargs:
        lr: 0.0001
    module_path: qlib.rl.order_execution.policy
runtime:
    seed: 42
    use_cuda: false
trainer:
    max_epoch: 2
    # Number of episodes collected in each training iteration
    repeat_per_collect: 5
    earlystop_patience: 2
    # Episodes per collect at training.
    episode_per_collect: 20
    batch_size: 16
    # Perform validation every n iterations
    val_every_n_epoch: 1
    checkpoint_path: ./checkpoints
    checkpoint_every_n_iters: 1
```

And the config file for backtesting:

```
order_file: ./data/backtest_orders.csv
start_time: "9:45"
end_time: "14:44"
qlib:
    provider_uri_1min: ./data/bin
    feature_root_dir: ./data/pickle
    # feature generated by today's information
    feature_columns_today: [
        "$open", "$high", "$low", "$close", "$vwap", "$volume",
    ]
```

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```
    # feature generated by yesterday's information
    feature_columns_yesterday: [
        "$open_v1", "$high_v1", "$low_v1", "$close_v1", "$vwap_v1", "$volume_v1",
    ]
exchange:
    # the expression for buying and selling stock limitation
    limit_threshold: ['$close == 0', '$close == 0']
    # deal price for buying and selling
    deal_price: ["If($close == 0, $vwap, $close)", "If($close == 0, $vwap, $close)"]
volume_threshold:
    # volume limits are both buying and selling, "cum" means that this is a␣
↪cumulative value over time
    all: ["cum", "0.2 * DayCumsum($volume, '9:45', '14:44')"]
    # the volume limits of buying
    buy: ["current", "$close"]
    # the volume limits of selling, "current" means that this is a real-time value␣
↪and will not accumulate over time
    sell: ["current", "$close"]
strategies:
    30min:
        class: TWAPStrategy
        module_path: qlib.contrib.strategy.rule_strategy
        kwargs: {}
    1day:
        class: SAOEIntStrategy
        module_path: qlib.rl.order_execution.strategy
        kwargs:
        state_interpreter:
            class: FullHistoryStateInterpreter
            module_path: qlib.rl.order_execution.interpreter
            kwargs:
            max_step: 8
            data_ticks: 240
            data_dim: 6
            processed_data_provider:
                class: PickleProcessedDataProvider
                module_path: qlib.rl.data.pickle_styled
                kwargs:
                data_dir: ./data/pickle_dataframe/feature
        action_interpreter:
            class: CategoricalActionInterpreter
            module_path: qlib.rl.order_execution.interpreter
            kwargs:
            values: 14
            max_step: 8
        network:
            class: Recurrent
            module_path: qlib.rl.order_execution.network
            kwargs: {}
        policy:
            class: PPO
            module_path: qlib.rl.order_execution.policy
            kwargs:
                lr: 1.0e-4
                # Local path to the latest model. The model is generated during␣
↪training, so please run training first if you want to run backtest with a trained␣
↪policy. You could also remove this parameter file to run backtest with a randomly␣
↪initialized policy.
```

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```
                weight_file: ./checkpoints/latest.pth
# Concurrent environment workers.
concurrency: 5
```

With the above config files, you can start training the agent by the following command:

```
$ python -m qlib.rl.contrib.train_onpolicy.py --config_path train_config.yml
```

After the training, you can backtest with the following command:

```
$ python -m qlib.rl.contrib.backtest.py --config_path backtest_config.yml
```

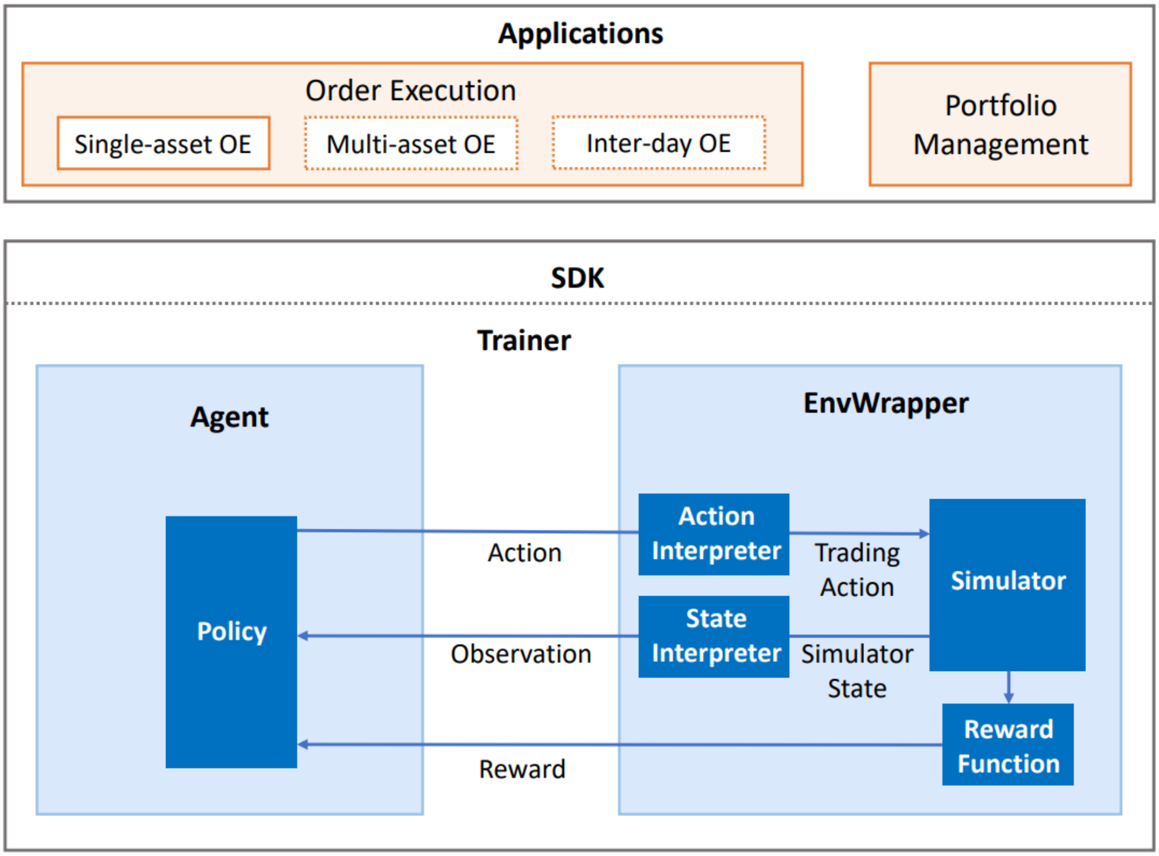
In that case, `SingleAssetOrderExecution` and `SingleAssetOrderExecutionSimple` as examples for simulator, `qlib.rl.order_execution.interpreter.FullHistoryStateInterpreter` and `qlib.rl.order_execution.interpreter.CategoricalActionInterpreter` as examples for interpreter, `qlib.rl.order_execution.policy.PPO` as an example for policy, and `qlib.rl.order_execution.reward.PAPenaltyReward` as an example for reward. For the single asset order execution task, if developers have already defined their simulator/interpreters/reward function/policy, they could launch the training and backtest pipeline by simply modifying the corresponding settings in the config files. The details about the example can be found here.

In the future, we will provide more examples for different scenarios such as RL-based portfolio construction.

1.16.3 The Framework of QlibRL

QlibRL contains a full set of components that cover the entire lifecycle of an RL pipeline, including building the simulator of the market, shaping states & actions, training policies (strategies), and backtesting strategies in the simulated environment.

QlibRL is basically implemented with the support of Tianshou and Gym frameworks. The high-level structure of QlibRL is demonstrated below:



Here, we briefly introduce each component in the figure.

EnvWrapper

EnvWrapper is the complete capsulation of the simulated environment. It receives actions from outside (policy/strategy/agent), simulates the changes in the market, and then replies rewards and updated states, thus forming an interaction loop.

In QlibRL, EnvWrapper is a subclass of gym.Env, so it implements all necessary interfaces of gym.Env. Any classes or pipelines that accept gym.Env should also accept EnvWrapper. Developers do not need to implement their own EnvWrapper to build their own environment. Instead, they only need to implement 4 components of the EnvWrapper:

- ***Simulator*** The simulator is the core component responsible for the environment simulation. Developers could implement all the logic that is directly related to the environment simulation in the Simulator in any way they like. In QlibRL, there are already two implementations of Simulator for single asset trading: 1) `SingleAssetOrderExecution`, which is built based on Qlib's backtest toolkits and hence considers a lot of practical trading details but is slow. 2) `SimpleSingleAssetOrderExecution`, which is built based on a simplified trading simulator, which ignores a lot of details (e.g. trading limitations, rounding) but is quite fast.
- ***State interpreter*** The state interpreter is responsible for "interpret" states in the original format (format provided by the simulator) into states in a format that the policy could understand. For example, transform unstructured raw features into numerical tensors.
- ***Action interpreter*** The action interpreter is similar to the state interpreter. But instead of states, it interprets actions generated by the policy, from the format provided by the policy to the format that is acceptable to

the simulator.

- ***Reward function*** The reward function returns a numerical reward to the policy after each time the policy takes an action.

EnvWrapper will organically organize these components. Such decomposition allows for better flexibility in development. For example, if the developers want to train multiple types of policies in the same environment, they only need to design one simulator and design different state interpreters/action interpreters/reward functions for different types of policies.

QlibRL has well-defined base classes for all these 4 components. All the developers need to do is define their own components by inheriting the base classes and then implementing all interfaces required by the base classes. The API for the above base components can be found here.

Policy

QlibRL directly uses Tianshou's policy. Developers could use policies provided by Tianshou off the shelf, or implement their own policies by inheriting Tianshou's policies.

Training Vessel & Trainer

As stated by their names, training vessels and trainers are helper classes used in training. A training vessel is a ship that contains a simulator/interpreters/reward function/policy, and it controls algorithm-related parts of training. Correspondingly, the trainer is responsible for controlling the runtime parts of training.

As you may have noticed, a training vessel itself holds all the required components to build an EnvWrapper rather than holding an instance of EnvWrapper directly. This allows the training vessel to create duplicates of EnvWrapper dynamically when necessary (for example, under parallel training).

With a training vessel, the trainer could finally launch the training pipeline by simple, Scikit-learn-like interfaces (i.e., `trainer.fit()`).

The API for Trainer and TrainingVessel and can be found here.

1.17 Building Formulaic Alphas

1.17.1 Introduction

In quantitative trading practice, designing novel factors that can explain and predict future asset returns are of vital importance to the profitability of a strategy. Such factors are usually called alpha factors, or alphas in short.

A formulaic alpha, as the name suggests, is a kind of alpha that can be presented as a formula or a mathematical expression.

1.17.2 Building Formulaic Alphas in `Qlib`

In `Qlib`, users can easily build formulaic alphas.

Example

MACD, short for moving average convergence/divergence, is a formulaic alpha used in technical analysis of stock prices. It is designed to reveal changes in the strength, direction, momentum, and duration of a trend in a stock's price.

MACD can be presented as the following formula:

$$MACD = 2 \times (DIF - DEA)$$

Note: *DIF* means Differential value, which is 12-period EMA minus 26-period EMA.

$$DIF = \frac{EMA(CLOSE, 12) - EMA(CLOSE, 26)}{CLOSE}$$

DEA means a 9-period EMA of the DIF.

$$DEA = \frac{EMA(DIF, 9)}{CLOSE}$$

Users can use `Data Handler` to build formulaic alphas *MACD* in qlib:

Note: Users need to initialize `Qlib` with *qlib.init* first. Please refer to initialization.

```
>> from qlib.data.dataset.loader import QlibDataLoader
>> MACD_EXP = '(EMA($close, 12) - EMA($close, 26))/$close - EMA((EMA($close, 12) -
↪EMA($close, 26))/$close, 9)/$close'
>> fields = [MACD_EXP] # MACD
>> names = ['MACD']
>> labels = ['Ref($close, -2)/Ref($close, -1) - 1'] # label
>> label_names = ['LABEL']
>> data_loader_config = {
..     "feature": (fields, names),
..     "label": (labels, label_names)
.. }
>> data_loader = QlibDataLoader(config=data_loader_config)
>> df = data_loader.load(instruments='csi300', start_time='2010-01-01', end_time=
↪'2017-12-31')
>> print(df)
                        feature     label
                           MACD     LABEL
datetime   instrument
2010-01-04 SH600000   -0.011547 -0.019672
           SH600004    0.002745 -0.014721
           SH600006    0.010133  0.002911
           SH600008   -0.001113  0.009818
           SH600009    0.025878 -0.017758
...                         ...       ...
2017-12-29 SZ300124    0.007306 -0.005074
           SZ300136   -0.013492  0.056352
           SZ300144   -0.000966  0.011853
           SZ300251    0.004383  0.021739
           SZ300315   -0.030557  0.012455
```

1.17.3 Reference

To learn more about `Data Loader`, please refer to Data Loader

To learn more about `Data API`, please refer to Data API

1.18 `Online` & `Offline` mode

1.18.1 Introduction

`Qlib` supports `Online` mode and `Offline` mode. Only the `Offline` mode is introduced in this document.

The `Online` mode is designed to solve the following problems:

- Manage the data in a centralized way. Users don't have to manage data of different versions.
- Reduce the amount of cache to be generated.
- Make the data can be accessed in a remote way.

1.18.2 Qlib-Server

`Qlib-Server` is the assorted server system for `Qlib`, which utilizes `Qlib` for basic calculations and provides extensive server system and cache mechanism. With QLibServer, the data provided for `Qlib` can be managed in a centralized manner. With `Qlib-Server`, users can use `Qlib` in `Online` mode.

1.18.3 Reference

If users are interested in `Qlib-Server` and `Online` mode, please refer to Qlib-Server Project and Qlib-Server Document.

1.19 Serialization

1.19.1 Introduction

`Qlib` supports dumping the state of `DataHandler`, `DataSet`, `Processor` and `Model`, etc. into a disk and reloading them.

1.19.2 Serializable Class

`Qlib` provides a base class `qlib.utils.serial.Serializable`, whose state can be dumped into or loaded from disk in *pickle* format. When users dump the state of a `Serializable` instance, the attributes of the instance whose name **does not** start with _ will be saved on the disk. However, users can use `config` method or override `default_dump_all` attribute to prevent this feature.

Users can also override `pickle_backend` attribute to choose a pickle backend. The supported value is "pickle" (default and common) and "dill" (dump more things such as function, more information in here).

1.19.3 Example

`Qlib`'s serializable class includes `DataHandler`, `DataSet`, `Processor` and `Model`, etc., which are subclass of `qlib.utils.serial.Serializable`. Specifically, `qlib.data.dataset.DatasetH` is one of them. Users can serialize `DatasetH` as follows.

```
##=============dump dataset=============
dataset.to_pickle(path="dataset.pkl") # dataset is an instance of qlib.data.dataset.
↪DatasetH

##=============reload dataset=============
with open("dataset.pkl", "rb") as file_dataset:
    dataset = pickle.load(file_dataset)
```

Note: Only state of `DatasetH` should be saved on the disk, such as some *mean* and *variance* used for data normalization, etc.

After reloading the `DatasetH`, users need to reinitialize it. It means that users can reset some states of `DatasetH` or `QlibDataHandler` such as *instruments*, *start_time*, *end_time* and *segments*, etc., and generate new data according to the states (data is not state and should not be saved on the disk).

A more detailed example is in this link.

1.19.4 API

Please refer to Serializable API.

1.20 Task Management

1.20.1 Introduction

The Workflow part introduces how to run research workflow in a loosely-coupled way. But it can only execute one `task` when you use `qrun`. To automatically generate and execute different tasks, `Task Management` provides a whole process including *Task Generating*, *Task Storing*, *Task Training* and *Task Collecting*. With this module, users can run their `task` automatically at different periods, in different losses, or even by different models.The processes of task generation, model training and combine and collect data are shown in the following figure.

This whole process can be used in Online Serving.

An example of the entire process is shown here.

1.20.2 Task Generating

A `task` consists of *Model*, *Dataset*, *Record*, or anything added by users. The specific task template can be viewed in Task Section. Even though the task template is fixed, users can customize their `TaskGen` to generate different `task` by task template.

Here is the base class of `TaskGen`:

class `qlib.workflow.task.gen.`**`TaskGen`**

The base class for generating different tasks

Example 1:

input: a specific task template and rolling steps

output: rolling version of the tasks

Example 2:

input: a specific task template and losses list

output: a set of tasks with different losses

generate (*task: dict*) → List[dict]
Generate different tasks based on a task template

Parameters **task** (*dict*) – a task template

Returns A list of tasks

Return type typing.List[dict]

`Qlib` provides a class RollingGen to generate a list of `task` of the dataset in different date segments. This class allows users to verify the effect of data from different periods on the model in one experiment. More information is here.

1.20.3 Task Storing

To achieve higher efficiency and the possibility of cluster operation, `Task Manager` will store all tasks in MongoDB. `TaskManager` can fetch undone tasks automatically and manage the lifecycle of a set of tasks with error handling. Users **MUST** finish the configuration of MongoDB when using this module.

Users need to provide the MongoDB URL and database name for using `TaskManager` in initialization or make a statement like this.

```
from qlib.config import C
C["mongo"] = {
    "task_url" : "mongodb://localhost:27017/", # your MongoDB url
    "task_db_name" : "rolling_db" # database name
}
```

class qlib.workflow.task.manage.**TaskManager** (*task_pool: str*)
Here is what will a task looks like when it created by TaskManager

```
{
    'def': pickle serialized task definition.  using pickle will make it easier
    'filter': json-like data. This is for filtering the tasks.
    'status': 'waiting' | 'running' | 'done'
    'res': pickle serialized task result,
}
```

The tasks manager assumes that you will only update the tasks you fetched. The mongo fetch one and update will make it date updating secure.

This class can be used as a tool from commandline. Here are several examples. You can view the help of manage module with the following commands: python -m qlib.workflow.task.manage -h # show manual of manage module CLI python -m qlib.workflow.task.manage wait -h # show manual of the wait command of manage

```
python -m qlib.workflow.task.manage -t <pool_name> wait
python -m qlib.workflow.task.manage -t <pool_name> task_stat
```

Note: Assumption: the data in MongoDB was encoded and the data out of MongoDB was decoded

---

Here are four status which are:

STATUS_WAITING: waiting for training

STATUS_RUNNING: training

STATUS_PART_DONE: finished some step and waiting for next step

STATUS_DONE: all work done

`__init__`(*task_pool: str*)

Init Task Manager, remember to make the statement of MongoDB url and database name firstly. A TaskManager instance serves a specific task pool. The static method of this module serves the whole MongoDB.

Parameters **`task_pool`** (`str`) – the name of Collection in MongoDB

`static list`() → list

List the all collection(task_pool) of the db.

Returns list

`replace_task`(*task*, *new_task*)

Use a new task to replace a old one

Parameters

- **`task`** – old task
- **`new_task`** – new task

`insert_task`(*task*)

Insert a task.

Parameters **`task`** – the task waiting for insert

Returns pymongo.results.InsertOneResult

`insert_task_def`(*task_def*)

Insert a task to task_pool

Parameters **`task_def`** (`dict`) – the task definition

Returns

Return type pymongo.results.InsertOneResult

`create_task`(*task_def_l*, *dry_run=False*, *print_nt=False*) → List[str]

If the tasks in task_def_l are new, then insert new tasks into the task_pool, and record inserted_id. If a task is not new, then just query its _id.

Parameters

- **`task_def_l`** (`list`) – a list of task
- **`dry_run`** (`bool`) – if insert those new tasks to task pool
- **`print_nt`** (`bool`) – if print new task

Returns a list of the _id of task_def_l

Return type List[str]

`fetch_task`(*query={}*, *status='waiting'*) → dict

Use query to fetch tasks.

Parameters

- **`query`** (`dict, optional`) – query dict. Defaults to {}.

- **status** (*str, optional*) – [description]. Defaults to STATUS_WAITING.

Returns a task(document in collection) after decoding

Return type dict

safe_fetch_task(*query={}*, *status='waiting'*)
Fetch task from task_pool using query with contextmanager

Parameters **query** (*dict*) – the dict of query

Returns **dict**

Return type a task(document in collection) after decoding

query(*query={}*, *decode=True*)
Query task in collection. This function may raise exception *pymongo.errors.CursorNotFound: cursor id not found* if it takes too long to iterate the generator

python -m qlib.workflow.task.manage -t <your task pool> query '{"_id": "615498be837d0053acbc5d58"}'

Parameters

- **query** (*dict*) – the dict of query
- **decode** (*bool*) –

Returns **dict**

Return type a task(document in collection) after decoding

re_query(*_id*) → dict
Use _id to query task.

Parameters **_id** (*str*) – _id of a document

Returns a task(document in collection) after decoding

Return type dict

commit_task_res(*task*, *res*, *status='done'*)
Commit the result to task['res'].

Parameters

- **task** (*[type]*) – [description]
- **res** (*object*) – the result you want to save
- **status** (*str, optional*) – STATUS_WAITING, STATUS_RUNNING, STATUS_DONE, STATUS_PART_DONE. Defaults to STATUS_DONE.

return_task(*task*, *status='waiting'*)
Return a task to status. Always using in error handling.

Parameters

- **task** (*[type]*) – [description]
- **status** (*str, optional*) – STATUS_WAITING, STATUS_RUNNING, STATUS_DONE, STATUS_PART_DONE. Defaults to STATUS_WAITING.

remove(*query={}*)
Remove the task using query

Parameters **query** (*dict*) – the dict of query

task_stat (*query={}*) → dict
Count the tasks in every status.

Parameters **query** (`dict, optional`) – the query dict. Defaults to {}.

Returns dict

reset_waiting (*query={}*)
Reset all running task into waiting status. Can be used when some running task exit unexpected.

Parameters **query** (`dict, optional`) – the query dict. Defaults to {}.

prioritize (*task, priority: int*)
Set priority for task

Parameters

- **task** (`dict`) – The task query from the database
- **priority** (`int`) – the target priority

wait (*query={}*)
When multiprocessing, the main progress may fetch nothing from TaskManager because there are still some running tasks. So main progress should wait until all tasks are trained well by other progress or machines.

Parameters **query** (`dict, optional`) – the query dict. Defaults to {}.

More information of `Task Manager` can be found in here.

1.20.4 Task Training

After generating and storing those `task`, it's time to run the `task` which is in the *WAITING* status. `Qlib` provides a method called `run_task` to run those `task` in task pool, however, users can also customize how tasks are executed. An easy way to get the `task_func` is using `qlib.model.trainer.task_train` directly. It will run the whole workflow defined by `task`, which includes *Model*, *Dataset*, *Record*.

`qlib.workflow.task.manage.`**run_task** (*task_func: Callable, task_pool: str, query: dict = {}, force_release: bool = False, before_status: str = 'waiting', after_status: str = 'done', **kwargs*)
While the task pool is not empty (has WAITING tasks), use task_func to fetch and run tasks in task_pool

After running this method, here are 4 situations (before_status -> after_status):

STATUS_WAITING -> STATUS_DONE: use task["def"] as *task_func* param, it means that the task has not been started

STATUS_WAITING -> STATUS_PART_DONE: use task["def"] as *task_func* param

STATUS_PART_DONE -> STATUS_PART_DONE: use task["res"] as *task_func* param, it means that the task has been started but not completed

STATUS_PART_DONE -> STATUS_DONE: use task["res"] as *task_func* param

Parameters

- **task_func** (`Callable`) – def (task_def, **kwargs) -> <res which will be committed>

  the function to run the task
- **task_pool** (`str`) – the name of the task pool (Collection in MongoDB)
- **query** (`dict`) – will use this dict to query task_pool when fetching task

- **force_release** (*bool*) – will the program force to release the resource
- **before_status** (*str:*) – the tasks in before_status will be fetched and trained. Can be STATUS_WAITING, STATUS_PART_DONE.
- **after_status** (*str:*) – the tasks after trained will become after_status. Can be STATUS_WAITING, STATUS_PART_DONE.
- **kwargs** – the params for *task_func*

Meanwhile, `Qlib` provides a module called `Trainer`.

class qlib.model.trainer.**Trainer**

The trainer can train a list of models. There are Trainer and DelayTrainer, which can be distinguished by when it will finish real training.

__init__()

Initialize self. See help(type(self)) for accurate signature.

train(*tasks: list*, **args*, ***kwargs*) → list

Given a list of task definitions, begin training, and return the models.

For Trainer, it finishes real training in this method. For DelayTrainer, it only does some preparation in this method.

Parameters **tasks** – a list of tasks

Returns a list of models

Return type list

end_train(*models: list*, **args*, ***kwargs*) → list

Given a list of models, finished something at the end of training if you need. The models may be Recorder, txt file, database, and so on.

For Trainer, it does some finishing touches in this method. For DelayTrainer, it finishes real training in this method.

Parameters **models** – a list of models

Returns a list of models

Return type list

is_delay() → bool

If Trainer will delay finishing *end_train*.

Returns if DelayTrainer

Return type bool

has_worker() → bool

Some trainer has backend worker to support parallel training This method can tell if the worker is enabled.

Returns if the worker is enabled

Return type bool

worker()

start the worker

Raises NotImplementedError: – If the worker is not supported

`Trainer` will train a list of tasks and return a list of model recorders. `Qlib` offer two kinds of Trainer, TrainerR is the simplest way and TrainerRM is based on TaskManager to help manager tasks lifecycle automatically. If you do not want to use `Task Manager` to manage tasks, then use TrainerR to train a list of tasks generated by `TaskGen` is enough. Here are the details about different `Trainer`.

1.20.5 Task Collecting

Before collecting model training results, you need to use the `qlib.init` to specify the path of mlruns.

To collect the results of `task` after training, `Qlib` provides Collector, Group and Ensemble to collect the results in a readable, expandable and loosely-coupled way.

Collector can collect objects from everywhere and process them such as merging, grouping, averaging and so on. It has 2 step action including `collect` (collect anything in a dict) and `process_collect` (process collected dict).

Group also has 2 steps including `group` (can group a set of object based on *group_func* and change them to a dict) and `reduce` (can make a dict become an ensemble based on some rule). For example: {(A,B,C1): object, (A,B,C2): object} —`group`—> {(A,B): {C1: object, C2: object}} —`reduce`—> {(A,B): object}

Ensemble can merge the objects in an ensemble. For example: {C1: object, C2: object} —`Ensemble`—> object. You can set the ensembles you want in the `Collector`'s process_list. Common ensembles include `AverageEnsemble` and `RollingEnsemble`. Average ensemble is used to ensemble the results of different models in the same time period. Rollingensemble is used to ensemble the results of different models in the same time period

So the hierarchy is `Collector`'s second step corresponds to `Group`. And `Group`'s second step correspond to `Ensemble`.

For more information, please see Collector, Group and Ensemble, or the example.

1.21 (P)oint-(I)n-(T)ime Database

1.21.1 Introduction

Point-in-time data is a very important consideration when performing any sort of historical market analysis.

For example, let's say we are backtesting a trading strategy and we are using the past five years of historical data as our input. Our model is assumed to trade once a day, at the market close, and we'll say we are calculating the trading signal for 1 January 2020 in our backtest. At that point, we should only have data for 1 January 2020, 31 December 2019, 30 December 2019 etc.

In financial data (especially financial reports), the same piece of data may be amended for multiple times overtime. If we only use the latest version for historical backtesting, data leakage will happen. Point-in-time database is designed for solving this problem to make sure user get the right version of data at any historical timestamp. It will keep the performance of online trading and historical backtesting the same.

1.21.2 Data Preparation

Qlib provides a crawler to help users to download financial data and then a converter to dump the data in Qlib format. Please follow scripts/data_collector/pit/README.md to download and convert data. Besides, you can find some additional usage examples there.

1.21.3 File-based design for PIT data

Qlib provides a file-based storage for PIT data.

For each feature, it contains 4 columns, i.e. date, period, value, _next. Each row corresponds to a statement.

The meaning of each feature with filename like *XXX_a.data*:

- *date*: the statement's date of publication.
- ***period*: the period of the statement. (e.g. it will be quarterly frequency in most of the markets)**
  - If it is an annual period, it will be an integer corresponding to the year
  - If it is an quarterly periods, it will be an integer like *<year><index of quarter>*. The last two decimal digits represents the index of quarter. Others represent the year.
- *value*: the described value
- *_next*: the byte index of the next occurance of the field.

Besides the feature data, an index *XXX_a.index* is included to speed up the querying performance

The statements are soted by the *date* in ascending order from the beginning of the file.

```
# the data format from XXXX.data
array([(20070428, 200701, 0.090219  , 4294967295),
       (20070817, 200702, 0.13933   , 4294967295),
       (20071023, 200703, 0.24586301, 4294967295),
       (20080301, 200704, 0.3479    ,         80),
       (20080313, 200704, 0.395989  , 4294967295),
       (20080422, 200801, 0.100724  , 4294967295),
       (20080828, 200802, 0.24996801, 4294967295),
       (20081027, 200803, 0.33412001, 4294967295),
       (20090325, 200804, 0.39011699, 4294967295),
       (20090421, 200901, 0.102675  , 4294967295),
       (20090807, 200902, 0.230712  , 4294967295),
       (20091024, 200903, 0.30072999, 4294967295),
       (20100402, 200904, 0.33546099, 4294967295),
       (20100426, 201001, 0.083825  , 4294967295),
       (20100812, 201002, 0.200545  , 4294967295),
       (20101029, 201003, 0.260986  , 4294967295),
       (20110321, 201004, 0.30739301, 4294967295),
       (20110423, 201101, 0.097411  , 4294967295),
       (20110831, 201102, 0.24825101, 4294967295),
       (20111018, 201103, 0.318919  , 4294967295),
       (20120323, 201104, 0.4039    ,        420),
       (20120411, 201104, 0.403925  , 4294967295),
       (20120426, 201201, 0.112148  , 4294967295),
       (20120810, 201202, 0.26484701, 4294967295),
       (20121026, 201203, 0.370487  , 4294967295),
       (20130329, 201204, 0.45004699, 4294967295),
       (20130418, 201301, 0.099958  , 4294967295),
       (20130831, 201302, 0.21044201, 4294967295),
       (20131016, 201303, 0.30454299, 4294967295),
       (20140325, 201304, 0.394328  , 4294967295),
       (20140425, 201401, 0.083217  , 4294967295),
       (20140829, 201402, 0.16450299, 4294967295),
       (20141030, 201403, 0.23408499, 4294967295),
       (20150421, 201404, 0.319612  , 4294967295),
       (20150421, 201501, 0.078494  , 4294967295),
       (20150828, 201502, 0.137504  , 4294967295),
       (20151023, 201503, 0.201709  , 4294967295),
       (20160324, 201504, 0.26420501, 4294967295),
       (20160421, 201601, 0.073664  , 4294967295),
       (20160827, 201602, 0.136576  , 4294967295),
       (20161029, 201603, 0.188062  , 4294967295),
```

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```
        (20170415, 201604, 0.244385  , 4294967295),
        (20170425, 201701, 0.080614  , 4294967295),
        (20170728, 201702, 0.15151   , 4294967295),
        (20171026, 201703, 0.25416601, 4294967295),
        (20180328, 201704, 0.32954201, 4294967295),
        (20180428, 201801, 0.088887  , 4294967295),
        (20180802, 201802, 0.170563  , 4294967295),
        (20181029, 201803, 0.25522   , 4294967295),
        (20190329, 201804, 0.34464401, 4294967295),
        (20190425, 201901, 0.094737  , 4294967295),
        (20190713, 201902, 0.        ,       1040),
        (20190718, 201902, 0.175322  , 4294967295),
        (20191016, 201903, 0.25581899, 4294967295)],
       dtype=[('date', '<u4'), ('period', '<u4'), ('value', '<f8'), ('_next', '<u4')])
# - each row contains 20 byte


# The data format from XXXX.index.  It consists of two parts
# 1) the start index of the data. So the first part of the info will be like
2007
# 2) the remain index data will be like information below
#    - The data indicate the **byte index** of first data update of a period.
#    - e.g. Because the info at both byte 80 and 100 corresponds to 200704. The byte␣
↪index of first occurance (i.e. 100) is recorded in the data.
array([         0,         20,         40,         60,        100,
              120,        140,        160,        180,        200,
              220,        240,        260,        280,        300,
              320,        340,        360,        380,        400,
              440,        460,        480,        500,        520,
              540,        560,        580,        600,        620,
              640,        660,        680,        700,        720,
              740,        760,        780,        800,        820,
              840,        860,        880,        900,        920,
              940,        960,        980,       1000,       1020,
             1060, 4294967295], dtype=uint32)
```

Known limitations:

- Currently, the PIT database is designed for quarterly or annually factors, which can handle fundamental data of financial reports in most markets.
- Qlib leverage the file name to identify the type of the data. File with name like *XXX_q.data* corresponds to quarterly data. File with name like *XXX_a.data* corresponds to annual data.
- The caclulation of PIT is not performed in the optimal way. There is great potential to boost the performance of PIT data calcuation.

1.22 Code Standard

1.22.1 Docstring

Please use the Numpydoc Style.

1.22.2 Continuous Integration

Continuous Integration (CI) tools help you stick to the quality standards by running tests every time you push a new commit and reporting the results to a pull request.

When you submit a PR request, you can check whether your code passes the CI tests in the "check" section at the bottom of the web page.

1. Qlib will check the code format with black. The PR will raise error if your code does not align to the standard of Qlib(e.g. a common error is the mixed use of space and tab).

   You can fix the bug by inputting the following code in the command line.

```
pip install black
python -m black . -l 120
```

2. Qlib will check your code style pylint. The checking command is implemented in [github action workflow](https://github.com/microsoft/qlib/blob/0e8b94a552f1c457cfa6cd2c1bb3b87ebb3fb279/.github/workflows/test.yml#L66). Sometime pylint's restrictions are not that reasonable. You can ignore specific errors like this

```
return -ICLoss()(pred, target, index)  # pylint: disable=E1130
```

3. Qlib will check your code style flake8. The checking command is implemented in [github action workflow](https://github.com/microsoft/qlib/blob/0e8b94a552f1c457cfa6cd2c1bb3b87ebb3fb279/.github/workflows/test.yml#L73).

   You can fix the bug by inputing the following code in the command line.

```
flake8 --ignore E501,F541,E402,F401,W503,E741,E266,E203,E302,E731,E262,F523,F821,F811,
↪F841,E713,E265,W291,E712,E722,W293 qlib
```

4. Qlib has integrated pre-commit, which will make it easier for developers to format their code.

   Just run the following two commands, and the code will be automatically formatted using black and flake8 when the git commit command is executed.

```
pip install -e .[dev]
pre-commit install
```

1.23 Development Guidance

As a developer, you often want make changes to *Qlib* and hope it would reflect directly in your environment without reinstalling it. You can install *Qlib* in editable mode with following command. The *[dev]* option will help you to install some related packages when developing *Qlib* (e.g. pytest, sphinx)

```
pip install -e .[dev]
```

1.24 API Reference

Here you can find all `Qlib` interfaces.

1.24.1 Data

Provider

class qlib.data.data.**ProviderBackendMixin**
This helper class tries to make the provider based on storage backend more convenient It is not necessary to inherent this class if that provider don't rely on the backend storage

class qlib.data.data.**CalendarProvider**
Calendar provider base class

Provide calendar data.

calendar(*start_time=None*, *end_time=None*, *freq='day'*, *future=False*)
Get calendar of certain market in given time range.

Parameters

- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.
- **freq** (*str*) – time frequency, available: year/quarter/month/week/day.
- **future** (*bool*) – whether including future trading day.

Returns calendar list

Return type list

locate_index(*start_time: Union[pandas._libs.tslibs.timestamps.Timestamp, str], end_time: Union[pandas._libs.tslibs.timestamps.Timestamp, str], freq: str, future: bool = False*)
Locate the start time index and end time index in a calendar under certain frequency.

Parameters

- **start_time** (*pd.Timestamp*) – start of the time range.
- **end_time** (*pd.Timestamp*) – end of the time range.
- **freq** (*str*) – time frequency, available: year/quarter/month/week/day.
- **future** (*bool*) – whether including future trading day.

Returns

- *pd.Timestamp* – the real start time.
- *pd.Timestamp* – the real end time.
- *int* – the index of start time.
- *int* – the index of end time.

load_calendar(*freq*, *future*)
Load original calendar timestamp from file.

Parameters

- **freq** (*str*) – frequency of read calendar file.
- **future** (*bool*) –

Returns list of timestamps

Return type list

class qlib.data.data.**InstrumentProvider**

Instrument provider base class

Provide instrument data.

static instruments(*market: Union[List[T], str] = 'all', filter_pipe: Optional[List[T]] = None*)

Get the general config dictionary for a base market adding several dynamic filters.

Parameters

- **market** (`Union[List, str]`) –

  str: market/industry/index shortname, e.g. all/sse/szse/sse50/csi300/csi500.

  list: ["ID1", "ID2"]. A list of stocks

- **filter_pipe** (`list`) – the list of dynamic filters.

Returns

- **dict** (*if isinstance(market, str)*) – dict of stockpool config.

  {*market* => base market name, *filter_pipe* => list of filters}

  example :

- **list** (*if isinstance(market, list)*) – just return the original list directly. NOTE: this will make the instruments compatible with more cases. The user code will be simpler.

list_instruments(*instruments, start_time=None, end_time=None, freq='day', as_list=False*)

List the instruments based on a certain stockpool config.

Parameters

- **instruments** (`dict`) – stockpool config.
- **start_time** (`str`) – start of the time range.
- **end_time** (`str`) – end of the time range.
- **as_list** (`bool`) – return instruments as list or dict.

Returns instruments list or dictionary with time spans

Return type dict or list

class qlib.data.data.**FeatureProvider**

Feature provider class

Provide feature data.

feature(*instrument, field, start_time, end_time, freq*)

Get feature data.

Parameters

- **instrument** (`str`) – a certain instrument.
- **field** (`str`) – a certain field of feature.
- **start_time** (`str`) – start of the time range.
- **end_time** (`str`) – end of the time range.
- **freq** (`str`) – time frequency, available: year/quarter/month/week/day.

Returns data of a certain feature

Return type pd.Series

`class qlib.data.data.`**`PITProvider`**

`period_feature`(*instrument*, *field*, *start_index: int*, *end_index: int*, *cur_time: pandas._libs.tslibs.timestamps.Timestamp*, *period: Optional[int] = None*) → pandas.core.series.Series

get the historical periods data series between *start_index* and *end_index*

Parameters

- **`start_index`** (*`int`*) – start_index is a relative index to the latest period to cur_time
- **`end_index`** (*`int`*) – end_index is a relative index to the latest period to cur_time in most cases, the start_index and end_index will be a non-positive values For example, start_index == -3 end_index == 0 and current period index is cur_idx, then the data between [start_index + cur_idx, end_index + cur_idx] will be retrieved.
- **`period`** (*`int`*) – This is used for query specific period. The period is represented with int in Qlib. (e.g. 202001 may represent the first quarter in 2020) NOTE: *period* will override *start_index* and *end_index*

Returns The index will be integers to indicate the periods of the data An typical examples will be TODO

Return type pd.Series

Raises `FileNotFoundError` – This exception will be raised if the queried data do not exist.

`class qlib.data.data.`**`ExpressionProvider`**

Expression provider class

Provide Expression data.

`__init__`()

Initialize self. See help(type(self)) for accurate signature.

`expression`(*instrument*, *field*, *start_time=None*, *end_time=None*, *freq='day'*) → pandas.core.series.Series

Get Expression data.

The responsibility of *expression* - parse the *field* and *load* the according data. - When loading the data, it should handle the time dependency of the data. *get_expression_instance* is commonly used in this method

Parameters

- **`instrument`** (*`str`*) – a certain instrument.
- **`field`** (*`str`*) – a certain field of feature.
- **`start_time`** (*`str`*) – start of the time range.
- **`end_time`** (*`str`*) – end of the time range.
- **`freq`** (*`str`*) – time frequency, available: year/quarter/month/week/day.

Returns

data of a certain expression

The data has two types of format

1) expression with datetime index

2) expression with integer index

   - because the datetime is not as good as

Return type pd.Series

class `qlib.data.data.`**`DatasetProvider`**

Dataset provider class

Provide Dataset data.

`dataset`(*instruments*, *fields*, *start_time=None*, *end_time=None*, *freq='day'*, *inst_processors=[]*)

Get dataset data.

Parameters

- **instruments** (*list or dict*) – list/dict of instruments or dict of stockpool config.
- **fields** (*list*) – list of feature instances.
- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.
- **freq** (*str*) – time frequency.
- **inst_processors** (*Iterable[Union[dict, InstProcessor]]*) – the operations performed on each instrument

Returns a pandas dataframe with <instrument, datetime> index.

Return type pd.DataFrame

static get_instruments_d(*instruments*, *freq*)

Parse different types of input instruments to output instruments_d Wrong format of input instruments will lead to exception.

static get_column_names(*fields*)

Get column names from input fields

static dataset_processor(*instruments_d*, *column_names*, *start_time*, *end_time*, *freq*, *inst_processors=[]*)

Load and process the data, return the data set. - default using multi-kernel method.

static inst_calculator(*inst*, *start_time*, *end_time*, *freq*, *column_names*, *spans=None*, *g_config=None*, *inst_processors=[]*)

Calculate the expressions for **one** instrument, return a df result. If the expression has been calculated before, load from cache.

return value: A data frame with index 'datetime' and other data columns.

class `qlib.data.data.`**`LocalCalendarProvider`**(*remote=False*, *backend={}*)

Local calendar data provider class

Provide calendar data from local data source.

`__init__`(*remote=False*, *backend={}*)

Initialize self. See help(type(self)) for accurate signature.

`load_calendar`(*freq*, *future*)

Load original calendar timestamp from file.

Parameters

- **freq** (*str*) – frequency of read calendar file.

- **future** (*bool*) –

Returns list of timestamps

Return type list

class qlib.data.data.**LocalInstrumentProvider**(*backend={}*)
Local instrument data provider class

Provide instrument data from local data source.

__init__(*backend={}*) → None
Initialize self. See help(type(self)) for accurate signature.

list_instruments(*instruments*, *start_time=None*, *end_time=None*, *freq='day'*, *as_list=False*)
List the instruments based on a certain stockpool config.

Parameters

- **instruments** (*dict*) – stockpool config.
- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.
- **as_list** (*bool*) – return instruments as list or dict.

Returns instruments list or dictionary with time spans

Return type dict or list

class qlib.data.data.**LocalFeatureProvider**(*remote=False*, *backend={}*)
Local feature data provider class

Provide feature data from local data source.

__init__(*remote=False*, *backend={}*)
Initialize self. See help(type(self)) for accurate signature.

feature(*instrument*, *field*, *start_index*, *end_index*, *freq*)
Get feature data.

Parameters

- **instrument** (*str*) – a certain instrument.
- **field** (*str*) – a certain field of feature.
- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.
- **freq** (*str*) – time frequency, available: year/quarter/month/week/day.

Returns data of a certain feature

Return type pd.Series

class qlib.data.data.**LocalPITProvider**

period_feature(*instrument*, *field*, *start_index*, *end_index*, *cur_time*, *period=None*)
get the historical periods data series between *start_index* and *end_index*

Parameters

- **start_index** (*int*) – start_index is a relative index to the latest period to cur_time

- **end_index** (*int*) – end_index is a relative index to the latest period to cur_time in most cases, the start_index and end_index will be a non-positive values For example, start_index == -3 end_index == 0 and current period index is cur_idx, then the data between [start_index + cur_idx, end_index + cur_idx] will be retrieved.
- **period** (*int*) – This is used for query specific period. The period is represented with int in Qlib. (e.g. 202001 may represent the first quarter in 2020) NOTE: *period* will override *start_index* and *end_index*

Returns The index will be integers to indicate the periods of the data An typical examples will be TODO

Return type pd.Series

Raises `FileNotFoundError` – This exception will be raised if the queried data do not exist.

class `qlib.data.data.`**LocalExpressionProvider**(*time2idx=True*)

Local expression data provider class

Provide expression data from local data source.

__init__(*time2idx=True*)

Initialize self. See help(type(self)) for accurate signature.

expression(*instrument*, *field*, *start_time=None*, *end_time=None*, *freq='day'*)

Get Expression data.

The responsibility of *expression* - parse the *field* and *load* the according data. - When loading the data, it should handle the time dependency of the data. *get_expression_instance* is commonly used in this method

Parameters

- **instrument** (*str*) – a certain instrument.
- **field** (*str*) – a certain field of feature.
- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.
- **freq** (*str*) – time frequency, available: year/quarter/month/week/day.

Returns

data of a certain expression

The data has two types of format

1) expression with datetime index
2) expression with integer index
   - because the datetime is not as good as

Return type pd.Series

class `qlib.data.data.`**LocalDatasetProvider**(*align_time: bool = True*)

Local dataset data provider class

Provide dataset data from local data source.

__init__(*align_time: bool = True*)

Parameters **align_time** (*bool*) – Will we align the time to calendar the frequency is flexible in some dataset and can't be aligned. For the data with fixed frequency with a shared calendar, the align data to the calendar will provides following benefits

- Align queries to the same parameters, so the cache can be shared.

dataset (*instruments*, *fields*, *start_time=None*, *end_time=None*, *freq='day'*, *inst_processors=[]*)
Get dataset data.

Parameters

- **instruments** (*list or dict*) – list/dict of instruments or dict of stockpool config.
- **fields** (*list*) – list of feature instances.
- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.
- **freq** (*str*) – time frequency.
- **inst_processors** (*Iterable[Union[dict, InstProcessor]]*) – the operations performed on each instrument

Returns a pandas dataframe with <instrument, datetime> index.

Return type pd.DataFrame

static multi_cache_walker (*instruments*, *fields*, *start_time=None*, *end_time=None*, *freq='day'*)
This method is used to prepare the expression cache for the client. Then the client will load the data from expression cache by itself.

static cache_walker (*inst*, *start_time*, *end_time*, *freq*, *column_names*)
If the expressions of one instrument haven't been calculated before, calculate it and write it into expression cache.

class qlib.data.data.**ClientCalendarProvider**
Client calendar data provider class

Provide calendar data by requesting data from server as a client.

__init__()
Initialize self. See help(type(self)) for accurate signature.

calendar (*start_time=None*, *end_time=None*, *freq='day'*, *future=False*)
Get calendar of certain market in given time range.

Parameters

- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.
- **freq** (*str*) – time frequency, available: year/quarter/month/week/day.
- **future** (*bool*) – whether including future trading day.

Returns calendar list

Return type list

class qlib.data.data.**ClientInstrumentProvider**
Client instrument data provider class

Provide instrument data by requesting data from server as a client.

__init__()
Initialize self. See help(type(self)) for accurate signature.

list_instruments (*instruments*, *start_time=None*, *end_time=None*, *freq='day'*, *as_list=False*)
List the instruments based on a certain stockpool config.

Parameters

- **instruments** (*dict*) – stockpool config.
- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.
- **as_list** (*bool*) – return instruments as list or dict.

Returns instruments list or dictionary with time spans

Return type dict or list

class qlib.data.data.**ClientDatasetProvider**
Client dataset data provider class

Provide dataset data by requesting data from server as a client.

__init__()
Initialize self. See help(type(self)) for accurate signature.

dataset (*instruments*, *fields*, *start_time=None*, *end_time=None*, *freq='day'*, *disk_cache=0*, *return_uri=False*, *inst_processors=[]*)
Get dataset data.

Parameters

- **instruments** (*list or dict*) – list/dict of instruments or dict of stockpool config.
- **fields** (*list*) – list of feature instances.
- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.
- **freq** (*str*) – time frequency.
- **inst_processors** (*Iterable[Union[dict, InstProcessor]]*) – the operations performed on each instrument

Returns a pandas dataframe with <instrument, datetime> index.

Return type pd.DataFrame

class qlib.data.data.**BaseProvider**
Local provider class It is a set of interface that allow users to access data. Because PITD is not exposed publicly to users, so it is not included in the interface.

To keep compatible with old qlib provider.

features (*instruments*, *fields*, *start_time=None*, *end_time=None*, *freq='day'*, *disk_cache=None*, *inst_processors=[]*)

Parameters **disk_cache** (*int*) – whether to skip(0)/use(1)/replace(2) disk_cache

This function will try to use cache method which has a keyword *disk_cache*, and will use provider method if a type error is raised because the DatasetD instance is a provider class.

class qlib.data.data.**LocalProvider**

features_uri (*instruments*, *fields*, *start_time*, *end_time*, *freq*, *disk_cache=1*)
Return the uri of the generated cache of features/dataset

Parameters

- **disk_cache** –
- **instruments** –
- **fields** –
- **start_time** –
- **end_time** –
- **freq** –

class qlib.data.data.**ClientProvider**

Client Provider

Requesting data from server as a client. Can propose requests:

- Calendar : Directly respond a list of calendars
- Instruments (without filter): Directly respond a list/dict of instruments
- Instruments (with filters): Respond a list/dict of instruments
- Features : Respond a cache uri

The general workflow is described as follows: When the user use client provider to propose a request, the client provider will connect the server and send the request. The client will start to wait for the response. The response will be made instantly indicating whether the cache is available. The waiting procedure will terminate only when the client get the response saying *feature_available* is true. *BUG* : Everytime we make request for certain data we need to connect to the server, wait for the response and disconnect from it. We can't make a sequence of requests within one connection. You can refer to https://python-socketio.readthedocs.io/en/latest/client.html for documentation of python-socketIO client.

__init__()

Initialize self. See help(type(self)) for accurate signature.

qlib.data.data.**CalendarProviderWrapper**

alias of *qlib.data.data.CalendarProvider*

qlib.data.data.**InstrumentProviderWrapper**

alias of *qlib.data.data.InstrumentProvider*

qlib.data.data.**FeatureProviderWrapper**

alias of *qlib.data.data.FeatureProvider*

qlib.data.data.**PITProviderWrapper**

alias of *qlib.data.data.PITProvider*

qlib.data.data.**ExpressionProviderWrapper**

alias of *qlib.data.data.ExpressionProvider*

qlib.data.data.**DatasetProviderWrapper**

alias of *qlib.data.data.DatasetProvider*

qlib.data.data.**BaseProviderWrapper**

alias of *qlib.data.data.BaseProvider*

qlib.data.data.**register_all_wrappers**(*C*)

Filter

class qlib.data.filter.**BaseDFilter**

Dynamic Instruments Filter Abstract class

Users can override this class to construct their own filter

Override __init__ to input filter regulations

Override filter_main to use the regulations to filter instruments

__init__()
Initialize self. See help(type(self)) for accurate signature.

static from_config(*config*)
Construct an instance from config dict.

Parameters **config** (*dict*) – dict of config parameters.

to_config()
Construct an instance from config dict.

Returns return the dict of config parameters.

Return type dict

class qlib.data.filter.**SeriesDFilter**(*fstart_time=None*, *fend_time=None*, *keep=False*)
Dynamic Instruments Filter Abstract class to filter a series of certain features

Filters should provide parameters:

- filter start time
- filter end time
- filter rule

Override __init__ to assign a certain rule to filter the series.

Override _getFilterSeries to use the rule to filter the series and get a dict of {inst => series}, or override filter_main for more advanced series filter rule

__init__(*fstart_time=None*, *fend_time=None*, *keep=False*)

Init function for filter base class. Filter a set of instruments based on a certain rule within a certain period assigned by fstart_time and fend_time.

Parameters

- **fstart_time** (*str*) – the time for the filter rule to start filter the instruments.
- **fend_time** (*str*) – the time for the filter rule to stop filter the instruments.
- **keep** (*bool*) – whether to keep the instruments of which features don't exist in the filter time span.

filter_main(*instruments*, *start_time=None*, *end_time=None*)
Implement this method to filter the instruments.

Parameters

- **instruments** (*dict*) – input instruments to be filtered.
- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.

Returns filtered instruments, same structure as input instruments.

Return type dict

class qlib.data.filter.**NameDFilter**(*name_rule_re*, *fstart_time=None*, *fend_time=None*)
Name dynamic instrument filter

Filter the instruments based on a regulated name format.

A name rule regular expression is required.

__init__(*name_rule_re*, *fstart_time=None*, *fend_time=None*)
Init function for name filter class

Parameters **name_rule_re** (*str*) – regular expression for the name rule.

static from_config(*config*)
Construct an instance from config dict.

Parameters **config** (*dict*) – dict of config parameters.

to_config()
Construct an instance from config dict.

Returns return the dict of config parameters.

Return type dict

class qlib.data.filter.**ExpressionDFilter**(*rule_expression*, *fstart_time=None*, *fend_time=None*, *keep=False*)
Expression dynamic instrument filter

Filter the instruments based on a certain expression.

An expression rule indicating a certain feature field is required.

Examples

- *basic features filter* : rule_expression = '$close/$open>5'
- *cross-sectional features filter* : rule_expression = '$rank($close)<10'
- *time-sequence features filter* : rule_expression = '$Ref($close, 3)>100'

__init__(*rule_expression*, *fstart_time=None*, *fend_time=None*, *keep=False*)
Init function for expression filter class

Parameters

- **fstart_time** (*str*) – filter the feature starting from this time.
- **fend_time** (*str*) – filter the feature ending by this time.
- **rule_expression** (*str*) – an input expression for the rule.

static from_config(*config*)
Construct an instance from config dict.

Parameters **config** (*dict*) – dict of config parameters.

to_config()
Construct an instance from config dict.

Returns return the dict of config parameters.

Return type dict

Class

class qlib.data.base.**Expression**
Expression base class

Expression is designed to handle the calculation of data with the format below data with two dimension for each instrument,

- feature
- time: it could be observation time or period time.

   – period time is designed for Point-in-time database. For example, the period time maybe 2014Q4, its value can observed for multiple times(different value may be observed at different time due to amendment).

load(*instrument*, *start_index*, *end_index*, **args*)
load feature This function is responsible for loading feature/expression based on the expression engine.

The concrete implementation will be separated into two parts:

1) caching data, handle errors.
   - This part is shared by all the expressions and implemented in Expression
2) processing and calculating data based on the specific expression.
   - This part is different in each expression and implemented in each expression

Expression Engine is shared by different data. Different data will have different extra information for *args*.

Parameters

- **instrument** (*str*) – instrument code.
- **start_index** (*str*) – feature start index [in calendar].
- **end_index** (*str*) – feature end index [in calendar].
- **may contain following information** (**args*) –
- **if it is used in basic expression engine data, it contains following arguments** (*1)*) –

  freq: str feature frequency.
- **if is used in PIT data, it contains following arguments** (*2)*) –

  cur_pit: it is designed for the point-in-time data.

  period: int This is used for query specific period. The period is represented with int in Qlib. (e.g. 202001 may represent the first quarter in 2020)

Returns feature series: The index of the series is the calendar index

Return type pd.Series

get_longest_back_rolling()
Get the longest length of historical data the feature has accessed

This is designed for getting the needed range of the data to calculate the features in specific range at first. However, situations like Ref(Ref($close, -1), 1) can not be handled rightly.

So this will only used for detecting the length of historical data needed.

get_extended_window_size()
get_extend_window_size

For to calculate this Operator in range[start_index, end_index] We have to get the *leaf feature* in range[start_index - lft_etd, end_index + rght_etd].

Returns lft_etd, rght_etd

Return type (int, int)

class qlib.data.base.**Feature**(*name=None*)
Static Expression

This kind of feature will load data from provider

__init__(*name=None*)
Initialize self. See help(type(self)) for accurate signature.

get_longest_back_rolling()
Get the longest length of historical data the feature has accessed

This is designed for getting the needed range of the data to calculate the features in specific range at first. However, situations like Ref(Ref($close, -1), 1) can not be handled rightly.

So this will only used for detecting the length of historical data needed.

get_extended_window_size()
get_extend_window_size

For to calculate this Operator in range[start_index, end_index] We have to get the *leaf feature* in range[start_index - lft_etd, end_index + rght_etd].

Returns lft_etd, rght_etd

Return type (int, int)

class qlib.data.base.**PFeature**(*name=None*)

class qlib.data.base.**ExpressionOps**
Operator Expression

This kind of feature will use operator for feature construction on the fly.

Operator

class qlib.data.ops.**ElemOperator**(*feature*)
Element-wise Operator

Parameters **feature** (`Expression`) – feature instance

Returns feature operation output

Return type *Expression*

__init__(*feature*)
Initialize self. See help(type(self)) for accurate signature.

get_longest_back_rolling()
Get the longest length of historical data the feature has accessed

This is designed for getting the needed range of the data to calculate the features in specific range at first. However, situations like Ref(Ref($close, -1), 1) can not be handled rightly.

So this will only used for detecting the length of historical data needed.

get_extended_window_size()
get_extend_window_size

For to calculate this Operator in range[start_index, end_index] We have to get the *leaf feature* in range[start_index - lft_etd, end_index + rght_etd].

Returns lft_etd, rght_etd

Return type (int, int)

class qlib.data.ops.**ChangeInstrument**(*instrument*, *feature*)
Change Instrument Operator In some case, one may want to change to another instrument when calculating, for example, to calculate beta of a stock with respect to a market index. This would require changing the calculation of features from the stock (original instrument) to the index (reference instrument) :param instrument: i.e.,

SH000300 (CSI300 index), or ^GPSC (SP500 index). :type instrument: new instrument for which the downstream operations should be performed upon. :param feature: :type feature: the feature to be calculated for the new instrument.

Returns feature operation output

Return type *Expression*

`__init__`(*instrument, feature*)

Initialize self. See help(type(self)) for accurate signature.

`load`(*instrument, start_index, end_index, *args*)

load feature This function is responsible for loading feature/expression based on the expression engine.

The concrete implementation will be separated into two parts:

1) caching data, handle errors.
   - This part is shared by all the expressions and implemented in Expression
2) processing and calculating data based on the specific expression.
   - This part is different in each expression and implemented in each expression

Expression Engine is shared by different data. Different data will have different extra information for *args*.

Parameters

- **instrument** (*str*) – instrument code.
- **start_index** (*str*) – feature start index [in calendar].
- **end_index** (*str*) – feature end index [in calendar].
- **may contain following information** (**args*) –
- **if it is used in basic expression engine data, it contains following arguments** (*1)*) –

  freq: str feature frequency.

- **if is used in PIT data, it contains following arguments** (*2)*) –

  cur_pit: it is designed for the point-in-time data.

  period: int This is used for query specific period. The period is represented with int in Qlib. (e.g. 202001 may represent the first quarter in 2020)

Returns feature series: The index of the series is the calendar index

Return type pd.Series

class `qlib.data.ops.`**`NpElemOperator`**(*feature, func*)

Numpy Element-wise Operator

Parameters

- **feature** (`Expression`) – feature instance
- **func** (*str*) – numpy feature operation method

Returns feature operation output

Return type *Expression*

`__init__`(*feature, func*)

Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Abs** (*feature*)
Feature Absolute Value

Parameters **feature** (Expression) – feature instance

Returns a feature instance with absolute output

Return type *Expression*

__init__ (*feature*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Sign** (*feature*)
Feature Sign

Parameters **feature** (Expression) – feature instance

Returns a feature instance with sign

Return type *Expression*

__init__ (*feature*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Log** (*feature*)
Feature Log

Parameters **feature** (Expression) – feature instance

Returns a feature instance with log

Return type *Expression*

__init__ (*feature*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Mask** (*feature*, *instrument*)
Feature Mask

Parameters

- **feature** (Expression) – feature instance
- **instrument** (*str*) – instrument mask

Returns a feature instance with masked instrument

Return type *Expression*

__init__ (*feature*, *instrument*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Not** (*feature*)
Not Operator

Parameters **feature** (Expression) – feature instance

Returns feature elementwise not output

Return type *Feature*

__init__ (*feature*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**PairOperator** (*feature_left*, *feature_right*)
Pair-wise operator

Parameters

- **feature_left** (Expression) – feature instance or numeric value
- **feature_right** (Expression) – feature instance or numeric value

Returns two features' operation output

Return type *Feature*

__init__(*feature_left*, *feature_right*)
Initialize self. See help(type(self)) for accurate signature.

get_longest_back_rolling()
Get the longest length of historical data the feature has accessed

This is designed for getting the needed range of the data to calculate the features in specific range at first. However, situations like Ref(Ref($close, -1), 1) can not be handled rightly.

So this will only used for detecting the length of historical data needed.

get_extended_window_size()
get_extend_window_size

For to calculate this Operator in range[start_index, end_index] We have to get the *leaf feature* in range[start_index - lft_etd, end_index + rght_etd].

Returns lft_etd, rght_etd

Return type (int, int)

class qlib.data.ops.**NpPairOperator**(*feature_left*, *feature_right*, *func*)
Numpy Pair-wise operator

Parameters

- **feature_left** (`Expression`) – feature instance or numeric value
- **feature_right** (`Expression`) – feature instance or numeric value
- **func** (*str*) – operator function

Returns two features' operation output

Return type *Feature*

__init__(*feature_left*, *feature_right*, *func*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Power**(*feature_left*, *feature_right*)
Power Operator

Parameters

- **feature_left** (`Expression`) – feature instance
- **feature_right** (`Expression`) – feature instance

Returns The bases in feature_left raised to the exponents in feature_right

Return type *Feature*

__init__(*feature_left*, *feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Add**(*feature_left*, *feature_right*)
Add Operator

Parameters

- **feature_left** (`Expression`) – feature instance
- **feature_right** (`Expression`) – feature instance

Returns two features' sum

Return type *Feature*

__init__(*feature_left*, *feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Sub** (*feature_left*, *feature_right*)
Subtract Operator

Parameters

- **feature_left** (Expression) – feature instance
- **feature_right** (Expression) – feature instance

Returns two features' subtraction

Return type *Feature*

__init__ (*feature_left*, *feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Mul** (*feature_left*, *feature_right*)
Multiply Operator

Parameters

- **feature_left** (Expression) – feature instance
- **feature_right** (Expression) – feature instance

Returns two features' product

Return type *Feature*

__init__ (*feature_left*, *feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Div** (*feature_left*, *feature_right*)
Division Operator

Parameters

- **feature_left** (Expression) – feature instance
- **feature_right** (Expression) – feature instance

Returns two features' division

Return type *Feature*

__init__ (*feature_left*, *feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Greater** (*feature_left*, *feature_right*)
Greater Operator

Parameters

- **feature_left** (Expression) – feature instance
- **feature_right** (Expression) – feature instance

Returns greater elements taken from the input two features

Return type *Feature*

__init__ (*feature_left*, *feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Less** (*feature_left*, *feature_right*)
Less Operator

Parameters

- **feature_left** (Expression) – feature instance
- **feature_right** (Expression) – feature instance

Returns smaller elements taken from the input two features

Return type *Feature*

__init__(*feature_left, feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Gt**(*feature_left, feature_right*)
Greater Than Operator

Parameters

- **feature_left** (Expression) – feature instance
- **feature_right** (Expression) – feature instance

Returns bool series indicate *left > right*

Return type *Feature*

__init__(*feature_left, feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Ge**(*feature_left, feature_right*)
Greater Equal Than Operator

Parameters

- **feature_left** (Expression) – feature instance
- **feature_right** (Expression) – feature instance

Returns bool series indicate *left >= right*

Return type *Feature*

__init__(*feature_left, feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Lt**(*feature_left, feature_right*)
Less Than Operator

Parameters

- **feature_left** (Expression) – feature instance
- **feature_right** (Expression) – feature instance

Returns bool series indicate *left < right*

Return type *Feature*

__init__(*feature_left, feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Le**(*feature_left, feature_right*)
Less Equal Than Operator

Parameters

- **feature_left** (Expression) – feature instance
- **feature_right** (Expression) – feature instance

Returns bool series indicate *left <= right*

Return type *Feature*

__init__(*feature_left, feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Eq**(*feature_left, feature_right*)
Equal Operator

Parameters

- **feature_left** (Expression) – feature instance

- **feature_right** (`Expression`) – feature instance

Returns bool series indicate *left == right*

Return type *Feature*

__init__(*feature_left, feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Ne**(*feature_left, feature_right*)
Not Equal Operator

Parameters

- **feature_left** (`Expression`) – feature instance
- **feature_right** (`Expression`) – feature instance

Returns bool series indicate *left != right*

Return type *Feature*

__init__(*feature_left, feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**And**(*feature_left, feature_right*)
And Operator

Parameters

- **feature_left** (`Expression`) – feature instance
- **feature_right** (`Expression`) – feature instance

Returns two features' row by row & output

Return type *Feature*

__init__(*feature_left, feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Or**(*feature_left, feature_right*)
Or Operator

Parameters

- **feature_left** (`Expression`) – feature instance
- **feature_right** (`Expression`) – feature instance

Returns two features' row by row | outputs

Return type *Feature*

__init__(*feature_left, feature_right*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**If**(*condition, feature_left, feature_right*)
If Operator

Parameters

- **condition** (`Expression`) – feature instance with bool values as condition
- **feature_left** (`Expression`) – feature instance
- **feature_right** (`Expression`) – feature instance

__init__(*condition, feature_left, feature_right*)
Initialize self. See help(type(self)) for accurate signature.

get_longest_back_rolling()
Get the longest length of historical data the feature has accessed

This is designed for getting the needed range of the data to calculate the features in specific range at first. However, situations like Ref(Ref($close, -1), 1) can not be handled rightly.

So this will only used for detecting the length of historical data needed.

get_extended_window_size()

get_extend_window_size

For to calculate this Operator in range[start_index, end_index] We have to get the *leaf feature* in range[start_index - lft_etd, end_index + rght_etd].

Returns lft_etd, rght_etd

Return type (int, int)

class qlib.data.ops.**Rolling**(*feature*, *N*, *func*)

Rolling Operator The meaning of rolling and expanding is the same in pandas. When the window is set to 0, the behaviour of the operator should follow *expanding* Otherwise, it follows *rolling*

Parameters

- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size
- **func** (*str*) – rolling method

Returns rolling outputs

Return type *Expression*

__init__(*feature*, *N*, *func*)

Initialize self. See help(type(self)) for accurate signature.

get_longest_back_rolling()

Get the longest length of historical data the feature has accessed

This is designed for getting the needed range of the data to calculate the features in specific range at first. However, situations like Ref(Ref($close, -1), 1) can not be handled rightly.

So this will only used for detecting the length of historical data needed.

get_extended_window_size()

get_extend_window_size

For to calculate this Operator in range[start_index, end_index] We have to get the *leaf feature* in range[start_index - lft_etd, end_index + rght_etd].

Returns lft_etd, rght_etd

Return type (int, int)

class qlib.data.ops.**Ref**(*feature*, *N*)

Feature Reference

Parameters

- **feature** (Expression) – feature instance
- **N** (*int*) – N = 0, retrieve the first data; N > 0, retrieve data of N periods ago; N < 0, future data

Returns a feature instance with target reference

Return type *Expression*

__init__(*feature*, *N*)

Initialize self. See help(type(self)) for accurate signature.

get_longest_back_rolling()

Get the longest length of historical data the feature has accessed

This is designed for getting the needed range of the data to calculate the features in specific range at first. However, situations like Ref(Ref($close, -1), 1) can not be handled rightly.

So this will only used for detecting the length of historical data needed.

get_extended_window_size()

get_extend_window_size

For to calculate this Operator in range[start_index, end_index] We have to get the *leaf feature* in range[start_index - lft_etd, end_index + rght_etd].

Returns lft_etd, rght_etd

Return type (int, int)

class qlib.data.ops.**Mean**(*feature*, *N*)

Rolling Mean (MA)

Parameters

- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling average

Return type *Expression*

__init__(*feature*, *N*)

Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Sum**(*feature*, *N*)

Rolling Sum

Parameters

- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling sum

Return type *Expression*

__init__(*feature*, *N*)

Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Std**(*feature*, *N*)

Rolling Std

Parameters

- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling std

Return type *Expression*

__init__(*feature*, *N*)

Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Var**(*feature*, *N*)

Rolling Variance

Parameters

- **feature** (Expression) – feature instance

- **N** (*int*) – rolling window size

Returns a feature instance with rolling variance

Return type *Expression*

`__init__`(*feature*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class `qlib.data.ops.`**`Skew`**(*feature*, *N*)
Rolling Skewness

Parameters

- **feature** (`Expression`) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling skewness

Return type *Expression*

`__init__`(*feature*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class `qlib.data.ops.`**`Kurt`**(*feature*, *N*)
Rolling Kurtosis

Parameters

- **feature** (`Expression`) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling kurtosis

Return type *Expression*

`__init__`(*feature*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class `qlib.data.ops.`**`Max`**(*feature*, *N*)
Rolling Max

Parameters

- **feature** (`Expression`) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling max

Return type *Expression*

`__init__`(*feature*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class `qlib.data.ops.`**`IdxMax`**(*feature*, *N*)
Rolling Max Index

Parameters

- **feature** (`Expression`) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling max index

Return type *Expression*

`__init__`(*feature*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Min** (*feature*, *N*)

Rolling Min

Parameters

- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling min

Return type *Expression*

__init__ (*feature*, *N*)

Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**IdxMin** (*feature*, *N*)

Rolling Min Index

Parameters

- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling min index

Return type *Expression*

__init__ (*feature*, *N*)

Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Quantile** (*feature*, *N*, *qscore*)

Rolling Quantile

Parameters

- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling quantile

Return type *Expression*

__init__ (*feature*, *N*, *qscore*)

Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Med** (*feature*, *N*)

Rolling Median

Parameters

- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling median

Return type *Expression*

__init__ (*feature*, *N*)

Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Mad** (*feature*, *N*)

Rolling Mean Absolute Deviation

Parameters

- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling mean absolute deviation

Return type *Expression*

__init__(*feature*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Rank**(*feature*, *N*)
Rolling Rank (Percentile)

Parameters

- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling rank

Return type *Expression*

__init__(*feature*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Count**(*feature*, *N*)
Rolling Count

Parameters

- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling count of number of non-NaN elements

Return type *Expression*

__init__(*feature*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Delta**(*feature*, *N*)
Rolling Delta

Parameters

- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with end minus start in rolling window

Return type *Expression*

__init__(*feature*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Slope**(*feature*, *N*)
Rolling Slope This operator calculate the slope between *idx* and *feature*. (e.g. [<feature_t1>, <feature_t2>, <feature_t3>] and [1, 2, 3])

Usage Example: - "Slope($close, %d)/$close"

TODO: # Some users may want pair-wise rolling like *Slope(A, B, N)*

Parameters

- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with linear regression slope of given window

Return type *Expression*

__init__(*feature*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Rsquare**(*feature*, *N*)
Rolling R-value Square

Parameters
- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with linear regression r-value square of given window

Return type *Expression*

__init__(*feature*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**Resi**(*feature*, *N*)
Rolling Regression Residuals

Parameters
- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with regression residuals of given window

Return type *Expression*

__init__(*feature*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**WMA**(*feature*, *N*)
Rolling WMA

Parameters
- **feature** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with weighted moving average output

Return type *Expression*

__init__(*feature*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**EMA**(*feature*, *N*)
Rolling Exponential Mean (EMA)

Parameters
- **feature** (Expression) – feature instance
- **N** (*int, float*) – rolling window size

Returns a feature instance with regression r-value square of given window

Return type *Expression*

__init__(*feature*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.ops.**PairRolling**(*feature_left*, *feature_right*, *N*, *func*)
Pair Rolling Operator

Parameters
- **feature_left** (Expression) – feature instance
- **feature_right** (Expression) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling output of two input features

Return type *Expression*

`__init__`(*feature_left*, *feature_right*, *N*, *func*)
Initialize self. See help(type(self)) for accurate signature.

`get_longest_back_rolling`()
Get the longest length of historical data the feature has accessed

This is designed for getting the needed range of the data to calculate the features in specific range at first. However, situations like Ref(Ref($close, -1), 1) can not be handled rightly.

So this will only used for detecting the length of historical data needed.

`get_extended_window_size`()
get_extend_window_size

For to calculate this Operator in range[start_index, end_index] We have to get the *leaf feature* in range[start_index - lft_etd, end_index + rght_etd].

Returns lft_etd, rght_etd

Return type (int, int)

class `qlib.data.ops.Corr`(*feature_left*, *feature_right*, *N*)
Rolling Correlation

Parameters

- **feature_left** (`Expression`) – feature instance
- **feature_right** (`Expression`) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling correlation of two input features

Return type *Expression*

`__init__`(*feature_left*, *feature_right*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class `qlib.data.ops.Cov`(*feature_left*, *feature_right*, *N*)
Rolling Covariance

Parameters

- **feature_left** (`Expression`) – feature instance
- **feature_right** (`Expression`) – feature instance
- **N** (*int*) – rolling window size

Returns a feature instance with rolling max of two input features

Return type *Expression*

`__init__`(*feature_left*, *feature_right*, *N*)
Initialize self. See help(type(self)) for accurate signature.

class `qlib.data.ops.TResample`(*feature*, *freq*, *func*)

`__init__`(*feature*, *freq*, *func*)
Resampling the data to target frequency. The resample function of pandas is used.

- the timestamp will be at the start of the time span after resample.

Parameters

- **feature** (Expression) – An expression for calculating the feature
- **freq** (*str*) – It will be passed into the resample method for resampling basedn on given frequency
- **func** (*method*) – The method to get the resampled values Some expression are high frequently used

class qlib.data.ops.**OpsWrapper**
Ops Wrapper

__init__()
Initialize self. See help(type(self)) for accurate signature.

register(*ops_list: List[Union[Type[qlib.data.base.ExpressionOps], dict]]*)
register operator

Parameters **ops_list** (*List[Union[Type[*ExpressionOps*], dict]]*) –

- if type(ops_list) is List[Type[ExpressionOps]], each element of ops_list represents the operator class, which should be the subclass of *ExpressionOps*.
- if type(ops_list) is List[dict], each element of ops_list represents the config of operator, which has the following format:

```
{
    "class": class_name,
    "module_path": path,
}
```

Note: *class* should be the class name of operator, *module_path* should be a python module or path of file.

qlib.data.ops.**register_all_ops**(*C*)
register all operator

Cache

class qlib.data.cache.**MemCacheUnit**(**args*, ***kwargs*)
Memory Cache Unit.

__init__(**args*, ***kwargs*)
Initialize self. See help(type(self)) for accurate signature.

limited
whether memory cache is limited

class qlib.data.cache.**MemCache**(*mem_cache_size_limit=None*, *limit_type='length'*)
Memory cache.

__init__(*mem_cache_size_limit=None*, *limit_type='length'*)

Parameters

- **mem_cache_size_limit** – cache max size.
- **limit_type** – length or sizeof; length(call fun: len), size(call fun: sys.getsizeof).

class qlib.data.cache.**ExpressionCache**(*provider*)
Expression cache mechanism base class.

This class is used to wrap expression provider with self-defined expression cache mechanism.

Note: Override the *_uri* and *_expression* method to create your own expression cache mechanism.

expression(*instrument*, *field*, *start_time*, *end_time*, *freq*)
Get expression data.

Note: Same interface as *expression* method in expression provider

update(*cache_uri: Union[str, pathlib.Path], freq: str = 'day'*)
Update expression cache to latest calendar.

Override this method to define how to update expression cache corresponding to users' own cache mechanism.

Parameters

- **cache_uri** (*str or Path*) – the complete uri of expression cache file (include dir path).
- **freq** (*str*) –

Returns 0(successful update)/ 1(no need to update)/ 2(update failure).

Return type int

class qlib.data.cache.**DatasetCache**(*provider*)
Dataset cache mechanism base class.

This class is used to wrap dataset provider with self-defined dataset cache mechanism.

Note: Override the *_uri* and *_dataset* method to create your own dataset cache mechanism.

dataset(*instruments*, *fields*, *start_time=None*, *end_time=None*, *freq='day'*, *disk_cache=1*, *inst_processors=[]*)
Get feature dataset.

Note: Same interface as *dataset* method in dataset provider

Note: The server use redis_lock to make sure read-write conflicts will not be triggered but client readers are not considered.

update(*cache_uri: Union[str, pathlib.Path], freq: str = 'day'*)
Update dataset cache to latest calendar.

Override this method to define how to update dataset cache corresponding to users' own cache mechanism.

Parameters

- **cache_uri** (*str or Path*) – the complete uri of dataset cache file (include dir path).
- **freq** (*str*) –

Returns 0(successful update)/ 1(no need to update)/ 2(update failure)

Return type int

static cache_to_origin_data(*data*, *fields*)
cache data to origin data

Parameters

- **data** – pd.DataFrame, cache data.
- **fields** – feature fields.

Returns pd.DataFrame.

static normalize_uri_args(*instruments*, *fields*, *freq*)
normalize uri args

class qlib.data.cache.**DiskExpressionCache**(*provider*, ***kwargs*)
Prepared cache mechanism for server.

__init__(*provider*, ***kwargs*)
Initialize self. See help(type(self)) for accurate signature.

gen_expression_cache(*expression_data*, *cache_path*, *instrument*, *field*, *freq*, *last_update*)
use bin file to save like feature-data.

update(*sid*, *cache_uri*, *freq: str = 'day'*)
Update expression cache to latest calendar.

Override this method to define how to update expression cache corresponding to users' own cache mechanism.

Parameters

- **cache_uri** (*str or Path*) – the complete uri of expression cache file (include dir path).
- **freq** (*str*) –

Returns 0(successful update)/ 1(no need to update)/ 2(update failure).

Return type int

class qlib.data.cache.**DiskDatasetCache**(*provider*, ***kwargs*)
Prepared cache mechanism for server.

__init__(*provider*, ***kwargs*)
Initialize self. See help(type(self)) for accurate signature.

classmethod read_data_from_cache(*cache_path: Union[str, pathlib.Path], start_time, end_time, fields*)
read_cache_from

This function can read data from the disk cache dataset

Parameters

- **cache_path** –
- **start_time** –
- **end_time** –
- **fields** – The fields order of the dataset cache is sorted. So rearrange the columns to make it consistent.

Returns

class IndexManager(*cache_path: Union[str, pathlib.Path]*)
The lock is not considered in the class. Please consider the lock outside the code. This class is the proxy of the disk data.

__init__(*cache_path: Union[str, pathlib.Path]*)
Initialize self. See help(type(self)) for accurate signature.

gen_dataset_cache(*cache_path: Union[str, pathlib.Path], instruments, fields, freq, inst_processors=[]*)

Note: This function does not consider the cache read write lock. Please acquire the lock outside this function

The format the cache contains 3 parts(followed by typical filename).

- index : cache/d41366901e25de3ec47297f12e2ba11d.index
  - The content of the file may be in following format(pandas.Series)

```
                     start end
1999-11-10 00:00:00     0   1
1999-11-11 00:00:00     1   2
1999-11-12 00:00:00     2   3
...
```

Note: The start is closed. The end is open!!!!!

  - Each line contains two element <start_index, end_index> with a timestamp as its index.
  - It indicates the *start_index* (included) and *end_index* (excluded) of the data for *timestamp*
- meta data: cache/d41366901e25de3ec47297f12e2ba11d.meta
- data : cache/d41366901e25de3ec47297f12e2ba11d
  - This is a hdf file sorted by datetime

Parameters

- **cache_path** – The path to store the cache.
- **instruments** – The instruments to store the cache.
- **fields** – The fields to store the cache.
- **freq** – The freq to store the cache.
- **inst_processors** – Instrument processors.

:return type pd.DataFrame; The fields of the returned DataFrame are consistent with the parameters of the function.

update(*cache_uri, freq: str = 'day'*)
Update dataset cache to latest calendar.

Override this method to define how to update dataset cache corresponding to users' own cache mechanism.

Parameters

- **cache_uri** (*str or Path*) – the complete uri of dataset cache file (include dir path).
- **freq** (*str*) –

Returns 0(successful update)/ 1(no need to update)/ 2(update failure)

Return type int

Storage

class qlib.data.storage.storage.**BaseStorage**

class qlib.data.storage.storage.**CalendarStorage**(*freq: str*, *future: bool*, ***kwargs*)
The behavior of CalendarStorage's methods and List's methods of the same name remain consistent

__init__(*freq: str*, *future: bool*, ***kwargs*)
Initialize self. See help(type(self)) for accurate signature.

data
get all data

Raises `ValueError` – If the data(storage) does not exist, raise ValueError

index(*value: str*) → int

Raises `ValueError` – If the data(storage) does not exist, raise ValueError

class qlib.data.storage.storage.**InstrumentStorage**(*market: str*, *freq: str*, ***kwargs*)

__init__(*market: str*, *freq: str*, ***kwargs*)
Initialize self. See help(type(self)) for accurate signature.

data
get all data

Raises `ValueError` – If the data(storage) does not exist, raise ValueError

update([*E*], ***F*) → None. Update D from mapping/iterable E and F.

Notes

If E present and has a .keys() method, does: for k in E: D[k] = E[k]

If E present and lacks .keys() method, does: for (k, v) in E: D[k] = v

In either case, this is followed by: for k, v in F.items(): D[k] = v

class qlib.data.storage.storage.**FeatureStorage**(*instrument: str*, *field: str*, *freq: str*, ***kwargs*)

__init__(*instrument: str*, *field: str*, *freq: str*, ***kwargs*)
Initialize self. See help(type(self)) for accurate signature.

data
get all data

Notes

if data(storage) does not exist, return empty pd.Series: *return pd.Series(dtype=np.float32)*

start_index
get FeatureStorage start index

Notes

If the data(storage) does not exist, return None

end_index
get FeatureStorage end index

Notes

The right index of the data range (both sides are closed)

The next data appending point will be *end_index + 1*

If the data(storage) does not exist, return None

write(*data_array: Union[List[T], numpy.ndarray, Tuple], index: int = None*)
Write data_array to FeatureStorage starting from index.

Notes

If index is None, append data_array to feature.

If len(data_array) == 0; return

If (index - self.end_index) >= 1, self[end_index+1: index] will be filled with np.nan

Examples

rebase(*start_index: int = None*, *end_index: int = None*)
Rebase the start_index and end_index of the FeatureStorage.

start_index and end_index are closed intervals: [start_index, end_index]

Examples

rewrite(*data: Union[List[T], numpy.ndarray, Tuple], index: int*)
overwrite all data in FeatureStorage with data

Parameters

- **data** (`Union[List, np.ndarray, Tuple]`) – data
- **index** (`int`) – data start index

class `qlib.data.storage.file_storage.`**FileStorageMixin**
FileStorageMixin, applicable to FileXXXStorage Subclasses need to have provider_uri, freq, storage_name, file_name attributes

check()
check self.uri

Raises `ValueError`

class `qlib.data.storage.file_storage.`**`FileCalendarStorage`**(*freq: str*, *future: bool*, *provider_uri: dict = None*, ***kwargs*)

`__init__`(*freq: str*, *future: bool*, *provider_uri: dict = None*, ***kwargs*)
Initialize self. See help(type(self)) for accurate signature.

`data`
get all data

Raises `ValueError` – If the data(storage) does not exist, raise ValueError

`index`(*value: str*) → int

Raises `ValueError` – If the data(storage) does not exist, raise ValueError

class `qlib.data.storage.file_storage.`**`FileInstrumentStorage`**(*market: str*, *freq: str*, *provider_uri: dict = None*, ***kwargs*)

`__init__`(*market: str*, *freq: str*, *provider_uri: dict = None*, ***kwargs*)
Initialize self. See help(type(self)) for accurate signature.

`data`
get all data

Raises `ValueError` – If the data(storage) does not exist, raise ValueError

`update`([*E*], ***F*) → None. Update D from mapping/iterable E and F.

Notes

If E present and has a .keys() method, does: for k in E: D[k] = E[k]

If E present and lacks .keys() method, does: for (k, v) in E: D[k] = v

In either case, this is followed by: for k, v in F.items(): D[k] = v

class `qlib.data.storage.file_storage.`**`FileFeatureStorage`**(*instrument: str*, *field: str*, *freq: str*, *provider_uri: dict = None*, ***kwargs*)

`__init__`(*instrument: str*, *field: str*, *freq: str*, *provider_uri: dict = None*, ***kwargs*)
Initialize self. See help(type(self)) for accurate signature.

`data`
get all data

Notes

if data(storage) does not exist, return empty pd.Series: *return pd.Series(dtype=np.float32)*

`write`(*data_array: Union[List[T], numpy.ndarray], index: int = None*) → None
Write data_array to FeatureStorage starting from index.

Notes

If index is None, append data_array to feature.

If len(data_array) == 0; return

If (index - self.end_index) >= 1, self[end_index+1: index] will be filled with np.nan

Examples

start_index
get FeatureStorage start index

Notes

If the data(storage) does not exist, return None

end_index
get FeatureStorage end index

Notes

The right index of the data range (both sides are closed)

The next data appending point will be *end_index + 1*

If the data(storage) does not exist, return None

Dataset

Dataset Class

class qlib.data.dataset.__init__.**Dataset**(***kwargs*)
Preparing data for model training and inferencing.

__init__(***kwargs*)
init is designed to finish following steps:

- **init the sub instance and the state of the dataset(info to prepare the data)**
  - The name of essential state for preparing data should not start with '_' so that it could be serialized on disk when serializing.
- **setup data**
  - The data related attributes' names should start with '_' so that it will not be saved on disk when serializing.

The data could specify the info to calculate the essential data for preparation

config(***kwargs*)
config is designed to configure and parameters that cannot be learned from the data

setup_data(***kwargs*)
Setup the data.

We split the setup_data function for following situation:

- User have a Dataset object with learned status on disk.
- User load the Dataset object from the disk.
- User call *setup_data* to load new data.
- User prepare data for model based on previous status.

prepare(***kwargs*) → object

The type of dataset depends on the model. (It could be pd.DataFrame, pytorch.DataLoader, etc.) The parameters should specify the scope for the prepared data The method should: - process the data

- return the processed data

Returns return the object

Return type object

class qlib.data.dataset.__init__.**DatasetH**(*handler: Union[Dict[KT, VT], qlib.data.dataset.handler.DataHandler], segments: Dict[str, Tuple], fetch_kwargs: Dict[KT, VT] = {}, **kwargs*)

Dataset with Data(H)andler

User should try to put the data preprocessing functions into handler. Only following data processing functions should be placed in Dataset:

- The processing is related to specific model.
- The processing is related to data split.

__init__(*handler: Union[Dict[KT, VT], qlib.data.dataset.handler.DataHandler], segments: Dict[str, Tuple], fetch_kwargs: Dict[KT, VT] = {}, **kwargs*)

Setup the underlying data.

Parameters

- **handler** (*Union[dict, DataHandler]*) – handler could be:
  - instance of *DataHandler*
  - config of *DataHandler*. Please refer to *DataHandler*
- **segments** (*dict*) – Describe the options to segment the data. Here are some examples:

config(*handler_kwargs: dict = None, **kwargs*)

Initialize the DatasetH

Parameters

- **handler_kwargs** (*dict*) – Config of DataHandler, which could include the following arguments:
  - arguments of DataHandler.conf_data, such as 'instruments', 'start_time' and 'end_time'.
- **kwargs** (*dict*) – Config of DatasetH, such as
  - **segments** [dict] Config of segments which is same as 'segments' in self.__init__

setup_data(*handler_kwargs: dict = None, **kwargs*)

Setup the Data

Parameters **handler_kwargs** (*dict*) – init arguments of DataHandler, which could include the following arguments:

- init_type : Init Type of Handler
- enable_cache : whether to enable cache

prepare (*segments: Union[List[str], Tuple[str], str, slice, pandas.core.indexes.base.Index], col_set='__all', data_key='infer', **kwargs*) → Union[List[pandas.core.frame.DataFrame], pandas.core.frame.DataFrame]

Prepare the data for learning and inference.

Parameters

- **segments** (*Union[List[Text], Tuple[Text], Text, slice]*) – Describe the scope of the data to be prepared Here are some examples:
  - 'train'
  - ['train', 'valid']
- **col_set** (*str*) – The col_set will be passed to self.handler when fetching data. TODO: make it automatic:
  - select DK_I for test data
  - select DK_L for training data.
- **data_key** (*str*) – The data to fetch: DK_* Default is DK_I, which indicate fetching data for **inference**.
- **kwargs** –

  The parameters that kwargs may contain:

  flt_col [str] It only exists in TSDatasetH, can be used to add a column of data(True or False) to filter data. This parameter is only supported when it is an instance of TSDatasetH.

Returns

Return type Union[List[pd.DataFrame], pd.DataFrame]

Raises NotImplementedError:

Data Loader

class qlib.data.dataset.loader.**DataLoader**

DataLoader is designed for loading raw data from original data source.

load (*instruments, start_time=None, end_time=None*) → pandas.core.frame.DataFrame

load the data as pd.DataFrame.

Example of the data (The multi-index of the columns is optional.):

```
                        feature                                                ␣
↪                         label
                        $close     $volume     Ref($close, 1)  Mean(
↪$close, 3)  $high-$low  LABEL0
datetime    instrument
2010-01-04  SH600000    81.807068  17145150.0       83.737389              ␣
↪ 83.016739    2.741058  0.0032
            SH600004    13.313329  11800983.0       13.313329              ␣
↪ 13.317701    0.183632  0.0042
            SH600005    37.796539  12231662.0       38.258602              ␣
↪ 37.919757    0.970325  0.0289
```

Parameters

- **instruments** (*str or dict*) – it can either be the market name or the config file of instruments generated by InstrumentProvider.
- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.

Returns data load from the under layer source

Return type pd.DataFrame

class qlib.data.dataset.loader.**DLWParser**(*config: Union[list, tuple, dict]*)

(D)ata(L)oader (W)ith (P)arser for features and names

Extracting this class so that QlibDataLoader and other dataloaders(such as QdbDataLoader) can share the fields.

__init__(*config: Union[list, tuple, dict]*)

Parameters config (*Union[list, tuple, dict]*) – Config will be used to describe the fields and column names

load_group_df(*instruments*, *exprs: list*, *names: list*, *start_time: Union[str, pandas._libs.tslibs.timestamps.Timestamp] = None*, *end_time: Union[str, pandas._libs.tslibs.timestamps.Timestamp] = None*, *gp_name: str = None*) → pandas.core.frame.DataFrame

load the dataframe for specific group

Parameters

- **instruments** – the instruments.
- **exprs** (*list*) – the expressions to describe the content of the data.
- **names** (*list*) – the name of the data.

Returns the queried dataframe.

Return type pd.DataFrame

load(*instruments=None*, *start_time=None*, *end_time=None*) → pandas.core.frame.DataFrame

load the data as pd.DataFrame.

Example of the data (The multi-index of the columns is optional.):

```
                        feature                                                     ␣
↪                        label
                        $close     $volume     Ref($close, 1)  Mean(
↪$close, 3)  $high-$low  LABEL0
datetime    instrument
2010-01-04  SH600000    81.807068  17145150.0       83.737389                  ␣
↪ 83.016739    2.741058  0.0032
            SH600004    13.313329  11800983.0       13.313329                  ␣
↪ 13.317701    0.183632  0.0042
            SH600005    37.796539  12231662.0       38.258602                  ␣
↪ 37.919757    0.970325  0.0289
```

Parameters

- **instruments** (*str or dict*) – it can either be the market name or the config file of instruments generated by InstrumentProvider.

- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.

Returns data load from the under layer source

Return type pd.DataFrame

class qlib.data.dataset.loader.**QlibDataLoader**(*config: Tuple[list, tuple, dict], filter_pipe: List[T] = None, swap_level: bool = True, freq: Union[str, dict] = 'day', inst_processor: dict = None*)

Same as QlibDataLoader. The fields can be define by config

__init__(*config: Tuple[list, tuple, dict], filter_pipe: List[T] = None, swap_level: bool = True, freq: Union[str, dict] = 'day', inst_processor: dict = None*)

Parameters

- **config** (*Tuple[list, tuple, dict]*) – Please refer to the doc of DLWParser
- **filter_pipe** – Filter pipe for the instruments
- **swap_level** – Whether to swap level of MultiIndex
- **freq** (*dict or str*) – If type(config) == dict and type(freq) == str, load config data using freq. If type(config) == dict and type(freq) == dict, load config[<group_name>] data using freq[<group_name>]
- **inst_processor** (*dict*) – If inst_processor is not None and type(config) == dict; load config[<group_name>] data using inst_processor[<group_name>]

load_group_df(*instruments, exprs: list, names: list, start_time: Union[str, pandas._libs.tslibs.timestamps.Timestamp] = None, end_time: Union[str, pandas._libs.tslibs.timestamps.Timestamp] = None, gp_name: str = None*) → pandas.core.frame.DataFrame

load the dataframe for specific group

Parameters

- **instruments** – the instruments.
- **exprs** (*list*) – the expressions to describe the content of the data.
- **names** (*list*) – the name of the data.

Returns the queried dataframe.

Return type pd.DataFrame

class qlib.data.dataset.loader.**StaticDataLoader**(*config: Union[dict, str, pandas.core.frame.DataFrame], join='outer'*)

DataLoader that supports loading data from file or as provided.

__init__(*config: Union[dict, str, pandas.core.frame.DataFrame], join='outer'*)

Parameters

- **config** (*dict*) – {fields_group: <path or object>}
- **join** (*str*) – How to align different dataframes

load(*instruments=None*, *start_time=None*, *end_time=None*) → pandas.core.frame.DataFrame
load the data as pd.DataFrame.

Example of the data (The multi-index of the columns is optional.):

```
                        feature                                                ␣
↪                         label
                        $close      $volume     Ref($close, 1)  Mean(
↪$close, 3)  $high-$low  LABEL0
datetime    instrument
2010-01-04  SH600000    81.807068  17145150.0       83.737389                  ␣
↪ 83.016739    2.741058  0.0032
            SH600004    13.313329  11800983.0       13.313329                  ␣
↪ 13.317701    0.183632  0.0042
            SH600005    37.796539  12231662.0       38.258602                  ␣
↪ 37.919757    0.970325  0.0289
```

Parameters

- **instruments** (*str or dict*) – it can either be the market name or the config file of instruments generated by InstrumentProvider.
- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.

Returns data load from the under layer source

Return type pd.DataFrame

class qlib.data.dataset.loader.**DataLoaderDH**(*handler_config: dict*, *fetch_kwargs: dict = {}*, *is_group=False*)
DataLoader based on (D)ata (H)andler It is designed to load multiple data from data handler - If you just want to load data from single datahandler, you can write them in single data handler

TODO: What make this module not that easy to use.

- For online scenario
  - The underlayer data handler should be configured. But data loader doesn't provide such interface & hook.

__init__(*handler_config: dict*, *fetch_kwargs: dict = {}*, *is_group=False*)

Parameters

- **handler_config** (*dict*) – handler_config will be used to describe the handlers
- **fetch_kwargs** (*dict*) – fetch_kwargs will be used to describe the different arguments of fetch method, such as col_set, squeeze, data_key, etc.
- **is_group** (*bool*) – is_group will be used to describe whether the key of handler_config is group

load(*instruments=None*, *start_time=None*, *end_time=None*) → pandas.core.frame.DataFrame
load the data as pd.DataFrame.

Example of the data (The multi-index of the columns is optional.):

```
                        feature                                                ␣
↪                         label
                        $close      $volume     Ref($close, 1)  Mean(
↪$close, 3)  $high-$low  LABEL0
```

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```
datetime     instrument
2010-01-04  SH600000    81.807068  17145150.0       83.737389      ␣
↪ 83.016739     2.741058  0.0032
            SH600004    13.313329  11800983.0       13.313329      ␣
↪ 13.317701     0.183632  0.0042
            SH600005    37.796539  12231662.0       38.258602      ␣
↪ 37.919757     0.970325  0.0289
```

Parameters

- **instruments** (*str or dict*) – it can either be the market name or the config file of instruments generated by InstrumentProvider.
- **start_time** (*str*) – start of the time range.
- **end_time** (*str*) – end of the time range.

Returns data load from the under layer source

Return type pd.DataFrame

Data Handler

class qlib.data.dataset.handler.**DataHandler**(*instruments=None*, *start_time=None*, *end_time=None*, *data_loader: Union[dict, str, qlib.data.dataset.loader.DataLoader] = None*, *init_data=True*, *fetch_orig=True*)

The steps to using a handler 1. initialized data handler (call by *init*). 2. use the data.

The data handler try to maintain a handler with 2 level. *datetime* & *instruments*.

Any order of the index level can be supported (The order will be implied in the data). The order <*datetime*, *instruments*> will be used when the dataframe index name is missed.

Example of the data: The multi-index of the columns is optional.

```
                        feature                                              ␣
↪          label
                        $close     $volume  Ref($close, 1)  Mean($close, 3)
↪$high-$low  LABEL0
datetime   instrument
2010-01-04 SH600000    81.807068  17145150.0       83.737389        83.016739    ␣
↪2.741058  0.0032
           SH600004    13.313329  11800983.0       13.313329        13.317701    ␣
↪0.183632  0.0042
           SH600005    37.796539  12231662.0       38.258602        37.919757    ␣
↪0.970325  0.0289
```

Tips for improving the performance of datahandler - Fetching data with *col_set=CS_RAW* will return the raw data and may avoid pandas from copying the data when calling *loc*

__init__(*instruments=None*, *start_time=None*, *end_time=None*, *data_loader: Union[dict, str, qlib.data.dataset.loader.DataLoader] = None*, *init_data=True*, *fetch_orig=True*)

Parameters

- **instruments** – The stock list to retrieve.
- **start_time** – start_time of the original data.

- **end_time** – end_time of the original data.
- **data_loader** (*Union[dict, str, DataLoader]*) – data loader to load the data.
- **init_data** – initialize the original data in the constructor.
- **fetch_orig** (*bool*) – Return the original data instead of copy if possible.

config(***kwargs*)
configuration of data. # what data to be loaded from data source

This method will be used when loading pickled handler from dataset. The data will be initialized with different time range.

setup_data(*enable_cache: bool = False*)
Set Up the data in case of running initialization for multiple time

It is responsible for maintaining following variable 1) self._data

Parameters **enable_cache** (*bool*) – default value is false:

- if *enable_cache* == True:

  the processed data will be saved on disk, and handler will load the cached data from the disk directly when we call *init* next time

fetch(*selector: Union[pandas._libs.tslibs.timestamps.Timestamp, slice, str, pandas.core.indexes.base.Index] = slice(None, None, None), level: Union[str, int] = 'datetime', col_set: Union[str, List[str]] = '__all', squeeze: bool = False, proc_func: Callable = None*) → pandas.core.frame.DataFrame
fetch data from underlying data source

Parameters

- **selector** (*Union[pd.Timestamp, slice, str]*) – describe how to select data by index It can be categories as following
  - fetch single index
  - fetch a range of index
    - a slice range
    - pd.Index for specific indexes

  Following conflicts may occur
  - Does ["20200101", "20210101"] mean selecting this slice or these two days?
    - slice have higher priorities
- **level** (*Union[str, int]*) – which index level to select the data
- **col_set** (*Union[str, List[str]]*) –
  - if isinstance(col_set, str):

    select a set of meaningful, pd.Index columns.(e.g. features, columns)
    - if col_set == CS_RAW:

      the raw dataset will be returned.
  - if isinstance(col_set, List[str]):

    select several sets of meaningful columns, the returned data has multiple levels

- **proc_func** (*Callable*) –
  - Give a hook for processing data before fetching
  - An example to explain the necessity of the hook:
    - A Dataset learned some processors to process data which is related to data segmentation
    - It will apply them every time when preparing data.
    - The learned processor require the dataframe remains the same format when fitting and applying
    - However the data format will change according to the parameters.
    - So the processors should be applied to the underlayer data.
- **squeeze** (*bool*) – whether squeeze columns and index

Returns

Return type pd.DataFrame.

get_cols(*col_set='__all'*) → list

get the column names

Parameters **col_set** (*str*) – select a set of meaningful columns.(e.g. features, columns)

Returns list of column names

Return type list

get_range_selector(*cur_date: Union[pandas._libs.tslibs.timestamps.Timestamp, str], periods: int*) → slice

get range selector by number of periods

Parameters

- **cur_date** (*pd.Timestamp or str*) – current date
- **periods** (*int*) – number of periods

get_range_iterator(*periods: int, min_periods: Optional[int] = None, **kwargs*) → Iterator[Tuple[pandas._libs.tslibs.timestamps.Timestamp, pandas.core.frame.DataFrame]]

get an iterator of sliced data with given periods

Parameters

- **periods** (*int*) – number of periods.
- **min_periods** (*int*) – minimum periods for sliced dataframe.
- **kwargs** (*dict*) – will be passed to *self.fetch*.

class qlib.data.dataset.handler.**DataHandlerLP**(*instruments=None, start_time=None, end_time=None, data_loader: Union[dict, str, qlib.data.dataset.loader.DataLoader] = None, infer_processors: List[T] = [], learn_processors: List[T] = [], shared_processors: List[T] = [], process_type='append', drop_raw=False, **kwargs*)

DataHandler with **(L)earnable (P)rocessor**

This handler will produce three pieces of data in pd.DataFrame format.

- DK_R / self._data: the raw data loaded from the loader

- DK_I / self._infer: the data processed for inference
- DK_L / self._learn: the data processed for learning model.

The motivation of using different processor workflows for learning and inference Here are some examples.

- The instrument universe for learning and inference may be different.
- The processing of some samples may rely on label (for example, some samples hit the limit may need extra processing or be dropped).
  - These processors only apply to the learning phase.

Tips to improve the performance of data handler

- To reduce the memory cost
  - *drop_raw=True*: this will modify the data inplace on raw data;

__init__(*instruments=None*, *start_time=None*, *end_time=None*, *data_loader: Union[dict, str, qlib.data.dataset.loader.DataLoader] = None*, *infer_processors: List[T] = []*, *learn_processors: List[T] = []*, *shared_processors: List[T] = []*, *process_type='append'*, *drop_raw=False*, ***kwargs*)

Parameters

- **infer_processors** (*list*) –
  - list of <description info> of processors to generate data for inference
  - example of <description info>:
- **learn_processors** (*list*) – similar to infer_processors, but for generating data for learning models
- **process_type** (*str*) – PTYPE_I = 'independent'
  - self._infer will be processed by infer_processors
  - self._learn will be processed by learn_processors

  PTYPE_A = 'append'
  - self._infer will be processed by infer_processors
  - self._learn will be processed by infer_processors + learn_processors
    - (e.g. self._infer processed by learn_processors)
- **drop_raw** (*bool*) – Whether to drop the raw data

fit()

fit data without processing the data

fit_process_data()

fit and process data

The input of the *fit* will be the output of the previous processor

process_data(*with_fit: bool = False*)

process_data data. Fun *processor.fit* if necessary

Notation: (data) [processor]

data processing flow of self.process_type == DataHandlerLP.PTYPE_I

```
(self._data)-[shared_processors]-(_shared_df)-[learn_processors]-(_learn_df)
                                             \
                                              -[infer_processors]-(_infer_df)
```

data processing flow of self.process_type == DataHandlerLP.PTYPE_A

```
(self._data)-[shared_processors]-(_shared_df)-[infer_processors]-(_infer_df)-
↪[learn_processors]-(_learn_df)
```

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Parameters **with_fit** (*bool*) – The input of the *fit* will be the output of the previous processor

config (*processor_kwargs: dict = None*, ***kwargs*)
configuration of data. # what data to be loaded from data source

This method will be used when loading pickled handler from dataset. The data will be initialized with different time range.

setup_data (*init_type: str = 'fit_seq'*, ***kwargs*)
Set up the data in case of running initialization for multiple time

Parameters

- **init_type** (*str*) – The type *IT_** listed above.
- **enable_cache** (*bool*) – default value is false:
  - if *enable_cache* == True:

    the processed data will be saved on disk, and handler will load the cached data from the disk directly when we call *init* next time

fetch (*selector: Union[pandas._libs.tslibs.timestamps.Timestamp, slice, str] = slice(None, None, None)*, *level: Union[str, int] = 'datetime'*, *col_set='__all'*, *data_key: str = 'infer'*, *squeeze: bool = False*, *proc_func: Callable = None*) → pandas.core.frame.DataFrame
fetch data from underlying data source

Parameters

- **selector** (*Union[pd.Timestamp, slice, str]*) – describe how to select data by index.
- **level** (*Union[str, int]*) – which index level to select the data.
- **col_set** (*str*) – select a set of meaningful columns.(e.g. features, columns).
- **data_key** (*str*) – the data to fetch: DK_*.
- **proc_func** (*Callable*) – please refer to the doc of DataHandler.fetch

Returns

Return type pd.DataFrame

get_cols (*col_set='__all'*, *data_key: str = 'infer'*) → list
get the column names

Parameters

- **col_set** (*str*) – select a set of meaningful columns.(e.g. features, columns).
- **data_key** (*str*) – the data to fetch: DK_*.

Returns list of column names

Return type list

classmethod cast (*handler: qlib.data.dataset.handler.DataHandlerLP*) → qlib.data.dataset.handler.DataHandlerLP
Motivation

- A user creates a datahandler in his customized package. Then he wants to share the processed handler to other users without introduce the package dependency and complicated data processing logic.
- This class make it possible by casting the class to DataHandlerLP and only keep the processed data

Parameters **handler** (DataHandlerLP) – A subclass of DataHandlerLP

Returns the converted processed data

Return type *DataHandlerLP*

Processor

qlib.data.dataset.processor.**get_group_columns**(*df: pandas.core.frame.DataFrame, group: Optional[str]*)

get a group of columns from multi-index columns DataFrame

Parameters

- **df** (*pd.DataFrame*) – with multi of columns.
- **group** (*str*) – the name of the feature group, i.e. the first level value of the group index.

class qlib.data.dataset.processor.**Processor**

fit(*df: pandas.core.frame.DataFrame = None*)

learn data processing parameters

Parameters **df** (*pd.DataFrame*) – When we fit and process data with processor one by one. The fit function reiles on the output of previous processor, i.e. *df*.

is_for_infer() → bool

Is this processor usable for inference Some processors are not usable for inference.

Returns if it is usable for infenrece.

Return type bool

readonly() → bool

Does the processor treat the input data readonly (i.e. does not write the input data) when processing

Knowning the readonly information is helpful to the Handler to avoid uncessary copy

config(***kwargs*)

configure the serializable object

Parameters

- **may include following keys** (*kwargs*) –

  dump_all [bool] will the object dump all object

  exclude [list] What attribute will not be dumped

  include [list] What attribute will be dumped

- **recursive** (*bool*) – will the configuration be recursive

class qlib.data.dataset.processor.**DropnaProcessor**(*fields_group=None*)

__init__(*fields_group=None*)

Initialize self. See help(type(self)) for accurate signature.

readonly()

Does the processor treat the input data readonly (i.e. does not write the input data) when processing

Knowning the readonly information is helpful to the Handler to avoid uncessary copy

class qlib.data.dataset.processor.**DropnaLabel**(*fields_group='label'*)

__init__(*fields_group='label'*)
Initialize self. See help(type(self)) for accurate signature.

is_for_infer() → bool
The samples are dropped according to label. So it is not usable for inference

class qlib.data.dataset.processor.**DropCol**(*col_list=[]*)

__init__(*col_list=[]*)
Initialize self. See help(type(self)) for accurate signature.

readonly()
Does the processor treat the input data readonly (i.e. does not write the input data) when processing

Knowning the readonly information is helpful to the Handler to avoid uncessary copy

class qlib.data.dataset.processor.**FilterCol**(*fields_group='feature'*, *col_list=[]*)

__init__(*fields_group='feature'*, *col_list=[]*)
Initialize self. See help(type(self)) for accurate signature.

readonly()
Does the processor treat the input data readonly (i.e. does not write the input data) when processing

Knowning the readonly information is helpful to the Handler to avoid uncessary copy

class qlib.data.dataset.processor.**TanhProcess**
Use tanh to process noise data

class qlib.data.dataset.processor.**ProcessInf**
Process infinity

class qlib.data.dataset.processor.**Fillna**(*fields_group=None*, *fill_value=0*)
Process NaN

__init__(*fields_group=None*, *fill_value=0*)
Initialize self. See help(type(self)) for accurate signature.

class qlib.data.dataset.processor.**MinMaxNorm**(*fit_start_time*, *fit_end_time*, *fields_group=None*)

__init__(*fit_start_time*, *fit_end_time*, *fields_group=None*)
Initialize self. See help(type(self)) for accurate signature.

fit(*df: pandas.core.frame.DataFrame = None*)
learn data processing parameters

Parameters **df** (*pd.DataFrame*) – When we fit and process data with processor one by one. The fit function reiles on the output of previous processor, i.e. *df*.

class qlib.data.dataset.processor.**ZScoreNorm**(*fit_start_time*, *fit_end_time*, *fields_group=None*)
ZScore Normalization

__init__(*fit_start_time*, *fit_end_time*, *fields_group=None*)
Initialize self. See help(type(self)) for accurate signature.

fit(*df: pandas.core.frame.DataFrame = None*)
learn data processing parameters

Parameters **df** (*pd.DataFrame*) – When we fit and process data with processor one by one. The fit function reiles on the output of previous processor, i.e. *df*.

class qlib.data.dataset.processor.**RobustZScoreNorm**(*fit_start_time*, *fit_end_time*, *fields_group=None*, *clip_outlier=True*)

Robust ZScore Normalization

Use robust statistics for Z-Score normalization: mean(x) = median(x) std(x) = MAD(x) * 1.4826

Reference: https://en.wikipedia.org/wiki/Median_absolute_deviation.

__init__(*fit_start_time*, *fit_end_time*, *fields_group=None*, *clip_outlier=True*)

Initialize self. See help(type(self)) for accurate signature.

fit(*df: pandas.core.frame.DataFrame = None*)

learn data processing parameters

Parameters df (`pd.DataFrame`) – When we fit and process data with processor one by one. The fit function reiles on the output of previous processor, i.e. *df*.

class qlib.data.dataset.processor.**CSZScoreNorm**(*fields_group=None*, *method='zscore'*)

Cross Sectional ZScore Normalization

__init__(*fields_group=None*, *method='zscore'*)

Initialize self. See help(type(self)) for accurate signature.

class qlib.data.dataset.processor.**CSRankNorm**(*fields_group=None*)

Cross Sectional Rank Normalization. "Cross Sectional" is often used to describe data operations. The operations across different stocks are often called Cross Sectional Operation.

For example, CSRankNorm is an operation that grouping the data by each day and rank *across* all the stocks in each day.

Explanation about 3.46 & 0.5

```
import numpy as np
import pandas as pd
x = np.random.random(10000)  # for any variable
x_rank = pd.Series(x).rank(pct=True)  # if it is converted to rank, it will be a␣
↪uniform distributed
x_rank_norm = (x_rank - x_rank.mean()) / x_rank.std()  # Normally, we will␣
↪normalize it to make it like normal distribution

x_rank.mean()   # accounts for 0.5
1 / x_rank.std()  # accounts for 3.46
```

__init__(*fields_group=None*)

Initialize self. See help(type(self)) for accurate signature.

class qlib.data.dataset.processor.**CSZFillna**(*fields_group=None*)

Cross Sectional Fill Nan

__init__(*fields_group=None*)

Initialize self. See help(type(self)) for accurate signature.

class qlib.data.dataset.processor.**HashStockFormat**

Process the storage of from df into hasing stock format

1.24.2 Contrib

Model

class qlib.model.base.**BaseModel**

Modeling things

predict (**args*, ***kwargs*) → object
Make predictions after modeling things

class qlib.model.base.**Model**
Learnable Models

fit (*dataset: qlib.data.dataset.Dataset*, *reweighter: qlib.data.dataset.weight.Reweighter*)
Learn model from the base model

Note: The attribute names of learned model should *not* start with '_'. So that the model could be dumped to disk.

The following code example shows how to retrieve *x_train*, *y_train* and *w_train* from the *dataset*:

```
# get features and labels
df_train, df_valid = dataset.prepare(
    ["train", "valid"], col_set=["feature", "label"], data_
↪key=DataHandlerLP.DK_L
)
x_train, y_train = df_train["feature"], df_train["label"]
x_valid, y_valid = df_valid["feature"], df_valid["label"]

# get weights
try:
    wdf_train, wdf_valid = dataset.prepare(["train", "valid"], col_
↪set=["weight"],
                                           data_key=DataHandlerLP.
↪DK_L)
    w_train, w_valid = wdf_train["weight"], wdf_valid["weight"]
except KeyError as e:
    w_train = pd.DataFrame(np.ones_like(y_train.values), index=y_
↪train.index)
    w_valid = pd.DataFrame(np.ones_like(y_valid.values), index=y_
↪valid.index)
```

Parameters **dataset** (Dataset) – dataset will generate the processed data from model training.

predict (*dataset: qlib.data.dataset.Dataset*, *segment: Union[str, slice] = 'test'*) → object
give prediction given Dataset

Parameters

- **dataset** (Dataset) – dataset will generate the processed dataset from model training.
- **segment** (*Text or slice*) – dataset will use this segment to prepare data. (default=test)

Returns

Return type Prediction results with certain type such as *pandas.Series*.

class qlib.model.base.**ModelFT**
Model (F)ine(t)unable

finetune (*dataset: qlib.data.dataset.Dataset*)
finetune model based given dataset

A typical use case of finetuning model with qlib.workflow.R

```
# start exp to train init model
with R.start(experiment_name="init models"):
    model.fit(dataset)
    R.save_objects(init_model=model)
    rid = R.get_recorder().id

# Finetune model based on previous trained model
with R.start(experiment_name="finetune model"):
    recorder = R.get_recorder(recorder_id=rid, experiment_name="init models")
    model = recorder.load_object("init_model")
    model.finetune(dataset, num_boost_round=10)
```

Parameters **dataset** (`Dataset`) – dataset will generate the processed dataset from model training.

Strategy

class qlib.contrib.strategy.**TopkDropoutStrategy**(**, topk, n_drop, method_sell='bottom', method_buy='top', hold_thresh=1, only_tradable=False, **kwargs*)

__init__(**, topk, n_drop, method_sell='bottom', method_buy='top', hold_thresh=1, only_tradable=False, **kwargs*)

Parameters

- **topk** (*int*) – the number of stocks in the portfolio.
- **n_drop** (*int*) – number of stocks to be replaced in each trading date.
- **method_sell** (*str*) – dropout method_sell, random/bottom.
- **method_buy** (*str*) – dropout method_buy, random/top.
- **hold_thresh** (*int*) – minimum holding days before sell stock , will check current.get_stock_count(order.stock_id) >= self.hold_thresh.
- **only_tradable** (*bool*) – will the strategy only consider the tradable stock when buying and selling.

  if only_tradable:

  strategy will make decision with the tradable state of the stock info and avoid buy and sell them.

  else:

  strategy will make buy sell decision without checking the tradable state of the stock.

generate_trade_decision(*execute_result=None*)

Generate trade decision in each trading bar

Parameters **execute_result** (*List[object], optional*) – the executed result for trade decision, by default None

- When call the generate_trade_decision firstly, *execute_result* could be None

class qlib.contrib.strategy.**WeightStrategyBase**(**, order_generator_cls_or_obj=<class 'qlib.contrib.strategy.order_generator.OrderGenWOInteract'>, **kwargs*)

__init__(*, *order_generator_cls_or_obj=<class 'qlib.contrib.strategy.order_generator.OrderGenWOInteract'>, **kwargs*)

signal : the information to describe a signal. Please refer to the docs of *qlib.backtest.signal.create_signal_from* the decision of the strategy will base on the given signal

trade_exchange [Exchange] exchange that provides market info, used to deal order and generate report

- If *trade_exchange* is None, self.trade_exchange will be set with common_infra
- It allowes different trade_exchanges is used in different executions.
- For example:
  - In daily execution, both daily exchange and minutely are usable, but the daily exchange is recommended because it run faster.
  - In minutely execution, the daily exchange is not usable, only the minutely exchange is recommended.

generate_target_weight_position(*score*, *current*, *trade_start_time*, *trade_end_time*)

Generate target position from score for this date and the current position.The cash is not considered in the position

Parameters

- **score** (`pd.Series`) – pred score for this trade date, index is stock_id, contain 'score' column.
- **current** (`Position()`) – current position.
- **trade_exchange** (`Exchange()`) –
- **trade_date** (`pd.Timestamp`) – trade date.

generate_trade_decision(*execute_result=None*)

Generate trade decision in each trading bar

Parameters **execute_result** (`List[object], optional`) – the executed result for trade decision, by default None

- When call the generate_trade_decision firstly, *execute_result* could be None

class qlib.contrib.strategy.**EnhancedIndexingStrategy**(*, *riskmodel_root*, *market='csi500'*, *turn_limit=None*, *name_mapping={}*, *optimizer_kwargs={}*, *verbose=False*, ***kwargs*)

Enhanced Indexing Strategy

Enhanced indexing combines the arts of active management and passive management, with the aim of outperforming a benchmark index (e.g., S&P 500) in terms of portfolio return while controlling the risk exposure (a.k.a. tracking error).

Users need to prepare their risk model data like below:

```
├── /path/to/riskmodel
├──── 20210101
├────── factor_exp.{csv|pkl|h5}
├────── factor_cov.{csv|pkl|h5}
├────── specific_risk.{csv|pkl|h5}
├────── blacklist.{csv|pkl|h5}  # optional
```

The risk model data can be obtained from risk data provider. You can also use *qlib.model.riskmodel.structured.StructuredCovEstimator* to prepare these data.

Parameters

- **riskmodel_path** (*str*) – risk model path
- **name_mapping** (*dict*) – alternative file names

__init__(**, riskmodel_root, market='csi500', turn_limit=None, name_mapping={}, optimizer_kwargs={}, verbose=False, **kwargs*)

signal : the information to describe a signal. Please refer to the docs of *qlib.backtest.signal.create_signal_from* the decision of the strategy will base on the given signal

trade_exchange [Exchange] exchange that provides market info, used to deal order and generate report

- If *trade_exchange* is None, self.trade_exchange will be set with common_infra
- It allowes different trade_exchanges is used in different executions.
- For example:
  - In daily execution, both daily exchange and minutely are usable, but the daily exchange is recommended because it run faster.
  - In minutely execution, the daily exchange is not usable, only the minutely exchange is recommended.

generate_target_weight_position(*score, current, trade_start_time, trade_end_time*)

Generate target position from score for this date and the current position.The cash is not considered in the position

Parameters

- **score** (*pd.Series*) – pred score for this trade date, index is stock_id, contain 'score' column.
- **current** (*Position()*) – current position.
- **trade_exchange** (*Exchange()*) –
- **trade_date** (*pd.Timestamp*) – trade date.

class qlib.contrib.strategy.**TWAPStrategy**(*outer_trade_decision: BaseTradeDecision = None, level_infra: LevelInfrastructure = None, common_infra: CommonInfrastructure = None, trade_exchange: Exchange = None*)

TWAP Strategy for trading

Note:

- This TWAP strategy will celling round when trading. This will make the TWAP trading strategy produce the order earlier when the total trade unit of amount is less than the trading step

reset(*outer_trade_decision: qlib.backtest.decision.BaseTradeDecision = None, **kwargs*)

Parameters **outer_trade_decision** (*BaseTradeDecision, optional*) –

generate_trade_decision(*execute_result=None*)

Generate trade decision in each trading bar

Parameters **execute_result** (*List[object], optional*) – the executed result for trade decision, by default None

- When call the generate_trade_decision firstly, *execute_result* could be None

class qlib.contrib.strategy.**SBBStrategyBase**(*outer_trade_decision: BaseTradeDecision = None, level_infra: LevelInfrastructure = None, common_infra: CommonInfrastructure = None, trade_exchange: Exchange = None*)

(S)elect the (B)etter one among every two adjacent trading (B)ars to sell or buy.

reset(*outer_trade_decision: qlib.backtest.decision.BaseTradeDecision = None, **kwargs*)

Parameters **outer_trade_decision** (*BaseTradeDecision, optional*) –

generate_trade_decision(*execute_result=None*)

Generate trade decision in each trading bar

Parameters **execute_result** (*List[object], optional*) – the executed result for trade decision, by default None

- When call the generate_trade_decision firstly, *execute_result* could be None

class qlib.contrib.strategy.**SBBStrategyEMA**(*outer_trade_decision: qlib.backtest.decision.BaseTradeDecision = None, instruments: Union[List[T], str] = 'csi300', freq: str = 'day', trade_exchange: qlib.backtest.exchange.Exchange = None, level_infra: qlib.backtest.utils.LevelInfrastructure = None, common_infra: qlib.backtest.utils.CommonInfrastructure = None, **kwargs*)

(S)elect the (B)etter one among every two adjacent trading (B)ars to sell or buy with (EMA) signal.

__init__(*outer_trade_decision: qlib.backtest.decision.BaseTradeDecision = None, instruments: Union[List[T], str] = 'csi300', freq: str = 'day', trade_exchange: qlib.backtest.exchange.Exchange = None, level_infra: qlib.backtest.utils.LevelInfrastructure = None, common_infra: qlib.backtest.utils.CommonInfrastructure = None, **kwargs*)

Parameters

- **instruments** (*Union[List, str], optional*) – instruments of EMA signal, by default "csi300"
- **freq** (*str, optional*) – freq of EMA signal, by default "day" Note: *freq* may be different from *time_per_step*

reset_level_infra(*level_infra*)

reset level-shared infra - After reset the trade calendar, the signal will be changed

class qlib.contrib.strategy.**SoftTopkStrategy**(*model, dataset, topk, order_generator_cls_or_obj=<class 'qlib.contrib.strategy.order_generator.OrderGenWInteract'>, max_sold_weight=1.0, risk_degree=0.95, buy_method='first_fill', trade_exchange=None, level_infra=None, common_infra=None, **kwargs*)

__init__(*model, dataset, topk, order_generator_cls_or_obj=<class 'qlib.contrib.strategy.order_generator.OrderGenWInteract'>, max_sold_weight=1.0, risk_degree=0.95, buy_method='first_fill', trade_exchange=None, level_infra=None, common_infra=None, **kwargs*)

Parameters

- **topk** (*int*) – top-N stocks to buy

- **risk_degree** (*float*) – position percentage of total value buy_method:

  rank_fill: assign the weight stocks that rank high first(1/topk max) average_fill: assign the weight to the stocks rank high averagely.

get_risk_degree (*trade_step=None*)
Return the proportion of your total value you will used in investment. Dynamically risk_degree will result in Market timing

generate_target_weight_position (*score*, *current*, *trade_start_time*, *trade_end_time*)
Parameters

- **score** – pred score for this trade date, pd.Series, index is stock_id, contain 'score' column
- **current** – current position, use Position() class
- **trade_date** – trade date

  generate target position from score for this date and the current position

  The cache is not considered in the position

Evaluate

qlib.contrib.evaluate.**risk_analysis** (*r*, *N: int = None*, *freq: str = 'day'*)
Risk Analysis NOTE: The calculation of annulaized return is different from the definition of annualized return. It is implemented by design. Qlib tries to cumulated returns by summation instead of production to avoid the cumulated curve being skewed exponentially. All the calculation of annualized returns follows this principle in Qlib.

TODO: add a parameter to enable calculating metrics with production accumulation of return.
Parameters

- **r** (*pandas.Series*) – daily return series.
- **N** (*int*) – scaler for annualizing information_ratio (day: 252, week: 50, month: 12), at least one of *N* and *freq* should exist
- **freq** (*str*) – analysis frequency used for calculating the scaler, at least one of *N* and *freq* should exist

qlib.contrib.evaluate.**indicator_analysis** (*df*, *method='mean'*)
analyze statistical time-series indicators of trading
Parameters

- **df** (*pandas.DataFrame*) –

  columns: like ['pa', 'pos', 'ffr', 'deal_amount', 'value'].

  Necessary fields:

  - 'pa' is the price advantage in trade indicators
  - 'pos' is the positive rate in trade indicators
  - 'ffr' is the fulfill rate in trade indicators

  Optional fields:

  - 'deal_amount' is the total deal deal_amount, only necessary when method is 'amount_weighted'

  – 'value' is the total trade value, only necessary when method is 'value_weighted'

  index: Index(datetime)

- **method** (*str, optional*) – statistics method of pa/ffr, by default "mean"
  - if method is 'mean', count the mean statistical value of each trade indicator
  - if method is 'amount_weighted', count the deal_amount weighted mean statistical value of each trade indicator
  - if method is 'value_weighted', count the value weighted mean statistical value of each trade indicator

  Note: statistics method of pos is always "mean"

Returns statistical value of each trade indicators

Return type pd.DataFrame

qlib.contrib.evaluate.**backtest_daily**(*start_time: Union[str, pandas._libs.tslibs.timestamps.Timestamp], end_time: Union[str, pandas._libs.tslibs.timestamps.Timestamp], strategy: Union[str, dict, qlib.strategy.base.BaseStrategy], executor: Union[str, dict, qlib.backtest.executor.BaseExecutor] = None, account: Union[float, int, qlib.backtest.position.Position] = 100000000.0, benchmark: str = 'SH000300', exchange_kwargs: dict = None, pos_type: str = 'Position'*)

initialize the strategy and executor, then executor the backtest of daily frequency

Parameters

- **start_time** (*Union[str, pd.Timestamp]*) – closed start time for backtest **NOTE**: This will be applied to the outmost executor's calendar.
- **end_time** (*Union[str, pd.Timestamp]*) – closed end time for backtest **NOTE**: This will be applied to the outmost executor's calendar. E.g. Executor[day](Executor[1min]), setting *end_time == 20XX0301* will include all the minutes on 20XX0301
- **strategy** (*Union[str, dict, BaseStrategy]*) – for initializing outermost portfolio strategy. Please refer to the docs of init_instance_by_config for more information.

  E.g.

```
# dict
strategy = {
    "class": "TopkDropoutStrategy",
    "module_path": "qlib.contrib.strategy.signal_strategy",
    "kwargs": {
        "signal": (model, dataset),
        "topk": 50,
        "n_drop": 5,
    },
}
# BaseStrategy
pred_score = pd.read_pickle("score.pkl")["score"]
STRATEGY_CONFIG = {
    "topk": 50,
```

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```
    "n_drop": 5,
    "signal": pred_score,
}
strategy = TopkDropoutStrategy(**STRATEGY_CONFIG)
# str example.
# 1) specify a pickle object
#     - path like 'file:///<path to pickle file>/obj.pkl'
# 2) specify a class name
#     - "ClassName":  getattr(module, "ClassName")() will be␣
↪used.
# 3) specify module path with class name
#     - "a.b.c.ClassName" getattr(<a.b.c.module>, "ClassName
↪")() will be used.
```

- **executor** (*Union[str, dict, BaseExecutor]*) – for initializing the outermost executor.
- **benchmark** (*str*) – the benchmark for reporting.
- **account** (*Union[float, int, Position]*) – information for describing how to creating the account

  For *float* or *int*:

    Using Account with only initial cash

  For *Position*:

    Using Account with a Position

- **exchange_kwargs** (*dict*) – the kwargs for initializing Exchange E.g.

```
exchange_kwargs = {
    "freq": freq,
    "limit_threshold": None, # limit_threshold is None, using␣
↪C.limit_threshold
    "deal_price": None, # deal_price is None, using C.deal_
↪price
    "open_cost": 0.0005,
    "close_cost": 0.0015,
    "min_cost": 5,
}
```

- **pos_type** (*str*) – the type of Position.

Returns

- **report_normal** (*pd.DataFrame*) – backtest report
- **positions_normal** (*pd.DataFrame*) – backtest positions

qlib.contrib.evaluate.**long_short_backtest**(*pred, topk=50, deal_price=None, shift=1, open_cost=0, close_cost=0, trade_unit=None, limit_threshold=None, min_cost=5, subscribe_fields=[], extract_codes=False*)

A backtest for long-short strategy

Parameters

- **pred** – The trading signal produced on day *T*.
- **topk** – The short topk securities and long topk securities.

- **deal_price** – The price to deal the trading.
- **shift** – Whether to shift prediction by one day. The trading day will be T+1 if shift==1.
- **open_cost** – open transaction cost.
- **close_cost** – close transaction cost.
- **trade_unit** – 100 for China A.
- **limit_threshold** – limit move 0.1 (10%) for example, long and short with same limit.
- **min_cost** – min transaction cost.
- **subscribe_fields** – subscribe fields.
- **extract_codes** – bool. will we pass the codes extracted from the pred to the exchange. NOTE: This will be faster with offline qlib.

Returns The result of backtest, it is represented by a dict. { "long": long_returns(excess), "short": short_returns(excess), "long_short": long_short_returns}

Report

qlib.contrib.report.analysis_position.report.**report_graph**(*report_df: pandas.core.frame.DataFrame*, *show_notebook: bool = True*) → [<class 'list'>, <class 'tuple'>]

display backtest report

Example:

```
import qlib
import pandas as pd
from qlib.utils.time import Freq
from qlib.utils import flatten_dict
from qlib.backtest import backtest, executor
from qlib.contrib.evaluate import risk_analysis
from qlib.contrib.strategy import TopkDropoutStrategy

# init qlib
qlib.init(provider_uri=<qlib data dir>)

CSI300_BENCH = "SH000300"
FREQ = "day"
STRATEGY_CONFIG = {
    "topk": 50,
    "n_drop": 5,
    # pred_score, pd.Series
    "signal": pred_score,
}

EXECUTOR_CONFIG = {
    "time_per_step": "day",
    "generate_portfolio_metrics": True,
}

backtest_config = {
```

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```
    "start_time": "2017-01-01",
    "end_time": "2020-08-01",
    "account": 100000000,
    "benchmark": CSI300_BENCH,
    "exchange_kwargs": {
        "freq": FREQ,
        "limit_threshold": 0.095,
        "deal_price": "close",
        "open_cost": 0.0005,
        "close_cost": 0.0015,
        "min_cost": 5,
    },
}

# strategy object
strategy_obj = TopkDropoutStrategy(**STRATEGY_CONFIG)
# executor object
executor_obj = executor.SimulatorExecutor(**EXECUTOR_CONFIG)
# backtest
portfolio_metric_dict, indicator_dict = 
↪backtest(executor=executor_obj, strategy=strategy_obj, 
↪**backtest_config)
analysis_freq = "{0}{1}".format(*Freq.parse(FREQ))
# backtest info
report_normal_df, positions_normal = portfolio_metric_dict.
↪get(analysis_freq)

qcr.analysis_position.report_graph(report_normal_df)
```

Parameters

- **report_df** – **df.index.name** must be **date**, **df.columns** must contain **return**, **turnover**, **cost**, **bench**.

```
            return      cost        bench       turnover
date
2017-01-04  0.003421    0.000864    0.011693    0.576325
2017-01-05  0.000508    0.000447    0.000721    0.227882
2017-01-06  -0.003321   0.000212    -0.004322   0.102765
2017-01-09  0.006753    0.000212    0.006874    0.105864
2017-01-10  -0.000416   0.000440    -0.003350   0.208396
```

- **show_notebook** – whether to display graphics in notebook, the default is **True**.

Returns if show_notebook is True, display in notebook; else return **plotly.graph_objs.Figure** list.

qlib.contrib.report.analysis_position.score_ic.**score_ic_graph**(*pred_label: pandas.core.frame.DataFrame*, *show_notebook: bool = True*) → [<class 'list'>, <class 'tuple'>]

score IC

Example:

```
from qlib.data import D
from qlib.contrib.report import analysis_position
pred_df_dates = pred_df.index.get_level_values(level='datetime
↪')
```

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```
features_df = D.features(D.instruments('csi500'), ['Ref($close,
↪ -2)/Ref($close, -1)-1'], pred_df_dates.min(), pred_df_dates.
↪max())
features_df.columns = ['label']
pred_label = pd.concat([features_df, pred], axis=1, sort=True).
↪reindex(features_df.index)
analysis_position.score_ic_graph(pred_label)
```

Parameters

- **pred_label** – index is **pd.MultiIndex**, index name is **[instrument, datetime]**; columns names is **[score, label]**.

```
instrument  datetime        score         label
SH600004  2017-12-11     -0.013502       -0.013502
            2017-12-12   -0.072367       -0.072367
            2017-12-13   -0.068605       -0.068605
            2017-12-14    0.012440        0.012440
            2017-12-15   -0.102778       -0.102778
```

- **show_notebook** – whether to display graphics in notebook, the default is **True**.

Returns if show_notebook is True, display in notebook; else return **plotly.graph_objs.Figure** list.

qlib.contrib.report.analysis_position.cumulative_return.**cumulative_return_graph**(*position: dict, report_normal: pandas.core.frame., label_data: pandas.core.frame., show_notebook, start_date=Non, end_date=None*) → Iterable[plotly.grap

Backtest buy, sell, and holding cumulative return graph

Example:

```
from qlib.data import D
from qlib.contrib.evaluate import risk_analysis, backtest,␣
↪long_short_backtest
from qlib.contrib.strategy import TopkDropoutStrategy

# backtest parameters
bparas = {}
bparas['limit_threshold'] = 0.095
bparas['account'] = 1000000000

sparas = {}
sparas['topk'] = 50
sparas['n_drop'] = 5
```

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```
strategy = TopkDropoutStrategy(**sparas)

report_normal_df, positions = backtest(pred_df, strategy,␣
↪**bparas)

pred_df_dates = pred_df.index.get_level_values(level='datetime
↪')
features_df = D.features(D.instruments('csi500'), ['Ref($close,
↪ -1)/$close - 1'], pred_df_dates.min(), pred_df_dates.max())
features_df.columns = ['label']

qcr.analysis_position.cumulative_return_graph(positions,␣
↪report_normal_df, features_df)
```

Graph desc:

- Axis X: Trading day.
- Axis Y:
- Above axis Y: *(((Ref($close, -1)/$close - 1) * weight).sum() / weight.sum()).cumsum()*.
- Below axis Y: Daily weight sum.
- In the **sell** graph, *y < 0* stands for profit; in other cases, *y > 0* stands for profit.
- In the **buy_minus_sell** graph, the **y** value of the **weight** graph at the bottom is *buy_weight* + *sell_weight*.
- In each graph, the **red line** in the histogram on the right represents the average.

Parameters

- **position** – position data
- **report_normal** –

```
                return      cost        bench       turnover
date
2017-01-04  0.003421    0.000864    0.011693    0.576325
2017-01-05  0.000508    0.000447    0.000721    0.227882
2017-01-06  -0.003321   0.000212    -0.004322   0.102765
2017-01-09  0.006753    0.000212    0.006874    0.105864
2017-01-10  -0.000416   0.000440    -0.003350   0.208396
```

- **label_data** – *D.features* result; index is *pd.MultiIndex*, index name is [*instrument*, *datetime*]; columns names is [*label*].

  The label T is the change from T to T+1, it is recommended to use `close`, example: *D.features(D.instruments('csi500'), ['Ref($close, -1)/$close-1'])*

```
                                label
instrument  datetime
SH600004        2017-12-11  -0.013502
                2017-12-12  -0.072367
                2017-12-13  -0.068605
                2017-12-14  0.012440
                2017-12-15  -0.102778
```

- **show_notebook** – True or False. If True, show graph in notebook, else return figures
- **start_date** – start date
- **end_date** – end date

Returns

`qlib.contrib.report.analysis_position.risk_analysis.`**`risk_analysis_graph`**(*analysis_df: pandas.core.frame.DataFrame = None, report_normal_df: pandas.core.frame.DataFrame = None, report_long_short_df: pandas.core.frame.DataFrame = None, show_notebook: bool = True*) → Iterable[plotly.graph_objs._figu

Generate analysis graph and monthly analysis

Example:

```
import qlib
import pandas as pd
from qlib.utils.time import Freq
from qlib.utils import flatten_dict
from qlib.backtest import backtest, executor
from qlib.contrib.evaluate import risk_analysis
from qlib.contrib.strategy import TopkDropoutStrategy

# init qlib
qlib.init(provider_uri=<qlib data dir>)

CSI300_BENCH = "SH000300"
FREQ = "day"
STRATEGY_CONFIG = {
    "topk": 50,
    "n_drop": 5,
    # pred_score, pd.Series
    "signal": pred_score,
}

EXECUTOR_CONFIG = {
    "time_per_step": "day",
    "generate_portfolio_metrics": True,
}

backtest_config = {
    "start_time": "2017-01-01",
    "end_time": "2020-08-01",
```

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```
    "account": 100000000,
    "benchmark": CSI300_BENCH,
    "exchange_kwargs": {
        "freq": FREQ,
        "limit_threshold": 0.095,
        "deal_price": "close",
        "open_cost": 0.0005,
        "close_cost": 0.0015,
        "min_cost": 5,
    },
}

# strategy object
strategy_obj = TopkDropoutStrategy(**STRATEGY_CONFIG)
# executor object
executor_obj = executor.SimulatorExecutor(**EXECUTOR_CONFIG)
# backtest
portfolio_metric_dict, indicator_dict =␣
↪backtest(executor=executor_obj, strategy=strategy_obj,␣
↪**backtest_config)
analysis_freq = "{0}{1}".format(*Freq.parse(FREQ))
# backtest info
report_normal_df, positions_normal = portfolio_metric_dict.
↪get(analysis_freq)
analysis = dict()
analysis["excess_return_without_cost"] = risk_analysis(
    report_normal_df["return"] - report_normal_df["bench"],␣
↪freq=analysis_freq
)
analysis["excess_return_with_cost"] = risk_analysis(
    report_normal_df["return"] - report_normal_df["bench"] -␣
↪report_normal_df["cost"], freq=analysis_freq
)

analysis_df = pd.concat(analysis)  # type: pd.DataFrame
analysis_position.risk_analysis_graph(analysis_df, report_
↪normal_df)
```

Parameters

- **analysis_df** – analysis data, index is **pd.MultiIndex**; columns names is **[risk]**.

```
                                                  risk
excess_return_without_cost mean               0.000692
                           std                0.005374
                           annualized_return  0.174495
                           information_ratio  2.045576
                           max_drawdown      -0.079103
excess_return_with_cost    mean               0.000499
                           std                0.005372
                           annualized_return  0.125625
                           information_ratio  1.473152
                           max_drawdown      -0.088263
```

- **report_normal_df** – **df.index.name** must be **date**, df.columns must contain **return**, **turnover**, **cost**, **bench**.

```
              return      cost        bench       turnover
date
2017-01-04    0.003421    0.000864    0.011693    0.576325
2017-01-05    0.000508    0.000447    0.000721    0.227882
2017-01-06    -0.003321   0.000212    -0.004322   0.102765
2017-01-09    0.006753    0.000212    0.006874    0.105864
2017-01-10    -0.000416   0.000440    -0.003350   0.208396
```

- **report_long_short_df** – **df.index.name** must be **date**, df.columns contain **long**, **short**, **long_short**.

```
              long        short       long_short
date
2017-01-04    -0.001360   0.001394    0.000034
2017-01-05    0.002456    0.000058    0.002514
2017-01-06    0.000120    0.002739    0.002859
2017-01-09    0.001436    0.001838    0.003273
2017-01-10    0.000824    -0.001944   -0.001120
```

- **show_notebook** – Whether to display graphics in a notebook, default **True**. If True, show graph in notebook If False, return graph figure

Returns

qlib.contrib.report.analysis_position.rank_label.**rank_label_graph**(*position: dict, label_data: pandas.core.frame.DataFrame, start_date=None, end_date=None, show_notebook=True*) → Iterable[plotly.graph_objs._figure.Figure]

Ranking percentage of stocks buy, sell, and holding on the trading day. Average rank-ratio(similar to **sell_df['label'].rank(ascending=False) / len(sell_df)**) of daily trading

Example:

```python
from qlib.data import D
from qlib.contrib.evaluate import backtest
from qlib.contrib.strategy import TopkDropoutStrategy

# backtest parameters
bparas = {}
bparas['limit_threshold'] = 0.095
bparas['account'] = 1000000000

sparas = {}
sparas['topk'] = 50
sparas['n_drop'] = 230
strategy = TopkDropoutStrategy(**sparas)

_, positions = backtest(pred_df, strategy, **bparas)

pred_df_dates = pred_df.index.get_level_values(level='datetime
↪')
features_df = D.features(D.instruments('csi500'), ['Ref($close,
↪ -1)/$close-1'], pred_df_dates.min(), pred_df_dates.max())
```

(continues on next page)

(continued from previous page)

```
features_df.columns = ['label']

qcr.analysis_position.rank_label_graph(positions, features_df,␣
↪pred_df_dates.min(), pred_df_dates.max())
```

Parameters

- **position** – position data; **qlib.backtest.backtest** result.
- **label_data** – **D.features** result; index is **pd.MultiIndex**, index name is **[instrument, datetime]**; columns names is **[label]**.

  The label T is the change from T to T+1, it is recommended to use `close`, example: *D.features(D.instruments('csi500'), ['Ref($close, -1)/$close-1'])*.

  ```
                                  label
  instrument  datetime
  SH600004        2017-12-11  -0.013502
                  2017-12-12  -0.072367
                  2017-12-13  -0.068605
                  2017-12-14  0.012440
                  2017-12-15  -0.102778
  ```

- **start_date** – start date
- **end_date** – end_date
- **show_notebook** – **True** or **False**. If True, show graph in notebook, else return figures.

Returns

`qlib.contrib.report.analysis_model.analysis_model_performance.`**ic_figure**(*ic_df: pandas.core.frame.DataFrame*, *show_nature_day=True*, ***kwargs*) → plotly.graph_objs._figure.Fi

IC figure

Parameters

- **ic_df** – ic DataFrame
- **show_nature_day** – whether to display the abscissa of non-trading day

Returns plotly.graph_objs.Figure

qlib.contrib.report.analysis_model.analysis_model_performance.**model_performance_graph**(*pred_l pan- das.co lag: int = 1, N: int = 5, re- verse= rank= graph_ list = ['grou 'pred_ 'pred_ show_ bool = True, show_* → [<class 'list'>, <class 'tu- ple'>]

Model performance

Parameters

- **pred_label** – index is **pd.MultiIndex**, index name is **[instrument, datetime]**; columns names is **[score, label]**. It is usually same as the label of model training(e.g. "Ref($close, -2)/Ref($close, -1) - 1").

```
instrument  datetime        score       label
SH600004    2017-12-11  -0.013502       -0.013502
                2017-12-12  -0.072367       -0.072367
                2017-12-13  -0.068605       -0.068605
                2017-12-14  0.012440        0.012440
                2017-12-15  -0.102778       -0.102778
```

- **lag** – *pred.groupby(level='instrument')['score'].shift(lag)*. It will be only used in the auto-correlation computing.
- **N** – group number, default 5.
- **reverse** – if *True*, *pred['score'] *= -1*.
- **rank** – if **True**, calculate rank ic.
- **graph_names** – graph names; default ['cumulative_return', 'pred_ic', 'pred_autocorr', 'pred_turnover'].
- **show_notebook** – whether to display graphics in notebook, the default is *True*.

- **show_nature_day** – whether to display the abscissa of non-trading day.

Returns if show_notebook is True, display in notebook; else return *plotly.graph_objs.Figure* list.

1.24.3 Workflow

Experiment Manager

class qlib.workflow.expm.**ExpManager**(*uri: str, default_exp_name: Optional[str]*)

This is the *ExpManager* class for managing experiments. The API is designed similar to mlflow. (The link: https://mlflow.org/docs/latest/python_api/mlflow.html)

The *ExpManager* is expected to be a singleton (btw, we can have multiple *Experiment's with different uri. user can get different experiments from different uri, and then compare records of them). Global Config (i.e. 'C*) is also a singleton.

So we try to align them together. They share the same variable, which is called **default uri**. Please refer to *ExpManager.default_uri* for details of variable sharing.

When the user starts an experiment, the user may want to set the uri to a specific uri (it will override **default uri** during this period), and then unset the **specific uri** and fallback to the **default uri**. *ExpManager._active_exp_uri* is that **specific uri**.

__init__(*uri: str, default_exp_name: Optional[str]*)

Initialize self. See help(type(self)) for accurate signature.

start_exp(**, experiment_id: Optional[str] = None, experiment_name: Optional[str] = None, recorder_id: Optional[str] = None, recorder_name: Optional[str] = None, uri: Optional[str] = None, resume: bool = False, **kwargs*) → qlib.workflow.exp.Experiment

Start an experiment. This method includes first get_or_create an experiment, and then set it to be active.

Maintaining *_active_exp_uri* is included in start_exp, remaining implementation should be included in _end_exp in subclass

Parameters

- **experiment_id** (*str*) – id of the active experiment.
- **experiment_name** (*str*) – name of the active experiment.
- **recorder_id** (*str*) – id of the recorder to be started.
- **recorder_name** (*str*) – name of the recorder to be started.
- **uri** (*str*) – the current tracking URI.
- **resume** (*boolean*) – whether to resume the experiment and recorder.

Returns

Return type An active experiment.

end_exp(*recorder_status: str = 'SCHEDULED', **kwargs*)

End an active experiment.

Maintaining *_active_exp_uri* is included in end_exp, remaining implementation should be included in _end_exp in subclass

Parameters

- **experiment_name** (*str*) – name of the active experiment.
- **recorder_status** (*str*) – the status of the active recorder of the experiment.

create_exp(*experiment_name: Optional[str] = None*)

Create an experiment.

Parameters **`experiment_name`** (*str*) – the experiment name, which must be unique.

Returns

- *An experiment object.*
- *Raise*
- *—–*
- *ExpAlreadyExistError*

`search_records` (*experiment_ids=None*, ***kwargs*)

Get a pandas DataFrame of records that fit the search criteria of the experiment. Inputs are the search criteria user want to apply.

Returns

- *A pandas.DataFrame of records, where each metric, parameter, and tag*
- *are expanded into their own columns named metrics.*, params.*, and tags.**
- *respectively. For records that don't have a particular metric, parameter, or tag, their*
- *value will be (NumPy) Nan, None, or None respectively.*

`get_exp` (***, *experiment_id=None*, *experiment_name=None*, *create: bool = True*, *start: bool = False*)

Retrieve an experiment. This method includes getting an active experiment, and get_or_create a specific experiment.

When user specify experiment id and name, the method will try to return the specific experiment. When user does not provide recorder id or name, the method will try to return the current active experiment. The *create* argument determines whether the method will automatically create a new experiment according to user's specification if the experiment hasn't been created before.

- If *create* is True:
  - If *active experiment* exists:
    - no id or name specified, return the active experiment.
    - if id or name is specified, return the specified experiment. If no such exp found, create a new experiment with given id or name. If *start* is set to be True, the experiment is set to be active.
  - If *active experiment* not exists:
    - no id or name specified, create a default experiment.
    - if id or name is specified, return the specified experiment. If no such exp found, create a new experiment with given id or name. If *start* is set to be True, the experiment is set to be active.
- Else If *create* is False:
  - If *active experiment* exists:
    - no id or name specified, return the active experiment.
    - if id or name is specified, return the specified experiment. If no such exp found, raise Error.
  - If *active experiment* not exists:
    - no id or name specified. If the default experiment exists, return it, otherwise, raise Error.
    - if id or name is specified, return the specified experiment. If no such exp found, raise Error.

Parameters

- **experiment_id** (*str*) – id of the experiment to return.
- **experiment_name** (*str*) – name of the experiment to return.
- **create** (*boolean*) – create the experiment it if hasn't been created before.
- **start** (*boolean*) – start the new experiment if one is created.

Returns

Return type An experiment object.

delete_exp (*experiment_id=None*, *experiment_name=None*)
Delete an experiment.

Parameters

- **experiment_id** (*str*) – the experiment id.
- **experiment_name** (*str*) – the experiment name.

default_uri
Get the default tracking URI from qlib.config.C

uri
Get the default tracking URI or current URI.

Returns

Return type The tracking URI string.

list_experiments ()
List all the existing experiments.

Returns

Return type A dictionary (name -> experiment) of experiments information that being stored.

Experiment

class qlib.workflow.exp.**Experiment** (*id*, *name*)
This is the *Experiment* class for each experiment being run. The API is designed similar to mlflow. (The link: https://mlflow.org/docs/latest/python_api/mlflow.html)

__init__ (*id*, *name*)
Initialize self. See help(type(self)) for accurate signature.

start (*, *recorder_id=None*, *recorder_name=None*, *resume=False*)
Start the experiment and set it to be active. This method will also start a new recorder.

Parameters

- **recorder_id** (*str*) – the id of the recorder to be created.
- **recorder_name** (*str*) – the name of the recorder to be created.
- **resume** (*bool*) – whether to resume the first recorder

Returns

Return type An active recorder.

end (*recorder_status='SCHEDULED'*)
End the experiment.

Parameters **recorder_status** (*str*) – the status the recorder to be set with when ending (SCHEDULED, RUNNING, FINISHED, FAILED).

create_recorder (*recorder_name=None*)

Create a recorder for each experiment.

Parameters **recorder_name** (*str*) – the name of the recorder to be created.

Returns

Return type A recorder object.

search_records (***kwargs*)

Get a pandas DataFrame of records that fit the search criteria of the experiment. Inputs are the search criteria user want to apply.

Returns

- *A pandas.DataFrame of records, where each metric, parameter, and tag*
- *are expanded into their own columns named metrics.*, params.*, and tags.**
- *respectively. For records that don't have a particular metric, parameter, or tag, their*
- *value will be (NumPy) Nan, None, or None respectively.*

delete_recorder (*recorder_id*)

Create a recorder for each experiment.

Parameters **recorder_id** (*str*) – the id of the recorder to be deleted.

get_recorder (*recorder_id=None, recorder_name=None, create: bool = True, start: bool = False*) → qlib.workflow.recorder.Recorder

Retrieve a Recorder for user. When user specify recorder id and name, the method will try to return the specific recorder. When user does not provide recorder id or name, the method will try to return the current active recorder. The *create* argument determines whether the method will automatically create a new recorder according to user's specification if the recorder hasn't been created before.

- If *create* is True:
  - If *active recorder* exists:
    - no id or name specified, return the active recorder.
    - if id or name is specified, return the specified recorder. If no such exp found, create a new recorder with given id or name. If *start* is set to be True, the recorder is set to be active.
  - If *active recorder* not exists:
    - no id or name specified, create a new recorder.
    - if id or name is specified, return the specified experiment. If no such exp found, create a new recorder with given id or name. If *start* is set to be True, the recorder is set to be active.
- Else If *create* is False:
  - If *active recorder* exists:
    - no id or name specified, return the active recorder.
    - if id or name is specified, return the specified recorder. If no such exp found, raise Error.
  - If *active recorder* not exists:
    - no id or name specified, raise Error.
    - if id or name is specified, return the specified recorder. If no such exp found, raise Error.

Parameters

- **recorder_id** (*str*) – the id of the recorder to be deleted.
- **recorder_name** (*str*) – the name of the recorder to be deleted.
- **create** (*boolean*) – create the recorder if it hasn't been created before.
- **start** (*boolean*) – start the new recorder if one is **created**.

Returns

Return type A recorder object.

list_recorders(*rtype: typing_extensions.Literal['dict', 'list'][dict, list] = 'dict', **flt_kwargs*) → Union[List[qlib.workflow.recorder.Recorder], Dict[str, qlib.workflow.recorder.Recorder]]

List all the existing recorders of this experiment. Please first get the experiment instance before calling this method. If user want to use the method *R.list_recorders()*, please refer to the related API document in *QlibRecorder*.

flt_kwargs [dict] filter recorders by conditions e.g. list_recorders(status=Recorder.STATUS_FI)

Returns

if *rtype* == "dict": A dictionary (id -> recorder) of recorder information that being stored.

elif *rtype* == "list": A list of Recorder.

Return type The return type depends on *rtype*

Recorder

class qlib.workflow.recorder.**Recorder**(*experiment_id, name*)

This is the *Recorder* class for logging the experiments. The API is designed similar to mlflow. (The link: https://mlflow.org/docs/latest/python_api/mlflow.html)

The status of the recorder can be SCHEDULED, RUNNING, FINISHED, FAILED.

__init__(*experiment_id, name*)

Initialize self. See help(type(self)) for accurate signature.

save_objects(*local_path=None, artifact_path=None, **kwargs*)

Save objects such as prediction file or model checkpoints to the artifact URI. User can save object through keywords arguments (name:value).

Please refer to the docs of qlib.workflow:R.save_objects

Parameters

- **local_path** (*str*) – if provided, them save the file or directory to the artifact URI.
- **artifact_path=None** (*str*) – the relative path for the artifact to be stored in the URI.

load_object(*name*)

Load objects such as prediction file or model checkpoints.

Parameters **name** (*str*) – name of the file to be loaded.

Returns

Return type The saved object.

start_run()
Start running or resuming the Recorder. The return value can be used as a context manager within a *with* block; otherwise, you must call end_run() to terminate the current run. (See *ActiveRun* class in mlflow)

Returns

Return type An active running object (e.g. mlflow.ActiveRun object)

end_run()
End an active Recorder.

log_params(***kwargs*)
Log a batch of params for the current run.

Parameters **arguments** (`keyword`) – key, value pair to be logged as parameters.

log_metrics(*step=None*, ***kwargs*)
Log multiple metrics for the current run.

Parameters **arguments** (`keyword`) – key, value pair to be logged as metrics.

log_artifact(*local_path: str*, *artifact_path: Optional[str] = None*)
Log a local file or directory as an artifact of the currently active run.

Parameters

- **local_path** (`str`) – Path to the file to write.
- **artifact_path** (`Optional[str]`) – If provided, the directory in `artifact_uri` to write to.

set_tags(***kwargs*)
Log a batch of tags for the current run.

Parameters **arguments** (`keyword`) – key, value pair to be logged as tags.

delete_tags(**keys*)
Delete some tags from a run.

Parameters **keys** (`series of strs of the keys`) – all the name of the tag to be deleted.

list_artifacts(*artifact_path: str = None*)
List all the artifacts of a recorder.

Parameters **artifact_path** (`str`) – the relative path for the artifact to be stored in the URI.

Returns

Return type A list of artifacts information (name, path, etc.) that being stored.

download_artifact(*path: str*, *dst_path: Optional[str] = None*) → str
Download an artifact file or directory from a run to a local directory if applicable, and return a local path for it.

Parameters

- **path** (`str`) – Relative source path to the desired artifact.
- **dst_path** (`Optional[str]`) – Absolute path of the local filesystem destination directory to which to download the specified artifacts. This directory must already exist. If unspecified, the artifacts will either be downloaded to a new uniquely-named directory on the local filesystem.

Returns Local path of desired artifact.

Return type str

list_metrics()
List all the metrics of a recorder.

Returns

Return type A dictionary of metrics that being stored.

list_params()
List all the params of a recorder.

Returns

Return type A dictionary of params that being stored.

list_tags()
List all the tags of a recorder.

Returns

Return type A dictionary of tags that being stored.

Record Template

class qlib.workflow.record_temp.**RecordTemp**(*recorder*)
This is the Records Template class that enables user to generate experiment results such as IC and backtest in a certain format.

save(***kwargs*)
It behaves the same as self.recorder.save_objects. But it is an easier interface because users don't have to care about *get_path* and *artifact_path*

__init__(*recorder*)
Initialize self. See help(type(self)) for accurate signature.

generate(***kwargs*)
Generate certain records such as IC, backtest etc., and save them.

Parameters **kwargs** –

load(*name: str*, *parents: bool = True*)
It behaves the same as self.recorder.load_object. But it is an easier interface because users don't have to care about *get_path* and *artifact_path*

Parameters

- **name** (*str*) – the name for the file to be load.
- **parents** (*bool*) – Each recorder has different *artifact_path*. So parents recursively find the path in parents Sub classes has higher priority

Returns

Return type The stored records.

list()
List the supported artifacts. Users don't have to consider self.get_path

Returns

Return type A list of all the supported artifacts.

check(*include_self: bool = False*, *parents: bool = True*)
Check if the records is properly generated and saved. It is useful in following examples

- checking if the depended files complete before generating new things.
- checking if the final files is completed

Parameters

- **include_self** (*bool*) – is the file generated by self included
- **parents** (*bool*) – will we check parents

- **Raise** –
- **-------** –
- **FileNotFoundError** – whether the records are stored properly.

class qlib.workflow.record_temp.**SignalRecord**(*model=None*, *dataset=None*, *recorder=None*)

This is the Signal Record class that generates the signal prediction. This class inherits the `RecordTemp` class.

__init__(*model=None*, *dataset=None*, *recorder=None*)
Initialize self. See help(type(self)) for accurate signature.

generate(***kwargs*)
Generate certain records such as IC, backtest etc., and save them.
Parameters **kwargs** –

list()
List the supported artifacts. Users don't have to consider self.get_path
Returns

Return type A list of all the supported artifacts.

class qlib.workflow.record_temp.**ACRecordTemp**(*recorder*, *skip_existing=False*)
Automatically checking record template

__init__(*recorder*, *skip_existing=False*)
Initialize self. See help(type(self)) for accurate signature.

generate(**args*, ***kwargs*)
automatically checking the files and then run the concrete generating task

class qlib.workflow.record_temp.**HFSignalRecord**(*recorder*, ***kwargs*)
This is the Signal Analysis Record class that generates the analysis results such as IC and IR. This class inherits the `RecordTemp` class.

depend_cls
alias of `SignalRecord`

__init__(*recorder*, ***kwargs*)
Initialize self. See help(type(self)) for accurate signature.

generate()
Generate certain records such as IC, backtest etc., and save them.
Parameters **kwargs** –

list()
List the supported artifacts. Users don't have to consider self.get_path
Returns

Return type A list of all the supported artifacts.

class qlib.workflow.record_temp.**SigAnaRecord**(*recorder*, *ana_long_short=False*, *ann_scaler=252*, *label_col=0*, *skip_existing=False*)
This is the Signal Analysis Record class that generates the analysis results such as IC and IR. This class inherits the `RecordTemp` class.

depend_cls
alias of `SignalRecord`

__init__(*recorder*, *ana_long_short=False*, *ann_scaler=252*, *label_col=0*, *skip_existing=False*)
Initialize self. See help(type(self)) for accurate signature.

list()
List the supported artifacts. Users don't have to consider self.get_path

Returns

Return type A list of all the supported artifacts.

class qlib.workflow.record_temp.**PortAnaRecord**(*recorder, config=None, risk_analysis_freq: Union[List[T], str] = None, indicator_analysis_freq: Union[List[T], str] = None, indicator_analysis_method=None, skip_existing=False, **kwargs*)

This is the Portfolio Analysis Record class that generates the analysis results such as those of backtest. This class inherits the `RecordTemp` class.

The following files will be stored in recorder

- report_normal.pkl & positions_normal.pkl:
  - The return report and detailed positions of the backtest, returned by *qlib/contrib/evaluate.py:backtest*
- port_analysis.pkl : The risk analysis of your portfolio, returned by *qlib/contrib/evaluate.py:risk_analysis*

depend_cls
alias of *SignalRecord*

__init__(*recorder, config=None, risk_analysis_freq: Union[List[T], str] = None, indicator_analysis_freq: Union[List[T], str] = None, indicator_analysis_method=None, skip_existing=False, **kwargs*)

config["strategy"] [dict] define the strategy class as well as the kwargs.
config["executor"] [dict] define the executor class as well as the kwargs.
config["backtest"] [dict] define the backtest kwargs.
risk_analysis_freq [str|List[str]] risk analysis freq of report
indicator_analysis_freq [str|List[str]] indicator analysis freq of report
indicator_analysis_method [str, optional, default by None] the candidated values include 'mean', 'amount_weighted', 'value_weighted'

list()
List the supported artifacts. Users don't have to consider self.get_path

Returns

Return type A list of all the supported artifacts.

1.24.4 Task Management

TaskGen

TaskGenerator module can generate many tasks based on TaskGen and some task templates.

qlib.workflow.task.gen.**task_generator**(*tasks, generators*) → list
Use a list of TaskGen and a list of task templates to generate different tasks.

For examples:

There are 3 task templates a,b,c and 2 TaskGen A,B. A will generates 2 tasks from a template and B will generates 3 tasks from a template. task_generator([a, b, c], [A, B]) will finally generate 3*2*3 = 18 tasks.

Parameters

- **tasks** (*List[dict] or dict*) – a list of task templates or a single task

- **generators** (*List[TaskGen] or TaskGen*) – a list of TaskGen or a single TaskGen

Returns a list of tasks

Return type list

class qlib.workflow.task.gen.**TaskGen**

The base class for generating different tasks

Example 1:

input: a specific task template and rolling steps

output: rolling version of the tasks

Example 2:

input: a specific task template and losses list

output: a set of tasks with different losses

generate(*task: dict*) → List[dict]

Generate different tasks based on a task template

Parameters **task** (*dict*) – a task template

Returns A list of tasks

Return type typing.List[dict]

qlib.workflow.task.gen.**handler_mod**(*task: dict*, *rolling_gen*)

Help to modify the handler end time when using RollingGen It try to handle the following case

- Hander's data end_time is earlier than dataset's test_data's segments.
  - To handle this, handler's data's end_time is extended.

If the handler's end_time is None, then it is not necessary to change it's end time.

Parameters

- **task** (*dict*) – a task template
- **rg** (*RollingGen*) – an instance of RollingGen

qlib.workflow.task.gen.**trunc_segments**(*ta: qlib.workflow.task.utils.TimeAdjuster*, *segments: Dict[str, pandas._libs.tslibs.timestamps.Timestamp]*, *days*, *test_key='test'*)

To avoid the leakage of future information, the segments should be truncated according to the test start_time

Note: This function will change segments **inplace**

class qlib.workflow.task.gen.**RollingGen**(*step: int = 40*, *rtype: str = 'expanding'*, *ds_extra_mod_func: Union[None, Callable] = <function handler_mod>*, *test_key='test'*, *train_key='train'*, *trunc_days: int = None*, *task_copy_func: Callable = <function deepcopy>*)

__init__(*step: int = 40*, *rtype: str = 'expanding'*, *ds_extra_mod_func: Union[None, Callable] = <function handler_mod>*, *test_key='test'*, *train_key='train'*, *trunc_days: int = None*, *task_copy_func: Callable = <function deepcopy>*)

Generate tasks for rolling

Parameters

- **step** (*int*) – step to rolling
- **rtype** (*str*) – rolling type (expanding, sliding)

- **ds_extra_mod_func** (*Callable*) – A method like: handler_mod(task: dict, rg: RollingGen) Do some extra action after generating a task. For example, use `handler_mod` to modify the end time of the handler of a dataset.
- **trunc_days** (*int*) – trunc some data to avoid future information leakage
- **task_copy_func** (*Callable*) – the function to copy entire task. This is very useful when user want to share something between tasks

gen_following_tasks (*task: dict, test_end: pandas._libs.tslibs.timestamps.Timestamp*) → List[dict]

generating following rolling tasks for *task* until test_end

Parameters

- **task** (*dict*) – Qlib task format
- **test_end** (*pd.Timestamp*) – the latest rolling task includes *test_end*

Returns the following tasks of *task*'('*task* itself is excluded)

Return type List[dict]

generate (*task: dict*) → List[dict]

Converting the task into a rolling task.

Parameters **task** (*dict*) – A dict describing a task. For example.

```
DEFAULT_TASK = {
    "model": {
        "class": "LGBModel",
        "module_path": "qlib.contrib.model.gbdt",
    },
    "dataset": {
        "class": "DatasetH",
        "module_path": "qlib.data.dataset",
        "kwargs": {
            "handler": {
                "class": "Alpha158",
                "module_path": "qlib.contrib.data.handler",
                "kwargs": {
                    "start_time": "2008-01-01",
                    "end_time": "2020-08-01",
                    "fit_start_time": "2008-01-01",
                    "fit_end_time": "2014-12-31",
                    "instruments": "csi100",
                },
            },
            "segments": {
                "train": ("2008-01-01", "2014-12-31"),
                "valid": ("2015-01-01", "2016-12-20"),  #
↪Please avoid leaking the future test data into validation
                "test": ("2017-01-01", "2020-08-01"),
            },
        },
    },
    "record": [
        {
            "class": "SignalRecord",
            "module_path": "qlib.workflow.record_temp",
        },
    ]
}
```

Returns List[dict]

Return type a list of tasks

class qlib.workflow.task.gen.**MultiHorizonGenBase**(*horizon: List[int] = [5], label_leak_n=2*)

__init__(*horizon: List[int] = [5], label_leak_n=2*)
This task generator tries to generate tasks for different horizons based on an existing task

Parameters

- **horizon** (*List[int]*) – the possible horizons of the tasks
- **label_leak_n** (*int*) – How many future days it will take to get complete label after the day making prediction For example: - User make prediction on day *T'(after getting the close price on 'T*) - The label is the return of buying stock on *T + 1* and selling it on *T + 2* - the *label_leak_n* will be 2 (e.g. two days of information is leaked to leverage this sample)

set_horizon(*task: dict, hr: int*)
This method is designed to change the task **in place**

Parameters

- **task** (*dict*) – Qlib's task
- **hr** (*int*) – the horizon of task

generate(*task: dict*)
Generate different tasks based on a task template

Parameters **task** (*dict*) – a task template

Returns A list of tasks

Return type typing.List[dict]

TaskManager

TaskManager can fetch unused tasks automatically and manage the lifecycle of a set of tasks with error handling. These features can run tasks concurrently and ensure every task will be used only once. Task Manager will store all tasks in MongoDB. Users **MUST** finished the configuration of MongoDB when using this module.

A task in TaskManager consists of 3 parts - tasks description: the desc will define the task - tasks status: the status of the task - tasks result: A user can get the task with the task description and task result.

class qlib.workflow.task.manage.**TaskManager**(*task_pool: str*)
Here is what will a task looks like when it created by TaskManager

```
{
    'def': pickle serialized task definition.  using pickle will make it easier
    'filter': json-like data. This is for filtering the tasks.
    'status': 'waiting' | 'running' | 'done'
    'res': pickle serialized task result,
}
```

The tasks manager assumes that you will only update the tasks you fetched. The mongo fetch one and update will make it date updating secure.

This class can be used as a tool from commandline. Here are several examples. You can view the help of manage module with the following commands: python -m qlib.workflow.task.manage -h # show manual of manage module CLI python -m qlib.workflow.task.manage wait -h # show manual of the wait command of manage

```
python -m qlib.workflow.task.manage -t <pool_name> wait
python -m qlib.workflow.task.manage -t <pool_name> task_stat
```

Note: Assumption: the data in MongoDB was encoded and the data out of MongoDB was decoded

Here are four status which are:

STATUS_WAITING: waiting for training

STATUS_RUNNING: training

STATUS_PART_DONE: finished some step and waiting for next step

STATUS_DONE: all work done

`__init__`(*task_pool: str*)

Init Task Manager, remember to make the statement of MongoDB url and database name firstly. A TaskManager instance serves a specific task pool. The static method of this module serves the whole MongoDB.

Parameters **`task_pool`** (`str`) – the name of Collection in MongoDB

`static list`() → list

List the all collection(task_pool) of the db.

Returns list

`replace_task`(*task*, *new_task*)

Use a new task to replace a old one

Parameters

- **`task`** – old task
- **`new_task`** – new task

`insert_task`(*task*)

Insert a task.

Parameters **`task`** – the task waiting for insert

Returns pymongo.results.InsertOneResult

`insert_task_def`(*task_def*)

Insert a task to task_pool

Parameters **`task_def`** (`dict`) – the task definition

Returns

Return type pymongo.results.InsertOneResult

`create_task`(*task_def_l*, *dry_run=False*, *print_nt=False*) → List[str]

If the tasks in task_def_l are new, then insert new tasks into the task_pool, and record inserted_id. If a task is not new, then just query its _id.

Parameters

- **`task_def_l`** (`list`) – a list of task
- **`dry_run`** (`bool`) – if insert those new tasks to task pool
- **`print_nt`** (`bool`) – if print new task

Returns a list of the _id of task_def_l

Return type List[str]

fetch_task(*query={}*, *status='waiting'*) → dict

Use query to fetch tasks.

Parameters

- **query** (*dict, optional*) – query dict. Defaults to {}.
- **status** (*str, optional*) – [description]. Defaults to STATUS_WAITING.

Returns a task(document in collection) after decoding

Return type dict

safe_fetch_task(*query={}*, *status='waiting'*)

Fetch task from task_pool using query with contextmanager

Parameters **query** (*dict*) – the dict of query

Returns dict

Return type a task(document in collection) after decoding

query(*query={}*, *decode=True*)

Query task in collection. This function may raise exception *pymongo.errors.CursorNotFound: cursor id not found* if it takes too long to iterate the generator

python -m qlib.workflow.task.manage -t <your task pool> query '{"_id": "615498be837d0053acbc5d58"}'

Parameters

- **query** (*dict*) – the dict of query
- **decode** (*bool*) –

Returns dict

Return type a task(document in collection) after decoding

re_query(*_id*) → dict

Use _id to query task.

Parameters **_id** (*str*) – _id of a document

Returns a task(document in collection) after decoding

Return type dict

commit_task_res(*task*, *res*, *status='done'*)

Commit the result to task['res'].

Parameters

- **task** (*[type]*) – [description]
- **res** (*object*) – the result you want to save
- **status** (*str, optional*) – STATUS_WAITING, STATUS_RUNNING, STATUS_DONE, STATUS_PART_DONE. Defaults to STATUS_DONE.

return_task(*task*, *status='waiting'*)

Return a task to status. Always using in error handling.

Parameters

- **task** (*[type]*) – [description]
- **status** (*str, optional*) – STATUS_WAITING, STATUS_RUNNING, STATUS_DONE, STATUS_PART_DONE. Defaults to STATUS_WAITING.

remove(*query={}*)

Remove the task using query

Parameters **query** (*dict*) – the dict of query

task_stat (*query={}*) → dict

Count the tasks in every status.

Parameters **query** (*dict, optional*) – the query dict. Defaults to {}.

Returns dict

reset_waiting (*query={}*)

Reset all running task into waiting status. Can be used when some running task exit unexpected.

Parameters **query** (*dict, optional*) – the query dict. Defaults to {}.

prioritize (*task, priority: int*)

Set priority for task

Parameters

- **task** (*dict*) – The task query from the database
- **priority** (*int*) – the target priority

wait (*query={}*)

When multiprocessing, the main progress may fetch nothing from TaskManager because there are still some running tasks. So main progress should wait until all tasks are trained well by other progress or machines.

Parameters **query** (*dict, optional*) – the query dict. Defaults to {}.

qlib.workflow.task.manage.**run_task** (*task_func: Callable, task_pool: str, query: dict = {}, force_release: bool = False, before_status: str = 'waiting', after_status: str = 'done', **kwargs*)

While the task pool is not empty (has WAITING tasks), use task_func to fetch and run tasks in task_pool

After running this method, here are 4 situations (before_status -> after_status):

STATUS_WAITING -> STATUS_DONE: use task["def"] as *task_func* param, it means that the task has not been started

STATUS_WAITING -> STATUS_PART_DONE: use task["def"] as *task_func* param

STATUS_PART_DONE -> STATUS_PART_DONE: use task["res"] as *task_func* param, it means that the task has been started but not completed

STATUS_PART_DONE -> STATUS_DONE: use task["res"] as *task_func* param

Parameters

- **task_func** (*Callable*) – def (task_def, **kwargs) -> <res which will be committed>

  the function to run the task
- **task_pool** (*str*) – the name of the task pool (Collection in MongoDB)
- **query** (*dict*) – will use this dict to query task_pool when fetching task
- **force_release** (*bool*) – will the program force to release the resource
- **before_status** (*str:*) – the tasks in before_status will be fetched and trained. Can be STATUS_WAITING, STATUS_PART_DONE.
- **after_status** (*str:*) – the tasks after trained will become after_status. Can be STATUS_WAITING, STATUS_PART_DONE.
- **kwargs** – the params for *task_func*

Trainer

The Trainer will train a list of tasks and return a list of model recorders. There are two steps in each Trainer including `train` (make model recorder) and `end_train` (modify model recorder).

This is a concept called `DelayTrainer`, which can be used in online simulating for parallel training. In `DelayTrainer`, the first step is only to save some necessary info to model recorders, and the second step which will be finished in the end can do some concurrent and time-consuming operations such as model fitting.

`Qlib` offer two kinds of Trainer, `TrainerR` is the simplest way and `TrainerRM` is based on TaskManager to help manager tasks lifecycle automatically.

`qlib.model.trainer.`**`begin_task_train`**(*task_config: dict*, *experiment_name: str*, *recorder_name: str = None*) → qlib.workflow.recorder.Recorder

Begin task training to start a recorder and save the task config.

Parameters

- **`task_config`** (*`dict`*) – the config of a task
- **`experiment_name`** (*`str`*) – the name of experiment
- **`recorder_name`** (*`str`*) – the given name will be the recorder name. None for using rid.

Returns the model recorder

Return type *Recorder*

`qlib.model.trainer.`**`end_task_train`**(*rec: qlib.workflow.recorder.Recorder*, *experiment_name: str*) → qlib.workflow.recorder.Recorder

Finish task training with real model fitting and saving.

Parameters

- **`rec`** (`Recorder`) – the recorder will be resumed
- **`experiment_name`** (*`str`*) – the name of experiment

Returns the model recorder

Return type *Recorder*

`qlib.model.trainer.`**`task_train`**(*task_config: dict*, *experiment_name: str*, *recorder_name: str = None*) → qlib.workflow.recorder.Recorder

Task based training, will be divided into two steps.

Parameters

- **`task_config`** (*`dict`*) – The config of a task.
- **`experiment_name`** (*`str`*) – The name of experiment
- **`recorder_name`** (*`str`*) – The name of recorder

Returns **Recorder**

Return type The instance of the recorder

class `qlib.model.trainer.`**`Trainer`**

The trainer can train a list of models. There are Trainer and DelayTrainer, which can be distinguished by when it will finish real training.

`__init__`()

Initialize self. See help(type(self)) for accurate signature.

`train`(*tasks: list*, **args*, ***kwargs*) → list

Given a list of task definitions, begin training, and return the models.

For Trainer, it finishes real training in this method. For DelayTrainer, it only does some preparation in this method.

Parameters **`tasks`** – a list of tasks

Returns a list of models

Return type list

end_train (*models: list*, **args*, ***kwargs*) → list

Given a list of models, finished something at the end of training if you need. The models may be Recorder, txt file, database, and so on.

For Trainer, it does some finishing touches in this method. For DelayTrainer, it finishes real training in this method.

Parameters **models** – a list of models

Returns a list of models

Return type list

is_delay () → bool

If Trainer will delay finishing *end_train*.

Returns if DelayTrainer

Return type bool

has_worker () → bool

Some trainer has backend worker to support parallel training This method can tell if the worker is enabled.

Returns if the worker is enabled

Return type bool

worker ()

start the worker

Raises NotImplementedError: – If the worker is not supported

class qlib.model.trainer.**TrainerR** (*experiment_name: Optional[str] = None*, *train_func: Callable = <function task_train>*, *call_in_subproc: bool = False*, *default_rec_name: Optional[str] = None*)

Trainer based on (R)ecorder. It will train a list of tasks and return a list of model recorders in a linear way.

Assumption: models were defined by *task* and the results will be saved to *Recorder*.

__init__ (*experiment_name: Optional[str] = None*, *train_func: Callable = <function task_train>*, *call_in_subproc: bool = False*, *default_rec_name: Optional[str] = None*)

Init TrainerR.

Parameters

- **experiment_name** (*str, optional*) – the default name of experiment.
- **train_func** (*Callable, optional*) – default training method. Defaults to *task_train*.
- **call_in_subproc** (*bool*) – call the process in subprocess to force memory release

train (*tasks: list*, *train_func: Callable = None*, *experiment_name: str = None*, ***kwargs*) → List[qlib.workflow.recorder.Recorder]

Given a list of *tasks* and return a list of trained Recorder. The order can be guaranteed.

Parameters

- **tasks** (*list*) – a list of definitions based on *task* dict
- **train_func** (*Callable*) – the training method which needs at least *tasks* and *experiment_name*. None for the default training method.
- **experiment_name** (*str*) – the experiment name, None for use default name.
- **kwargs** – the params for train_func.

Returns a list of Recorders

Return type List[*Recorder*]

end_train (*models: list*, ***kwargs*) → List[qlib.workflow.recorder.Recorder]
Set STATUS_END tag to the recorders.

Parameters **models** (*list*) – a list of trained recorders.

Returns the same list as the param.

Return type List[*Recorder*]

class qlib.model.trainer.**DelayTrainerR** (*experiment_name: str = None*, *train_func=<function begin_task_train>*, *end_train_func=<function end_task_train>*, ***kwargs*)

A delayed implementation based on TrainerR, which means *train* method may only do some preparation and *end_train* method can do the real model fitting.

__init__ (*experiment_name: str = None*, *train_func=<function begin_task_train>*, *end_train_func=<function end_task_train>*, ***kwargs*)
Init TrainerRM.

Parameters

- **experiment_name** (*str*) – the default name of experiment.
- **train_func** (*Callable, optional*) – default train method. Defaults to *begin_task_train*.
- **end_train_func** (*Callable, optional*) – default end_train method. Defaults to *end_task_train*.

end_train (*models*, *end_train_func=None*, *experiment_name: str = None*, ***kwargs*) → List[qlib.workflow.recorder.Recorder]
Given a list of Recorder and return a list of trained Recorder. This class will finish real data loading and model fitting.

Parameters

- **models** (*list*) – a list of Recorder, the tasks have been saved to them
- **end_train_func** (*Callable, optional*) – the end_train method which needs at least *recorders* and *experiment_name*. Defaults to None for using self.end_train_func.
- **experiment_name** (*str*) – the experiment name, None for use default name.
- **kwargs** – the params for end_train_func.

Returns a list of Recorders

Return type List[*Recorder*]

class qlib.model.trainer.**TrainerRM** (*experiment_name: str = None*, *task_pool: str = None*, *train_func=<function task_train>*, *skip_run_task: bool = False*, *default_rec_name: Optional[str] = None*)

Trainer based on (R)ecorder and Task(M)anager. It can train a list of tasks and return a list of model recorders in a multiprocessing way.

Assumption: *task* will be saved to TaskManager and *task* will be fetched and trained from TaskManager

__init__ (*experiment_name: str = None*, *task_pool: str = None*, *train_func=<function task_train>*, *skip_run_task: bool = False*, *default_rec_name: Optional[str] = None*)
Init TrainerR.

Parameters

- **experiment_name** (*str*) – the default name of experiment.
- **task_pool** (*str*) – task pool name in TaskManager. None for use same name as experiment_name.
- **train_func** (*Callable, optional*) – default training method. Defaults to *task_train*.
- **skip_run_task** (*bool*) – If skip_run_task == True: Only run_task in the worker. Otherwise skip run_task.

train(*tasks: list*, *train_func: Callable = None*, *experiment_name: str = None*, *before_status: str = 'waiting'*, *after_status: str = 'done'*, *default_rec_name: Optional[str] = None*, ***kwargs*) → List[qlib.workflow.recorder.Recorder]

Given a list of *tasks* and return a list of trained Recorder. The order can be guaranteed.

This method defaults to a single process, but TaskManager offered a great way to parallel training. Users can customize their train_func to realize multiple processes or even multiple machines.

Parameters

- **tasks** (*list*) – a list of definitions based on *task* dict
- **train_func** (*Callable*) – the training method which needs at least *tasks* and *experiment_name*. None for the default training method.
- **experiment_name** (*str*) – the experiment name, None for use default name.
- **before_status** (*str*) – the tasks in before_status will be fetched and trained. Can be STATUS_WAITING, STATUS_PART_DONE.
- **after_status** (*str*) – the tasks after trained will become after_status. Can be STATUS_WAITING, STATUS_PART_DONE.
- **kwargs** – the params for train_func.

Returns a list of Recorders

Return type List[*Recorder*]

end_train(*recs: list*, ***kwargs*) → List[qlib.workflow.recorder.Recorder]

Set STATUS_END tag to the recorders.

Parameters **recs** (*list*) – a list of trained recorders.

Returns the same list as the param.

Return type List[*Recorder*]

worker(*train_func: Callable = None*, *experiment_name: str = None*)

The multiprocessing method for *train*. It can share a same task_pool with *train* and can run in other progress or other machines.

Parameters

- **train_func** (*Callable*) – the training method which needs at least *tasks* and *experiment_name*. None for the default training method.
- **experiment_name** (*str*) – the experiment name, None for use default name.

has_worker() → bool

Some trainer has backend worker to support parallel training This method can tell if the worker is enabled.

Returns if the worker is enabled

Return type bool

class qlib.model.trainer.**DelayTrainerRM**(*experiment_name: str = None*, *task_pool: str = None*, *train_func=<function begin_task_train>*, *end_train_func=<function end_task_train>*, *skip_run_task: bool = False*, ***kwargs*)

A delayed implementation based on TrainerRM, which means *train* method may only do some preparation and *end_train* method can do the real model fitting.

__init__(*experiment_name: str = None*, *task_pool: str = None*, *train_func=<function begin_task_train>*, *end_train_func=<function end_task_train>*, *skip_run_task: bool = False*, ***kwargs*)

Init DelayTrainerRM.

Parameters

- **experiment_name** (`str`) – the default name of experiment.
- **task_pool** (`str`) – task pool name in TaskManager. None for use same name as experiment_name.
- **train_func** (`Callable, optional`) – default train method. Defaults to *begin_task_train*.
- **end_train_func** (`Callable, optional`) – default end_train method. Defaults to *end_task_train*.
- **skip_run_task** (`bool`) – If skip_run_task == True: Only run_task in the worker. Otherwise skip run_task. E.g. Starting trainer on a CPU VM and then waiting tasks to be finished on GPU VMs.

train(*tasks: list*, *train_func=None*, *experiment_name: str = None*, ***kwargs*) → List[qlib.workflow.recorder.Recorder]

Same as *train* of TrainerRM, after_status will be STATUS_PART_DONE.

Parameters

- **tasks** (`list`) – a list of definition based on *task* dict
- **train_func** (`Callable`) – the train method which need at least *tasks* and *experiment_name*. Defaults to None for using self.train_func.
- **experiment_name** (`str`) – the experiment name, None for use default name.

Returns a list of Recorders

Return type List[*Recorder*]

end_train(*recs*, *end_train_func=None*, *experiment_name: str = None*, ***kwargs*) → List[qlib.workflow.recorder.Recorder]

Given a list of Recorder and return a list of trained Recorder. This class will finish real data loading and model fitting.

Parameters

- **recs** (`list`) – a list of Recorder, the tasks have been saved to them.
- **end_train_func** (`Callable, optional`) – the end_train method which need at least *recorders* and *experiment_name*. Defaults to None for using self.end_train_func.
- **experiment_name** (`str`) – the experiment name, None for use default name.
- **kwargs** – the params for end_train_func.

Returns a list of Recorders

Return type List[*Recorder*]

worker(*end_train_func=None*, *experiment_name: str = None*)
The multiprocessing method for *end_train*. It can share a same task_pool with *end_train* and can run in other progress or other machines.

Parameters

- **end_train_func** (*Callable, optional*) – the end_train method which need at least *recorders* and *experiment_name*. Defaults to None for using self.end_train_func.
- **experiment_name** (*str*) – the experiment name, None for use default name.

has_worker() → bool
Some trainer has backend worker to support parallel training This method can tell if the worker is enabled.

Returns if the worker is enabled

Return type bool

Collector

Collector module can collect objects from everywhere and process them such as merging, grouping, averaging and so on.

class qlib.workflow.task.collect.**Collector**(*process_list=[]*)
The collector to collect different results

__init__(*process_list=[]*)
Init Collector.

Parameters **process_list** (*list or Callable*) – the list of processors or the instance of a processor to process dict.

collect() → dict
Collect the results and return a dict like {key: things}

Returns

the dict after collecting.

For example:

{"prediction": pd.Series}

{"IC": {"Xgboost": pd.Series, "LSTM": pd.Series}}

…

Return type dict

static process_collect(*collected_dict*, *process_list=[]*, **args*, ***kwargs*) → dict
Do a series of processing to the dict returned by collect and return a dict like {key: things} For example, you can group and ensemble.

Parameters

- **collected_dict** (*dict*) – the dict return by *collect*
- **process_list** (*list or Callable*) – the list of processors or the instance of a processor to process dict. The processor order is the same as the list order. For example: [Group1(…, Ensemble1()), Group2(…, Ensemble2())]

Returns the dict after processing.

Return type dict

class qlib.workflow.task.collect.**MergeCollector**(*collector_dict: Dict[str, qlib.workflow.task.collect.Collector], process_list: List[Callable] = [], merge_func=None*)

A collector to collect the results of other Collectors

For example:

We have 2 collector, which named A and B. A can collect {"prediction": pd.Series} and B can collect {"IC": {"Xgboost": pd.Series, "LSTM": pd.Series}}. Then after this class's collect, we can collect {"A_prediction": pd.Series, "B_IC": {"Xgboost": pd.Series, "LSTM": pd.Series}}

…

__init__(*collector_dict: Dict[str, qlib.workflow.task.collect.Collector], process_list: List[Callable] = [], merge_func=None*)

Init MergeCollector.

Parameters

- **collector_dict** (*Dict[str,Collector]*) – the dict like {collector_key, Collector}
- **process_list** (*List[Callable]*) – the list of processors or the instance of processor to process dict.
- **merge_func** (*Callable*) – a method to generate outermost key. The given params are `collector_key` from collector_dict and `key` from every collector after collecting. None for using tuple to connect them, such as "ABC"+("a","b") -> ("ABC", ("a","b")).

collect() → dict

Collect all results of collector_dict and change the outermost key to a recombination key.

Returns the dict after collecting.

Return type dict

class qlib.workflow.task.collect.**RecorderCollector**(*experiment, process_list=[], rec_key_func=None, rec_filter_func=None, artifacts_path={'pred': 'pred.pkl'}, artifacts_key=None, list_kwargs={}, status: Iterable[T_co] = {'FINISHED'}*)

__init__(*experiment, process_list=[], rec_key_func=None, rec_filter_func=None, artifacts_path={'pred': 'pred.pkl'}, artifacts_key=None, list_kwargs={}, status: Iterable[T_co] = {'FINISHED'}*)

Init RecorderCollector.

Parameters

- **experiment** – (Experiment or str): an instance of an Experiment or the name of an Experiment (Callable): an callable function, which returns a list of experiments
- **process_list** (*list or Callable*) – the list of processors or the instance of a processor to process dict.
- **rec_key_func** (*Callable*) – a function to get the key of a recorder. If None, use recorder id.
- **rec_filter_func** (*Callable, optional*) – filter the recorder by return True or False. Defaults to None.

- **artifacts_path** (*dict, optional*) – The artifacts name and its path in Recorder. Defaults to {"pred": "pred.pkl", "IC": "sig_analysis/ic.pkl"}.
- **artifacts_key** (*str or List, optional*) – the artifacts key you want to get. If None, get all artifacts.
- **list_kwargs** (*str*) – arguments for list_recorders function.
- **status** (*Iterable*) – only collect recorders with specific status. None indicating collecting all the recorders

collect (*artifacts_key=None*, *rec_filter_func=None*, *only_exist=True*) → dict
Collect different artifacts based on recorder after filtering.

Parameters

- **artifacts_key** (*str or List, optional*) – the artifacts key you want to get. If None, use the default.
- **rec_filter_func** (*Callable, optional*) – filter the recorder by return True or False. If None, use the default.
- **only_exist** (*bool, optional*) – if only collect the artifacts when a recorder really has. If True, the recorder with exception when loading will not be collected. But if False, it will raise the exception.

Returns the dict after collected like {artifact: {rec_key: object}}

Return type dict

get_exp_name () → str
Get experiment name

Returns experiment name

Return type str

Group

Group can group a set of objects based on *group_func* and change them to a dict. After group, we provide a method to reduce them.

For example:

group: {(A,B,C1): object, (A,B,C2): object} -> {(A,B): {C1: object, C2: object}} reduce: {(A,B): {C1: object, C2: object}} -> {(A,B): object}

class qlib.model.ens.group.**Group** (*group_func=None*, *ens: qlib.model.ens.ensemble.Ensemble = None*)
Group the objects based on dict

__init__ (*group_func=None*, *ens: qlib.model.ens.ensemble.Ensemble = None*)
Init Group.

Parameters

- **group_func** (*Callable, optional*) – Given a dict and return the group key and one of the group elements.

  For example: {(A,B,C1): object, (A,B,C2): object} -> {(A,B): {C1: object, C2: object}}
- **to None.** (*Defaults*) –
- **ens** (*Ensemble, optional*) – If not None, do ensemble for grouped value after grouping.

group(**args*, ***kwargs*) → dict
Group a set of objects and change them to a dict.

For example: {(A,B,C1): object, (A,B,C2): object} -> {(A,B): {C1: object, C2: object}}

Returns grouped dict

Return type dict

reduce(**args*, ***kwargs*) → dict
Reduce grouped dict.

For example: {(A,B): {C1: object, C2: object}} -> {(A,B): object}

Returns reduced dict

Return type dict

class qlib.model.ens.group.**RollingGroup**(*ens=<qlib.model.ens.ensemble.RollingEnsemble object>*)
Group the rolling dict

group(*rolling_dict: dict*) → dict
Given an rolling dict likes {(A,B,R): things}, return the grouped dict likes {(A,B): {R:things}}

NOTE: There is an assumption which is the rolling key is at the end of the key tuple, because the rolling results always need to be ensemble firstly.

Parameters **rolling_dict** (*dict*) – an rolling dict. If the key is not a tuple, then do nothing.

Returns grouped dict

Return type dict

__init__(*ens=<qlib.model.ens.ensemble.RollingEnsemble object>*)
Init Group.

Parameters

- **group_func** (*Callable, optional*) – Given a dict and return the group key and one of the group elements.

  For example: {(A,B,C1): object, (A,B,C2): object} -> {(A,B): {C1: object, C2: object}}

- **to None.** (*Defaults*) –
- **ens** (*Ensemble, optional*) – If not None, do ensemble for grouped value after grouping.

Ensemble

Ensemble module can merge the objects in an Ensemble. For example, if there are many submodels predictions, we may need to merge them into an ensemble prediction.

class qlib.model.ens.ensemble.**Ensemble**
Merge the ensemble_dict into an ensemble object.

For example: {Rollinga_b: object, Rollingb_c: object} -> object

When calling this class:

Args: ensemble_dict (dict): the ensemble dict like {name: things} waiting for merging
Returns: object: the ensemble object

class qlib.model.ens.ensemble.**SingleKeyEnsemble**

Extract the object if there is only one key and value in the dict. Make the result more readable. {Only key: Only value} -> Only value

If there is more than 1 key or less than 1 key, then do nothing. Even you can run this recursively to make dict more readable.

NOTE: Default runs recursively.

When calling this class:
Args: ensemble_dict (dict): the dict. The key of the dict will be ignored.
Returns: dict: the readable dict.

class qlib.model.ens.ensemble.**RollingEnsemble**

Merge a dict of rolling dataframe like *prediction* or *IC* into an ensemble.

NOTE: The values of dict must be pd.DataFrame, and have the index "datetime".

When calling this class:
Args: ensemble_dict (dict): a dict like {"A": pd.DataFrame, "B": pd.DataFrame}. The key of the dict will be ignored.
Returns: pd.DataFrame: the complete result of rolling.

class qlib.model.ens.ensemble.**AverageEnsemble**

Average and standardize a dict of same shape dataframe like *prediction* or *IC* into an ensemble.

NOTE: The values of dict must be pd.DataFrame, and have the index "datetime". If it is a nested dict, then flat it.

When calling this class:
Args: ensemble_dict (dict): a dict like {"A": pd.DataFrame, "B": pd.DataFrame}. The key of the dict will be ignored.
Returns: pd.DataFrame: the complete result of averaging and standardizing.

Utils

Some tools for task management.

qlib.workflow.task.utils.**get_mongodb**() → pymongo.database.Database

Get database in MongoDB, which means you need to declare the address and the name of a database at first.

For example:
Using qlib.init():

```
mongo_conf = {
    "task_url": task_url,  # your MongoDB url
    "task_db_name": task_db_name,  # database name
}
qlib.init(..., mongo=mongo_conf)
```

After qlib.init():

```
C["mongo"] = {
    "task_url" : "mongodb://localhost:27017/",
    "task_db_name" : "rolling_db"
}
```

Returns the Database instance
Return type Database

qlib.workflow.task.utils.**list_recorders**(*experiment*, *rec_filter_func=None*)
List all recorders which can pass the filter in an experiment.

Parameters

- **experiment** (*str or Experiment*) – the name of an Experiment or an instance
- **rec_filter_func** (*Callable, optional*) – return True to retain the given recorder. Defaults to None.

Returns a dict {rid: recorder} after filtering.

Return type dict

class qlib.workflow.task.utils.**TimeAdjuster**(*future=True*, *end_time=None*)
Find appropriate date and adjust date.

__init__(*future=True*, *end_time=None*)
Initialize self. See help(type(self)) for accurate signature.

set_end_time(*end_time=None*)
Set end time. None for use calendar's end time.

Parameters **end_time** –

get(*idx: int*)
Get datetime by index.

Parameters **idx** (*int*) – index of the calendar

max() → pandas._libs.tslibs.timestamps.Timestamp
Return the max calendar datetime

align_idx(*time_point*, *tp_type='start'*) → int
Align the index of time_point in the calendar.

Parameters

- **time_point** –
- **tp_type** (*str*) –

Returns index

Return type int

cal_interval(*time_point_A*, *time_point_B*) → int
Calculate the trading day interval (time_point_A - time_point_B)

Parameters

- **time_point_A** – time_point_A
- **time_point_B** – time_point_B (is the past of time_point_A)

Returns the interval between A and B

Return type int

align_time(*time_point*, *tp_type='start'*) → pandas._libs.tslibs.timestamps.Timestamp
Align time_point to trade date of calendar

Parameters

- **time_point** – Time point
- **tp_type** – str time point type (*"start"*, *"end"*)

Returns pd.Timestamp

align_seg(*segment: Union[dict, tuple]*) → Union[dict, tuple]
Align the given date to the trade date

for example:

```
input: {'train': ('2008-01-01', '2014-12-31'), 'valid': ('2015-01-01
↪', '2016-12-31'), 'test': ('2017-01-01', '2020-08-01')}

output: {'train': (Timestamp('2008-01-02 00:00:00'), Timestamp(
↪'2014-12-31 00:00:00')),
        'valid': (Timestamp('2015-01-05 00:00:00'), Timestamp('2016-
↪12-30 00:00:00')),
        'test': (Timestamp('2017-01-03 00:00:00'), Timestamp('2020-
↪07-31 00:00:00'))}
```

Parameters **segment** –

Returns **Union[dict, tuple]**

Return type the start and end trade date (pd.Timestamp) between the given start and end date.

truncate (*segment: tuple*, *test_start*, *days: int*) → tuple

Truncate the segment based on the test_start date

Parameters

- **segment** (*tuple*) – time segment
- **test_start** –
- **days** (*int*) – The trading days to be truncated the data in this segment may need 'days' data *days* are based on the *test_start*. For example, if the label contains the information of 2 days in the near future, the prediction horizon 1 day. (e.g. the prediction target is *Ref($close, -2)/Ref($close, -1) - 1*) the days should be 2 + 1 == 3 days.

Returns **tuple**

Return type new segment

shift (*seg: tuple*, *step: int*, *rtype='sliding'*) → tuple

Shift the datatime of segment

If there are None (which indicates unbounded index) in the segment, this method will return None.

Parameters

- **seg** – datetime segment
- **step** (*int*) – rolling step
- **rtype** (*str*) – rolling type ("sliding" or "expanding")

Returns **tuple**

Return type new segment

Raises KeyError: – shift will raise error if the index(both start and end) is out of self.cal

1.24.5 Online Serving

Online Manager

OnlineManager can manage a set of *Online Strategy* and run them dynamically.

With the change of time, the decisive models will be also changed. In this module, we call those contributing models *online* models. In every routine(such as every day or every minute), the *online* models may be changed and the prediction of them needs to be updated. So this module provides a series of methods to control this process.

This module also provides a method to simulate *Online Strategy* in history. Which means you can verify your strategy or find a better one.

There are 4 total situations for using different trainers in different situations:

Situations	Description
Online + Trainer	When you want to do a REAL routine, the Trainer will help you train the models. It will train models task by task and strategy by strategy.
Online + DelayTrainer	DelayTrainer will skip concrete training until all tasks have been prepared by different strategies. It makes users can parallelly train all tasks at the end of *routine* or *first_train*. Otherwise, these functions will get stuck when each strategy prepare tasks.
Simulation + Trainer	It will behave in the same way as *Online + Trainer*. The only difference is that it is for simulation/backtesting instead of online trading
Simulation + DelayTrainer	When your models don't have any temporal dependence, you can use DelayTrainer for the ability to multitasking. It means all tasks in all routines can be REAL trained at the end of simulating. The signals will be prepared well at different time segments (based on whether or not any new model is online).

Here is some pseudo code that demonstrate the workflow of each situation

For simplicity

- Only one strategy is used in the strategy
- *update_online_pred* is only called in the online mode and is ignored

1) *Online + Trainer*

```
tasks = first_train()
models = trainer.train(tasks)
trainer.end_train(models)
for day in online_trading_days:
    # OnlineManager.routine
    models = trainer.train(strategy.prepare_tasks())  # for each strategy
    strategy.prepare_online_models(models)  # for each strategy

    trainer.end_train(models)
    prepare_signals()  # prepare trading signals daily
```

Online + DelayTrainer: the workflow is the same as *Online + Trainer*.

2) *Simulation + DelayTrainer*

```
# simulate
tasks = first_train()
models = trainer.train(tasks)
for day in historical_calendars:
    # OnlineManager.routine
    models = trainer.train(strategy.prepare_tasks())  # for each strategy
    strategy.prepare_online_models(models)  # for each strategy
# delay_prepare()
# FIXME: Currently the delay_prepare is not implemented in a proper way.
```

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```
trainer.end_train(<for all previous models>)
prepare_signals()
```

Can we simplify current workflow?

- Can reduce the number of state of tasks?
  - For each task, we have three phases (i.e. task, partly trained task, final trained task)

class qlib.workflow.online.manager.**OnlineManager**(*strategies: Union[qlib.workflow.online.strategy.OnlineStrategy, List[qlib.workflow.online.strategy.OnlineStrategy]], trainer: qlib.model.trainer.Trainer = None, begin_time: Union[str, pandas._libs.tslibs.timestamps.Timestamp] = None, freq='day'*)

OnlineManager can manage online models with *Online Strategy*. It also provides a history recording of which models are online at what time.

__init__(*strategies: Union[qlib.workflow.online.strategy.OnlineStrategy, List[qlib.workflow.online.strategy.OnlineStrategy]], trainer: qlib.model.trainer.Trainer = None, begin_time: Union[str, pandas._libs.tslibs.timestamps.Timestamp] = None, freq='day'*)

Init OnlineManager. One OnlineManager must have at least one OnlineStrategy.

Parameters

- **strategies** (*Union[*OnlineStrategy*, List[*OnlineStrategy*]]*) – an instance of OnlineStrategy or a list of OnlineStrategy
- **begin_time** (*Union[str,pd.Timestamp], optional*) – the OnlineManager will begin at this time. Defaults to None for using the latest date.
- **trainer** (qlib.model.trainer.Trainer) – the trainer to train task. None for using TrainerR.
- **freq** (*str, optional*) – data frequency. Defaults to "day".

first_train(*strategies: List[qlib.workflow.online.strategy.OnlineStrategy] = None, model_kwargs: dict = {}*)

Get tasks from every strategy's first_tasks method and train them. If using DelayTrainer, it can finish training all together after every strategy's first_tasks.

Parameters

- **strategies** (*List[*OnlineStrategy*]*) – the strategies list (need this param when adding strategies). None for use default strategies.
- **model_kwargs** (*dict*) – the params for *prepare_online_models*

routine(*cur_time: Union[str, pandas._libs.tslibs.timestamps.Timestamp] = None, task_kwargs: dict = {}, model_kwargs: dict = {}, signal_kwargs: dict = {}*)

Typical update process for every strategy and record the online history.

The typical update process after a routine, such as day by day or month by month. The process is: Update predictions -> Prepare tasks -> Prepare online models -> Prepare signals.

If using DelayTrainer, it can finish training all together after every strategy's prepare_tasks.

Parameters

- **cur_time** (*Union[str,pd.Timestamp], optional*) – run routine method in this time. Defaults to None.

- **task_kwargs** (*dict*) – the params for *prepare_tasks*
- **model_kwargs** (*dict*) – the params for *prepare_online_models*
- **signal_kwargs** (*dict*) – the params for *prepare_signals*

get_collector(***kwargs*) → qlib.workflow.task.collect.MergeCollector

Get the instance of Collector to collect results from every strategy. This collector can be a basis as the signals preparation.

Parameters ****kwargs** – the params for get_collector.

Returns the collector to merge other collectors.

Return type *MergeCollector*

add_strategy(*strategies: Union[qlib.workflow.online.strategy.OnlineStrategy, List[qlib.workflow.online.strategy.OnlineStrategy]]*)

Add some new strategies to OnlineManager.

Parameters **strategy** (*Union[OnlineStrategy, List[OnlineStrategy]]*) – a list of OnlineStrategy

prepare_signals(*prepare_func: Callable = <qlib.model.ens.ensemble.AverageEnsemble object>, over_write=False*)

After preparing the data of the last routine (a box in box-plot) which means the end of the routine, we can prepare trading signals for the next routine.

NOTE: Given a set prediction, all signals before these prediction end times will be prepared well.

Even if the latest signal already exists, the latest calculation result will be overwritten.

Note: Given a prediction of a certain time, all signals before this time will be prepared well.

Parameters

- **prepare_func** (*Callable, optional*) – Get signals from a dict after collecting. Defaults to AverageEnsemble(), the results collected by MergeCollector must be {xxx:pred}.
- **over_write** (*bool, optional*) – If True, the new signals will overwrite. If False, the new signals will append to the end of signals. Defaults to False.

Returns the signals.

Return type pd.DataFrame

get_signals() → Union[pandas.core.series.Series, pandas.core.frame.DataFrame]

Get prepared online signals.

Returns pd.Series for only one signals every datetime. pd.DataFrame for multiple signals, for example, buy and sell operations use different trading signals.

Return type Union[pd.Series, pd.DataFrame]

simulate(*end_time=None, frequency='day', task_kwargs={}, model_kwargs={}, signal_kwargs={}*) → Union[pandas.core.series.Series, pandas.core.frame.DataFrame]

Starting from the current time, this method will simulate every routine in OnlineManager until the end time.

Considering the parallel training, the models and signals can be prepared after all routine simulating.

The delay training way can be `DelayTrainer` and the delay preparing signals way can be `delay_prepare`.

Parameters

- **end_time** – the time the simulation will end
- **frequency** – the calendar frequency
- **task_kwargs** (*dict*) – the params for *prepare_tasks*
- **model_kwargs** (*dict*) – the params for *prepare_online_models*
- **signal_kwargs** (*dict*) – the params for *prepare_signals*

Returns pd.Series for only one signals every datetime. pd.DataFrame for multiple signals, for example, buy and sell operations use different trading signals.

Return type Union[pd.Series, pd.DataFrame]

delay_prepare (*model_kwargs={}*, *signal_kwargs={}*)
Prepare all models and signals if something is waiting for preparation.

Parameters

- **model_kwargs** – the params for *end_train*
- **signal_kwargs** – the params for *prepare_signals*

Online Strategy

OnlineStrategy module is an element of online serving.

class qlib.workflow.online.strategy.**OnlineStrategy** (*name_id: str*)
OnlineStrategy is working with *Online Manager*, responding to how the tasks are generated, the models are updated and signals are prepared.

__init__ (*name_id: str*)
Init OnlineStrategy. This module **MUST** use Trainer to finishing model training.

Parameters

- **name_id** (*str*) – a unique name or id.
- **trainer** (*qlib.model.trainer.Trainer, optional*) – a instance of Trainer. Defaults to None.

prepare_tasks (*cur_time*, ***kwargs*) → List[dict]
After the end of a routine, check whether we need to prepare and train some new tasks based on cur_time (None for latest).. Return the new tasks waiting for training.

You can find the last online models by OnlineTool.online_models.

prepare_online_models (*trained_models*, *cur_time=None*) → List[object]
Select some models from trained models and set them to online models. This is a typical implementation to online all trained models, you can override it to implement the complex method. You can find the last online models by OnlineTool.online_models if you still need them.

NOTE: Reset all online models to trained models. If there are no trained models, then do nothing.

NOTE: Current implementation is very naive. Here is a more complex situation which is more closer to the practical scenarios. 1. Train new models at the day before *test_start* (at time stamp *T*) 2. Switch models at the *test_start* (at time timestamp *T + 1* typically)

Parameters

- **models** (*list*) – a list of models.
- **cur_time** (*pd.Dataframe*) – current time from OnlineManger. None for the latest.

Returns a list of online models.

Return type List[object]

first_tasks() → List[dict]
Generate a series of tasks firstly and return them.

get_collector() → qlib.workflow.task.collect.Collector
Get the instance of Collector to collect different results of this strategy.
For example:

1) collect predictions in Recorder
2) collect signals in a txt file

Returns Collector

class qlib.workflow.online.strategy.**RollingStrategy**(*name_id: str, task_template: Union[dict, List[dict]], rolling_gen: qlib.workflow.task.gen.RollingGen*)
This example strategy always uses the latest rolling model sas online models.

__init__(*name_id: str, task_template: Union[dict, List[dict]], rolling_gen: qlib.workflow.task.gen.RollingGen*)
Init RollingStrategy.

Assumption: the str of name_id, the experiment name, and the trainer's experiment name are the same.
Parameters

- **name_id** (*str*) – a unique name or id. Will be also the name of the Experiment.
- **task_template** (*Union[dict, List[dict]]*) – a list of task_template or a single template, which will be used to generate many tasks using rolling_gen.
- **rolling_gen** (RollingGen) – an instance of RollingGen

get_collector(*process_list=[<qlib.model.ens.group.RollingGroup object>], rec_key_func=None, rec_filter_func=None, artifacts_key=None*)
Get the instance of Collector to collect results. The returned collector must distinguish results in different models.

Assumption: the models can be distinguished based on the model name and rolling test segments. If you do not want this assumption, please implement your method or use another rec_key_func.
Parameters

- **rec_key_func** (*Callable*) – a function to get the key of a recorder. If None, use recorder id.
- **rec_filter_func** (*Callable, optional*) – filter the recorder by return True or False. Defaults to None.
- **artifacts_key** (*List[str], optional*) – the artifacts key you want to get. If None, get all artifacts.

first_tasks() → List[dict]
Use rolling_gen to generate different tasks based on task_template.
Returns a list of tasks

Return type List[dict]

prepare_tasks(*cur_time*) → List[dict]
Prepare new tasks based on cur_time (None for the latest).

You can find the last online models by OnlineToolR.online_models.
Returns a list of new tasks.

Return type List[dict]

Online Tool

OnlineTool is a module to set and unset a series of *online* models. The *online* models are some decisive models in some time points, which can be changed with the change of time. This allows us to use efficient submodels as the market-style changing.

class qlib.workflow.online.utils.**OnlineTool**
OnlineTool will manage *online* models in an experiment that includes the model recorders.

__init__()
Init OnlineTool.

set_online_tag(*tag, recorder: Union[list, object]*)
Set *tag* to the model to sign whether online.

Parameters

- **tag** (*str*) – the tags in *ONLINE_TAG*, *OFFLINE_TAG*
- **recorder** (*Union[list,object]*) – the model's recorder

get_online_tag(*recorder: object*) → str
Given a model recorder and return its online tag.

Parameters **recorder** (*Object*) – the model's recorder

Returns the online tag

Return type str

reset_online_tag(*recorder: Union[list, object]*)
Offline all models and set the recorders to 'online'.

Parameters **recorder** (*Union[list,object]*) – the recorder you want to reset to 'online'.

online_models() → list
Get current *online* models

Returns a list of *online* models.

Return type list

update_online_pred(*to_date=None*)
Update the predictions of *online* models to to_date.

Parameters **to_date** (*pd.Timestamp*) – the pred before this date will be updated. None for updating to the latest.

class qlib.workflow.online.utils.**OnlineToolR**(*default_exp_name: str = None*)
The implementation of OnlineTool based on (R)ecorder.

__init__(*default_exp_name: str = None*)
Init OnlineToolR.

Parameters **default_exp_name** (*str*) – the default experiment name.

set_online_tag(*tag, recorder: Union[qlib.workflow.recorder.Recorder, List[T]]*)
Set *tag* to the model's recorder to sign whether online.

Parameters

- **tag** (*str*) – the tags in *ONLINE_TAG*, *NEXT_ONLINE_TAG*, *OFFLINE_TAG*
- **recorder** (*Union[Recorder, List]*) – a list of Recorder or an instance of Recorder

get_online_tag(*recorder: qlib.workflow.recorder.Recorder*) → str
Given a model recorder and return its online tag.

Parameters **recorder** (`Recorder`) – an instance of recorder

Returns the online tag

Return type str

reset_online_tag(*recorder: Union[qlib.workflow.recorder.Recorder, List[T]], exp_name: str = None*)
Offline all models and set the recorders to 'online'.

Parameters

- **recorder** (*Union[Recorder, List]*) – the recorder you want to reset to 'online'.
- **exp_name** (*str*) – the experiment name. If None, then use default_exp_name.

online_models(*exp_name: str = None*) → list
Get current *online* models

Parameters **exp_name** (*str*) – the experiment name. If None, then use default_exp_name.

Returns a list of *online* models.

Return type list

update_online_pred(*to_date=None, from_date=None, exp_name: str = None*)
Update the predictions of online models to to_date.

Parameters

- **to_date** (*pd.Timestamp*) – the pred before this date will be updated. None for updating to latest time in Calendar.
- **exp_name** (*str*) – the experiment name. If None, then use default_exp_name.

RecordUpdater

Updater is a module to update artifacts such as predictions when the stock data is updating.

class qlib.workflow.online.update.**RMDLoader**(*rec: qlib.workflow.recorder.Recorder*)
Recorder Model Dataset Loader

__init__(*rec: qlib.workflow.recorder.Recorder*)
Initialize self. See help(type(self)) for accurate signature.

get_dataset(*start_time, end_time, segments=None, unprepared_dataset: Optional[qlib.data.dataset.DatasetH] = None*) → qlib.data.dataset.DatasetH
Load, config and setup dataset.

This dataset is for inference.

Parameters

- **start_time** – the start_time of underlying data
- **end_time** – the end_time of underlying data
- **segments** – dict the segments config for dataset Due to the time series dataset (TSDatasetH), the test segments maybe different from start_time and end_time
- **unprepared_dataset** – Optional[DatasetH] if user don't want to load dataset from recorder, please specify user's dataset

Returns the instance of DatasetH

Return type *DatasetH*

class qlib.workflow.online.update.**RecordUpdater**(*record: qlib.workflow.recorder.Recorder*, **args*, ***kwargs*)

Update a specific recorders

__init__(*record: qlib.workflow.recorder.Recorder*, **args*, ***kwargs*)
Initialize self. See help(type(self)) for accurate signature.

update(**args*, ***kwargs*)
Update info for specific recorder

class qlib.workflow.online.update.**DSBasedUpdater**(*record: qlib.workflow.recorder.Recorder*, *to_date=None*, *from_date=None*, *hist_ref: Optional[int] = None*, *freq='day'*, *fname='pred.pkl'*, *loader_cls: type = <class 'qlib.workflow.online.update.RMDLoader'>*)

Dataset-Based Updater

- Providing updating feature for Updating data based on Qlib Dataset

Assumption

- Based on Qlib dataset
- The data to be updated is a multi-level index pd.DataFrame. For example label, prediction.

__init__(*record: qlib.workflow.recorder.Recorder*, *to_date=None*, *from_date=None*, *hist_ref: Optional[int] = None*, *freq='day'*, *fname='pred.pkl'*, *loader_cls: type = <class 'qlib.workflow.online.update.RMDLoader'>*)
Init PredUpdater.

Expected behavior in following cases:

- if *to_date* is greater than the max date in the calendar, the data will be updated to the latest date
- if there are data before *from_date* or after *to_date*, only the data between *from_date* and *to_date* are affected.

Parameters

- **record** – Recorder
- **to_date** – update to prediction to the *to_date*

  if to_date is None:

    data will updated to the latest date.

- **from_date** – the update will start from *from_date*

  if from_date is None:

    the updating will occur on the next tick after the latest data in historical data

- **hist_ref** – int Sometimes, the dataset will have historical depends. Leave the problem to users to set the length of historical dependency If user doesn't specify this parameter, Updater will try to load dataset to automatically determine the hist_ref

Note: the start_time is not included in the *hist_ref*; So the *hist_ref* will be *step_len - 1* in most cases

- **loader_cls** – type the class to load the model and dataset

prepare_data(*unprepared_dataset: Optional[qlib.data.dataset.DatasetH] = None*) → qlib.data.dataset.DatasetH
Load dataset - if unprepared_dataset is specified, then prepare the dataset directly - Otherwise,

Separating this function will make it easier to reuse the dataset

Returns the instance of DatasetH

Return type DatasetH

update(*dataset: qlib.data.dataset.DatasetH = None*, *write: bool = True*, *ret_new: bool = False*) → Optional[object]

Parameters

- **dataset** (DatasetH) – DatasetH: the instance of DatasetH. None for prepare it again.
- **write** (*bool*) – will the the write action be executed
- **ret_new** (*bool*) – will the updated data be returned

Returns the updated dataset

Return type Optional[object]

get_update_data(*dataset: qlib.data.dataset.Dataset*) → pandas.core.frame.DataFrame
return the updated data based on the given dataset

The difference between *get_update_data* and *update* - *update_date* only include some data specific feature - *update* include some general routine steps(e.g. prepare dataset, checking)

class qlib.workflow.online.update.**PredUpdater**(*record: qlib.workflow.recorder.Recorder*, *to_date=None*, *from_date=None*, *hist_ref: Optional[int] = None*, *freq='day'*, *fname='pred.pkl'*, *loader_cls: type = <class 'qlib.workflow.online.update.RMDLoader'>*)
Update the prediction in the Recorder

get_update_data(*dataset: qlib.data.dataset.Dataset*) → pandas.core.frame.DataFrame
return the updated data based on the given dataset

The difference between *get_update_data* and *update* - *update_date* only include some data specific feature - *update* include some general routine steps(e.g. prepare dataset, checking)

class qlib.workflow.online.update.**LabelUpdater**(*record: qlib.workflow.recorder.Recorder*, *to_date=None*, ***kwargs*)
Update the label in the recorder

Assumption - The label is generated from record_temp.SignalRecord.

__init__(*record: qlib.workflow.recorder.Recorder*, *to_date=None*, ***kwargs*)
Init PredUpdater.

Expected behavior in following cases:

- if *to_date* is greater than the max date in the calendar, the data will be updated to the latest date
- if there are data before *from_date* or after *to_date*, only the data between *from_date* and *to_date* are affected.

Parameters

- **record** – Recorder

- **to_date** – update to prediction to the *to_date*

  if to_date is None:

  data will updated to the latest date.

- **from_date** – the update will start from *from_date*

  if from_date is None:

  the updating will occur on the next tick after the latest data in historical data

- **hist_ref** – int Sometimes, the dataset will have historical depends. Leave the problem to users to set the length of historical dependency If user doesn't specify this parameter, Updater will try to load dataset to automatically determine the hist_ref

  ---

  Note: the start_time is not included in the *hist_ref*; So the *hist_ref* will be *step_len - 1* in most cases

  ---

- **loader_cls** – type the class to load the model and dataset

get_update_data(*dataset: qlib.data.dataset.Dataset*) → pandas.core.frame.DataFrame
return the updated data based on the given dataset

The difference between *get_update_data* and *update* - *update_date* only include some data specific feature - *update* include some general routine steps(e.g. prepare dataset, checking)

1.24.6 Utils

Serializable

class qlib.utils.serial.**Serializable**
Serializable will change the behaviors of pickle.
The rule to tell if a attribute will be kept or dropped when dumping. The rule with higher priorities is on the top - in the config attribute list -> always dropped - in the include attribute list -> always kept - in the exclude attribute list -> always dropped - name not starts with _ -> kept - name starts with _ -> kept if *dump_all* is true else dropped

It provides a syntactic sugar for distinguish the attributes which user doesn't want. - For examples, a learnable Datahandler just wants to save the parameters without data when dumping to disk

__init__()
Initialize self. See help(type(self)) for accurate signature.

dump_all
will the object dump all object

config(*recursive=False*, ***kwargs*)
configure the serializable object

Parameters

- **may include following keys** (*kwargs*) –

  dump_all [bool] will the object dump all object

  exclude [list] What attribute will not be dumped

  include [list] What attribute will be dumped

- **recursive** (*bool*) – will the configuration be recursive

to_pickle(*path: Union[pathlib.Path, str], **kwargs*)
Dump self to a pickle file.

path (Union[Path, str]): the path to dump

kwargs may include following keys
dump_all [bool] will the object dump all object

exclude [list] What attribute will not be dumped

include [list] What attribute will be dumped

classmethod load(*filepath*)
Load the serializable class from a filepath.
Parameters **filepath** (`str`) – the path of file

Raises `TypeError` – the pickled file must be *type(cls)*

Returns the instance of *type(cls)*

Return type *type(cls)*

classmethod get_backend()
Return the real backend of a Serializable class. The pickle_backend value can be "pickle" or "dill".
Returns pickle or dill module based on pickle_backend

Return type module

static general_dump(*obj, path: Union[pathlib.Path, str]*)
A general dumping method for object
Parameters

- **obj** (`object`) – the object to be dumped
- **path** (`Union[Path, str]`) – the target path the data will be dumped

1.24.7 RL

Base Component

class `qlib.rl.`**Interpreter**
Interpreter is a media between states produced by simulators and states needed by RL policies. Interpreters are two-way:

1. From simulator state to policy state (aka observation), see `StateInterpreter`.
2. From policy action to action accepted by simulator, see `ActionInterpreter`.

Inherit one of the two sub-classes to define your own interpreter. This super-class is only used for isinstance check.

Interpreters are recommended to be stateless, meaning that storing temporary information with `self.xxx` in interpreter is anti-pattern. In future, we might support register some interpreter-related states by calling `self.env.register_state()`, but it's not planned for first iteration.

class `qlib.rl.`**StateInterpreter**
State Interpreter that interpret execution result of qlib executor into rl env state

validate(*obs: ObsType*) → None
Validate whether an observation belongs to the pre-defined observation space.

interpret(*simulator_state: StateType*) → ObsType
Interpret the state of simulator.

Parameters **`simulator_state`** – Retrieved with `simulator.get_state()`.

Returns

Return type State needed by policy. Should conform with the state space defined in `observation_space`.

class `qlib.rl.`**`ActionInterpreter`**

Action Interpreter that interpret rl agent action into qlib orders

`validate`(*action: PolicyActType*) → None

Validate whether an action belongs to the pre-defined action space.

`interpret`(*simulator_state: StateType*, *action: PolicyActType*) → ActType

Convert the policy action to simulator action.

Parameters

- **`simulator_state`** – Retrieved with `simulator.get_state()`.
- **`action`** – Raw action given by policy.

Returns

Return type The action needed by simulator,

class `qlib.rl.`**`Reward`**

Reward calculation component that takes a single argument: state of simulator. Returns a real number: reward.

Subclass should implement `reward(simulator_state)` to implement their own reward calculation recipe.

`reward`(*simulator_state: SimulatorState*) → float

Implement this method for your own reward.

class `qlib.rl.`**`RewardCombination`**(*rewards: Dict[str, Tuple[qlib.rl.reward.Reward, float]]*)

Combination of multiple reward.

`__init__`(*rewards: Dict[str, Tuple[qlib.rl.reward.Reward, float]]*) → None

Initialize self. See help(type(self)) for accurate signature.

`reward`(*simulator_state: Any*) → float

Implement this method for your own reward.

class `qlib.rl.`**`Simulator`**(*initial: InitialStateType*, ***kwargs*)

Simulator that resets with `__init__`, and transits with `step(action)`.

To make the data-flow clear, we make the following restrictions to Simulator:

1. The only way to modify the inner status of a simulator is by using `step(action)`.
2. External modules can *read* the status of a simulator by using `simulator.get_state()`, and check whether the simulator is in the ending state by calling `simulator.done()`.

A simulator is defined to be bounded with three types:

- *InitialStateType* that is the type of the data used to create the simulator.
- *StateType* that is the type of the **status** (state) of the simulator.
- *ActType* that is the type of the **action**, which is the input received in each step.

Different simulators might share the same StateType. For example, when they are dealing with the same task, but with different simulation implementation. With the same type, they can safely share other components in the MDP.

Simulators are ephemeral. The lifecycle of a simulator starts with an initial state, and ends with the trajectory. In another word, when the trajectory ends, simulator is recycled. If simulators want to share context between (e.g., for speed-up purposes), this could be done by accessing the weak reference of environment wrapper.

env
A reference of env-wrapper, which could be useful in some corner cases. Simulators are discouraged to use this, because it's prone to induce errors.

__init__(*initial: InitialStateType*, ***kwargs*) → None
Initialize self. See help(type(self)) for accurate signature.

step(*action: ActType*) → None
Receives an action of ActType.

Simulator should update its internal state, and return None. The updated state can be retrieved with `simulator.get_state()`.

done() → bool
Check whether the simulator is in a "done" state. When simulator is in a "done" state, it should no longer receives any `step` request. As simulators are ephemeral, to reset the simulator, the old one should be destroyed and a new simulator can be created.

Strategy

class qlib.rl.strategy.**SingleOrderStrategy**(*order: qlib.backtest.decision.Order*, *trade_range: qlib.backtest.decision.TradeRange = None*)
Strategy used to generate a trade decision with exactly one order.

__init__(*order: qlib.backtest.decision.Order*, *trade_range: qlib.backtest.decision.TradeRange = None*) → None

Parameters

- **outer_trade_decision** (*BaseTradeDecision, optional*) – the trade decision of outer strategy which this strategy relies, and it will be traded in [start_time, end_time], by default None
  - If the strategy is used to split trade decision, it will be used
  - If the strategy is used for portfolio management, it can be ignored
- **level_infra** (*LevelInfrastructure, optional*) – level shared infrastructure for backtesting, including trade calendar
- **common_infra** (*CommonInfrastructure, optional*) – common infrastructure for backtesting, including trade_account, trade_exchange, .etc
- **trade_exchange** (*Exchange*) – exchange that provides market info, used to deal order and generate report
  - If *trade_exchange* is None, self.trade_exchange will be set with common_infra
  - It allows different trade_exchanges is used in different executions.
  - For example:
    * In daily execution, both daily exchange and minutely are usable, but the daily exchange is recommended because it run faster.
    * In minutely execution, the daily exchange is not usable, only the minutely exchange is recommended.

generate_trade_decision(*execute_result: list = None*) → qlib.backtest.decision.TradeDecisionWO
Generate trade decision in each trading bar

Parameters **execute_result** (*List[object], optional*) – the executed result for trade decision, by default None

- When call the generate_trade_decision firstly, *execute_result* could be None

Trainer

Train, test, inference utilities.

class qlib.rl.trainer.**Trainer**(**, max_iters: int | None = None, val_every_n_iters: int | None = None, loggers: LogWriter | List[LogWriter] | None = None, callbacks: List[Callback] | None = None, finite_env_type: FiniteEnvType = 'subproc', concurrency: int = 2, fast_dev_run: int | None = None*)

Utility to train a policy on a particular task.

Different from traditional DL trainer, the iteration of this trainer is "collect", rather than "epoch", or "mini-batch". In each collect, `Collector` collects a number of policy-env interactions, and accumulates them into a replay buffer. This buffer is used as the "data" to train the policy. At the end of each collect, the policy is *updated* several times.

The API has some resemblence with PyTorch Lightning, but it's essentially different because this trainer is built for RL applications, and thus most configurations are under RL context. We are still looking for ways to incorporate existing trainer libraries, because it looks like big efforts to build a trainer as powerful as those libraries, and also, that's not our primary goal.

It's essentially different tianshou's built-in trainers, as it's far much more complicated than that.

Parameters

- **max_iters** – Maximum iterations before stopping.
- **val_every_n_iters** – Perform validation every n iterations (i.e., training collects).
- **logger** – Logger to record the backtest results. Logger must be present because without logger, all information will be lost.
- **finite_env_type** – Type of finite env implementation.
- **concurrency** – Parallel workers.
- **fast_dev_run** – Create a subset for debugging. How this is implemented depends on the implementation of training vessel. For `TrainingVessel`, if greater than zero, a random subset sized `fast_dev_run` will be used instead of `train_initial_states` and `val_initial_states`.

should_stop = None

Set to stop the training.

metrics = None

Numeric metrics of produced in train/val/test. In the middle of training / validation, metrics will be of the latest episode. When each iteration of training / validation finishes, metrics will be the aggregation of all episodes encountered in this iteration.

Cleared on every new iteration of training.

In fit, validation metrics will be prefixed with `val/`.

current_iter = None

Current iteration (collect) of training.

__init__(**, max_iters: int | None = None, val_every_n_iters: int | None = None, loggers: LogWriter | List[LogWriter] | None = None, callbacks: List[Callback] | None = None, finite_env_type: FiniteEnvType = 'subproc', concurrency: int = 2, fast_dev_run: int | None = None*)
Initialize self. See help(type(self)) for accurate signature.

loggers = None
A list of log writers.

initialize()
Initialize the whole training process.

The states here should be synchronized with state_dict.

initialize_iter()
Initialize one iteration / collect.

state_dict() → dict
Putting every states of current training into a dict, at best effort.

It doesn't try to handle all the possible kinds of states in the middle of one training collect. For most cases at the end of each iteration, things should be usually correct.

Note that it's also intended behavior that replay buffer data in the collector will be lost.

load_state_dict(*state_dict: dict*) → None
Load all states into current trainer.

named_callbacks() → Dict[str, qlib.rl.trainer.callbacks.Callback]
Retrieve a collection of callbacks where each one has a name. Useful when saving checkpoints.

named_loggers() → Dict[str, qlib.rl.utils.log.LogWriter]
Retrieve a collection of loggers where each one has a name. Useful when saving checkpoints.

fit(*vessel: TrainingVesselBase, ckpt_path: Path | None = None*) → None
Train the RL policy upon the defined simulator.

Parameters

- **vessel** – A bundle of all elements used in training.
- **ckpt_path** – Load a pre-trained / paused training checkpoint.

test(*vessel: qlib.rl.trainer.vessel.TrainingVesselBase*) → None
Test the RL policy against the simulator.

The simulator will be fed with data generated in `test_seed_iterator`.

Parameters **vessel** – A bundle of all related elements.

venv_from_iterator(*iterator: Iterable[InitialStateType]*) → qlib.rl.utils.finite_env.FiniteVectorEnv
Create a vectorized environment from iterator and the training vessel.

class qlib.rl.trainer.**TrainingVessel**(**, simulator_fn: Callable[[InitialStateType], Simulator[InitialStateType, StateType, ActType]], state_interpreter: StateInterpreter[StateType, ObsType], action_interpreter: ActionInterpreter[StateType, PolicyActType, ActType], policy: BasePolicy, reward: Reward, train_initial_states: Sequence[InitialStateType] | None = None, val_initial_states: Sequence[InitialStateType] | None = None, test_initial_states: Sequence[InitialStateType] | None = None, buffer_size: int = 20000, episode_per_iter: int = 1000, update_kwargs: Dict[str, Any] = None*)

The default implementation of training vessel.

`__init__` accepts a sequence of initial states so that iterator can be created. `train`, `validate`, `test` each do one collect (and also update in train). By default, the train initial states will be repeated infinitely during training, and collector will control the number of episodes for each iteration. In validation and testing, the val / test initial states will be used exactly once.

Extra hyper-parameters (only used in train) include:

- `buffer_size`: Size of replay buffer.
- `episode_per_iter`: Episodes per collect at training. Can be overridden by fast dev run.
- `update_kwargs`: Keyword arguments appearing in `policy.update`. For example, `dict(repeat=10, batch_size=64)`.

`__init__`(**, simulator_fn: Callable[[InitialStateType], Simulator[InitialStateType, StateType, ActType]], state_interpreter: StateInterpreter[StateType, ObsType], action_interpreter: ActionInterpreter[StateType, PolicyActType, ActType], policy: BasePolicy, reward: Reward, train_initial_states: Sequence[InitialStateType] | None = None, val_initial_states: Sequence[InitialStateType] | None = None, test_initial_states: Sequence[InitialStateType] | None = None, buffer_size: int = 20000, episode_per_iter: int = 1000, update_kwargs: Dict[str, Any] = None*)

Initialize self. See help(type(self)) for accurate signature.

`train_seed_iterator`() → ContextManager[Iterable[InitialStateType]] | Iterable[InitialStateType]

Override this to create a seed iterator for training. If the iterable is a context manager, the whole training will be invoked in the with-block, and the iterator will be automatically closed after the training is done.

`val_seed_iterator`() → ContextManager[Iterable[InitialStateType]] | Iterable[InitialStateType]

Override this to create a seed iterator for validation.

`test_seed_iterator`() → ContextManager[Iterable[InitialStateType]] | Iterable[InitialStateType]

Override this to create a seed iterator for testing.

`train`(*vector_env: qlib.rl.utils.finite_env.FiniteVectorEnv*) → Dict[str, Any]

Create a collector and collects `episode_per_iter` episodes. Update the policy on the collected replay buffer.

`validate`(*vector_env: qlib.rl.utils.finite_env.FiniteVectorEnv*) → Dict[str, Any]

Implement this to validate the policy once.

`test`(*vector_env: qlib.rl.utils.finite_env.FiniteVectorEnv*) → Dict[str, Any]

Implement this to evaluate the policy on test environment once.

class `qlib.rl.trainer.`**`TrainingVesselBase`**

A ship that contains simulator, interpreter, and policy, will be sent to trainer. This class controls algorithm-related parts of training, while trainer is responsible for runtime part.

The ship also defines the most important logic of the core training part, and (optionally) some callbacks to insert customized logics at specific events.

`train_seed_iterator`() → ContextManager[Iterable[InitialStateType]] | Iterable[InitialStateType]

Override this to create a seed iterator for training. If the iterable is a context manager, the whole training will be invoked in the with-block, and the iterator will be automatically closed after the training is done.

`val_seed_iterator`() → ContextManager[Iterable[InitialStateType]] | Iterable[InitialStateType]

Override this to create a seed iterator for validation.

`test_seed_iterator`() → ContextManager[Iterable[InitialStateType]] | Iterable[InitialStateType]

Override this to create a seed iterator for testing.

train (*vector_env: tianshou.env.venvs.BaseVectorEnv*) → Dict[str, Any]
Implement this to train one iteration. In RL, one iteration usually refers to one collect.

validate (*vector_env: qlib.rl.utils.finite_env.FiniteVectorEnv*) → Dict[str, Any]
Implement this to validate the policy once.

test (*vector_env: qlib.rl.utils.finite_env.FiniteVectorEnv*) → Dict[str, Any]
Implement this to evaluate the policy on test environment once.

state_dict () → Dict[KT, VT]
Return a checkpoint of current vessel state.

load_state_dict (*state_dict: Dict[KT, VT]*) → None
Restore a checkpoint from a previously saved state dict.

class qlib.rl.trainer.**Checkpoint** (*dirpath: Path, filename: str = '{iter:03d}.pth', save_latest: Literal['link', 'copy')] | None = 'link', every_n_iters: int | None = None, time_interval: int | None = None, save_on_fit_end: bool = True*)
Save checkpoints periodically for persistence and recovery.

Reference: https://github.com/PyTorchLightning/pytorch-lightning/blob/bfa8b7be/pytorch_lightning/callbacks/model_checkpoint.py

Parameters

- **dirpath** – Directory to save the checkpoint file.
- **filename** – Checkpoint filename. Can contain named formatting options to be auto-filled. For example: `{iter:03d}-{reward:.2f}.pth`. Supported argument names are:
  - iter (int)
  - metrics in `trainer.metrics`
  - time string, in the format of `%Y%m%d%H%M%S`
- **save_latest** – Save the latest checkpoint in `latest.pth`. If `link`, `latest.pth` will be created as a softlink. If `copy`, `latest.pth` will be stored as an individual copy. Set to none to disable this.
- **every_n_iters** – Checkpoints are saved at the end of every n iterations of training, after validation if applicable.
- **time_interval** – Maximum time (seconds) before checkpoints save again.
- **save_on_fit_end** – Save one last checkpoint at the end to fit. Do nothing if a checkpoint is already saved there.

__init__ (*dirpath: Path, filename: str = '{iter:03d}.pth', save_latest: Literal['link', 'copy')] | None = 'link', every_n_iters: int | None = None, time_interval: int | None = None, save_on_fit_end: bool = True*)
Initialize self. See help(type(self)) for accurate signature.

on_fit_end (*trainer: Trainer, vessel: TrainingVesselBase*) → None
Called after the whole fit process ends.

on_iter_end (*trainer: Trainer, vessel: TrainingVesselBase*) → None
Called upon every end of iteration. This is called **after** the bump of `current_iter`, when the previous iteration is considered complete.

class qlib.rl.trainer.**EarlyStopping**(*monitor: str = 'reward', min_delta: float = 0.0, patience: int = 0, mode: Literal[('min', 'max')] = 'max', baseline: float | None = None, restore_best_weights: bool = False*)

Stop training when a monitored metric has stopped improving.

The earlystopping callback will be triggered each time validation ends. It will examine the metrics produced in validation, and get the metric with name `monitor`` (``monitor` is `reward` by default), to check whether it's no longer increasing / decreasing. It takes `min_delta` and `patience` if applicable. If it's found to be not increasing / decreasing any more. `trainer.should_stop` will be set to true, and the training terminates.

Implementation reference: https://github.com/keras-team/keras/blob/v2.9.0/keras/callbacks.py#L1744-L1893

__init__(*monitor: str = 'reward', min_delta: float = 0.0, patience: int = 0, mode: Literal[('min', 'max')] = 'max', baseline: float | None = None, restore_best_weights: bool = False*)

Initialize self. See help(type(self)) for accurate signature.

state_dict() → dict

Get a state dict of the callback for pause and resume.

load_state_dict(*state_dict: dict*) → None

Resume the callback from a saved state dict.

on_fit_start(*trainer: Trainer, vessel: TrainingVesselBase*) → None

Called before the whole fit process begins.

on_validate_end(*trainer: Trainer, vessel: TrainingVesselBase*) → None

Called when the validation ends.

qlib.rl.trainer.**train**(*simulator_fn: Callable[[InitialStateType], qlib.rl.simulator.Simulator], state_interpreter: qlib.rl.interpreter.StateInterpreter, action_interpreter: qlib.rl.interpreter.ActionInterpreter, initial_states: Sequence[InitialStateType], policy: tianshou.policy.base.BasePolicy, reward: qlib.rl.reward.Reward, vessel_kwargs: Dict[str, Any], trainer_kwargs: Dict[str, Any]*) → None

Train a policy with the parallelism provided by RL framework.

Experimental API. Parameters might change shortly.

Parameters

- **simulator_fn** – Callable receiving initial seed, returning a simulator.
- **state_interpreter** – Interprets the state of simulators.
- **action_interpreter** – Interprets the policy actions.
- **initial_states** – Initial states to iterate over. Every state will be run exactly once.
- **policy** – Policy to train against.
- **reward** – Reward function.
- **vessel_kwargs** – Keyword arguments passed to *TrainingVessel*, like `episode_per_iter`.
- **trainer_kwargs** – Keyword arguments passed to *Trainer*, like `finite_env_type`, `concurrency`.

qlib.rl.trainer.**backtest**(*simulator_fn: Callable[[InitialStateType], Simulator], state_interpreter: StateInterpreter, action_interpreter: ActionInterpreter, initial_states: Sequence[InitialStateType], policy: BasePolicy, logger: LogWriter | List[LogWriter], reward: Reward | None = None, finite_env_type: FiniteEnvType = 'subproc', concurrency: int = 2*) → None

Backtest with the parallelism provided by RL framework.

Experimental API. Parameters might change shortly.

Parameters

- **simulator_fn** – Callable receiving initial seed, returning a simulator.
- **state_interpreter** – Interprets the state of simulators.
- **action_interpreter** – Interprets the policy actions.
- **initial_states** – Initial states to iterate over. Every state will be run exactly once.
- **policy** – Policy to test against.
- **logger** – Logger to record the backtest results. Logger must be present because without logger, all information will be lost.
- **reward** – Optional reward function. For backtest, this is for testing the rewards and logging them only.
- **finite_env_type** – Type of finite env implementation.
- **concurrency** – Parallel workers.

Order Execution

Currently it supports single-asset order execution. Multi-asset is on the way.

class qlib.rl.order_execution.**FullHistoryStateInterpreter**(*max_step: int*, *data_ticks: int*, *data_dim: int*, *processed_data_provider: dict | ProcessedDataProvider*)

The observation of all the history, including today (until this moment), and yesterday.

Parameters

- **max_step** – Total number of steps (an upper-bound estimation). For example, 390min / 30min-per-step = 13 steps.
- **data_ticks** – Equal to the total number of records. For example, in SAOE per minute, the total ticks is the length of day in minutes.
- **data_dim** – Number of dimensions in data.
- **processed_data_provider** – Provider of the processed data.

__init__(*max_step: int*, *data_ticks: int*, *data_dim: int*, *processed_data_provider: dict | ProcessedDataProvider*) → None

Initialize self. See help(type(self)) for accurate signature.

interpret(*state: qlib.rl.order_execution.state.SAOEState*) → qlib.rl.order_execution.interpreter.FullHistoryObs

Interpret the state of simulator.

Parameters **simulator_state** – Retrieved with `simulator.get_state()`.

Returns

Return type State needed by policy. Should conform with the state space defined in `observation_space`.

class qlib.rl.order_execution.**CurrentStepStateInterpreter**(*max_step: int*)

The observation of current step.

Used when policy only depends on the latest state, but not history. The key list is not full. You can add more if more information is needed by your policy.

__init__(*max_step: int*) → None
Initialize self. See help(type(self)) for accurate signature.

interpret(*state: qlib.rl.order_execution.state.SAOEState*) → qlib.rl.order_execution.interpreter.CurrentStateObs
Interpret the state of simulator.

Parameters **simulator_state** – Retrieved with `simulator.get_state()`.

Returns

Return type State needed by policy. Should conform with the state space defined in `observation_space`.

class qlib.rl.order_execution.**CategoricalActionInterpreter**(*values: int | List[float], max_step: Optional[int] = None*)
Convert a discrete policy action to a continuous action, then multiplied by `order.amount`.

Parameters

- **values** – It can be a list of length L: $[a_1, a_2, ldots, a_L]$. Then when policy givens decision x, a_x times order amount is the output. It can also be an integer n, in which case the list of length $n+1$ is auto-generated, i.e., $[0, 1/n, 2/n, ldots, n/n]$.
- **max_step** – Total number of steps (an upper-bound estimation). For example, 390min / 30min-per-step = 13 steps.

__init__(*values: int | List[float], max_step: Optional[int] = None*) → None
Initialize self. See help(type(self)) for accurate signature.

interpret(*state: qlib.rl.order_execution.state.SAOEState, action: int*) → float
Convert the policy action to simulator action.

Parameters

- **simulator_state** – Retrieved with `simulator.get_state()`.
- **action** – Raw action given by policy.

Returns

Return type The action needed by simulator,

class qlib.rl.order_execution.**TwapRelativeActionInterpreter**
Convert a continuous ratio to deal amount.

The ratio is relative to TWAP on the remainder of the day. For example, there are 5 steps left, and the left position is 300. With TWAP strategy, in each position, 60 should be traded. When this interpreter receives action a, its output is $60 cdot a$.

interpret(*state: qlib.rl.order_execution.state.SAOEState, action: float*) → float
Convert the policy action to simulator action.

Parameters

- **simulator_state** – Retrieved with `simulator.get_state()`.
- **action** – Raw action given by policy.

Returns

Return type The action needed by simulator,

class qlib.rl.order_execution.**Recurrent**(*obs_space: qlib.rl.order_execution.interpreter.FullHistoryObs*, *hidden_dim: int = 64*, *output_dim: int = 32*, *rnn_type: typing_extensions.Literal['rnn', 'lstm', 'gru'][rnn, lstm, gru] = 'gru'*, *rnn_num_layers: int = 1*)

The network architecture proposed in OPD.

At every time step the input of policy network is divided into two parts, the public variables and the private variables. which are handled by `raw_rnn` and `pri_rnn` in this network, respectively.

One minor difference is that, in this implementation, we don't assume the direction to be fixed. Thus, another `dire_fc` is added to produce an extra direction-related feature.

__init__(*obs_space: qlib.rl.order_execution.interpreter.FullHistoryObs*, *hidden_dim: int = 64*, *output_dim: int = 32*, *rnn_type: typing_extensions.Literal['rnn', 'lstm', 'gru'][rnn, lstm, gru] = 'gru'*, *rnn_num_layers: int = 1*) → None

Initializes internal Module state, shared by both nn.Module and ScriptModule.

forward(*batch: tianshou.data.batch.Batch*) → torch.Tensor

Input should be a dict (at least) containing:

- data_processed: [N, T, C]
- cur_step: [N] (int)
- cur_time: [N] (int)
- position_history: [N, S] (S is number of steps)
- target: [N]
- num_step: [N] (int)
- acquiring: [N] (0 or 1)

class qlib.rl.order_execution.**AllOne**(*obs_space: gym.spaces.space.Space*, *action_space: gym.spaces.space.Space*)

Forward returns a batch full of 1.

Useful when implementing some baselines (e.g., TWAP).

forward(*batch: Batch*, *state: dict | Batch | np.ndarray = None*, ***kwargs*) → Batch

Compute action over the given batch data.

Returns

A `Batch` which MUST have the following keys:

- `act` an numpy.ndarray or a torch.Tensor, the action over given batch data.
- `state` a dict, an numpy.ndarray or a torch.Tensor, the internal state of the policy, `None` as default.

Other keys are user-defined. It depends on the algorithm. For example,

```
# some code
return Batch(logits=..., act=..., state=None, dist=...)
```

The keyword `policy` is reserved and the corresponding data will be stored into the replay buffer. For instance,

```
# some code
return Batch(..., policy=Batch(log_prob=dist.log_prob(act)))
# and in the sampled data batch, you can directly use
# batch.policy.log_prob to get your data.
```

Note: In continuous action space, you should do another step "map_action" to get the real action:

```
act = policy(batch).act  # doesn't map to the target action range
act = policy.map_action(act, batch)
```

class qlib.rl.order_execution.**PPO**(*network: torch.nn.modules.module.Module, obs_space: gym.spaces.space.Space, action_space: gym.spaces.space.Space, lr: float, weight_decay: float = 0.0, discount_factor: float = 1.0, max_grad_norm: float = 100.0, reward_normalization: bool = True, eps_clip: float = 0.3, value_clip: bool = True, vf_coef: float = 1.0, gae_lambda: float = 1.0, max_batch_size: int = 256, deterministic_eval: bool = True, weight_file: Optional[pathlib.Path] = None*)

A wrapper of tianshou PPOPolicy.

Differences:

- Auto-create actor and critic network. Supports discrete action space only.
- Dedup common parameters between actor network and critic network (not sure whether this is included in latest tianshou or not).
- Support a `weight_file` that supports loading checkpoint.
- Some parameters' default values are different from original.

__init__(*network: torch.nn.modules.module.Module, obs_space: gym.spaces.space.Space, action_space: gym.spaces.space.Space, lr: float, weight_decay: float = 0.0, discount_factor: float = 1.0, max_grad_norm: float = 100.0, reward_normalization: bool = True, eps_clip: float = 0.3, value_clip: bool = True, vf_coef: float = 1.0, gae_lambda: float = 1.0, max_batch_size: int = 256, deterministic_eval: bool = True, weight_file: Optional[pathlib.Path] = None*) → None

Initialize self. See help(type(self)) for accurate signature.

class qlib.rl.order_execution.**PAPenaltyReward**(*penalty: float = 100.0*)

Encourage higher PAs, but penalize stacking all the amounts within a very short time. Formally, for each time step, the reward is $(PA_t * vol_t / target - vol_t^2 * penalty)$.

Parameters **penalty** – The penalty for large volume in a short time.

__init__(*penalty: float = 100.0*)

Initialize self. See help(type(self)) for accurate signature.

reward(*simulator_state: qlib.rl.order_execution.state.SAOEState*) → float

Implement this method for your own reward.

class qlib.rl.order_execution.**SingleAssetOrderExecutionSimple**(*order: qlib.backtest.decision.Order, data_dir: pathlib.Path, ticks_per_step: int = 30, deal_price_type: typing_extensions.Literal['bid_or_ask', 'bid_or_ask_fill', 'close'][bid_or_ask, bid_or_ask_fill, close] = 'close', vol_threshold: Optional[float] = None*)

Single-asset order execution (SAOE) simulator.

As there's no "calendar" in the simple simulator, ticks are used to trade. A tick is a record (a line) in the pickle-styled data file. Each tick is considered as a individual trading opportunity. If such fine granularity is not needed, use `ticks_per_step` to lengthen the ticks for each step.

In each step, the traded amount are "equally" separated to each tick, then bounded by volume maximum execution volume (i.e., `vol_threshold`), and if it's the last step, try to ensure all the amount to be executed.

Parameters

- **order** – The seed to start an SAOE simulator is an order.
- **ticks_per_step** – How many ticks per step.
- **data_dir** – Path to load backtest data
- **vol_threshold** – Maximum execution volume (divided by market execution volume).

__init__(*order: qlib.backtest.decision.Order*, *data_dir: pathlib.Path*, *ticks_per_step: int = 30*, *deal_price_type: typing_extensions.Literal['bid_or_ask', 'bid_or_ask_fill', 'close'][bid_or_ask, bid_or_ask_fill, close] = 'close'*, *vol_threshold: Optional[float] = None*) → None

Initialize self. See help(type(self)) for accurate signature.

ticks_index = None

All available ticks for the day (not restricted to order).

ticks_for_order = None

Ticks that is available for trading (sliced by order).

twap_price = None

This price is used to compute price advantage. It"s defined as the average price in the period from order"s start time to end time.

history_exec = None

All execution history at every possible time ticks. See *SAOEMetrics* for available columns. Index is `datetime`.

history_steps = None

Positions at each step. The position before first step is also recorded. See *SAOEMetrics* for available columns. Index is `datetime`, which is the **starting** time of each step.

metrics = None

Metrics. Only available when done.

step(*amount: float*) → None

Execute one step or SAOE.

Parameters **amount** – The amount you wish to deal. The simulator doesn't guarantee all the amount to be successfully dealt.

done() → bool

Check whether the simulator is in a "done" state. When simulator is in a "done" state, it should no longer receives any `step` request. As simulators are ephemeral, to reset the simulator, the old one should be destroyed and a new simulator can be created.

class qlib.rl.order_execution.**SAOEStateAdapter**(*order: qlib.backtest.decision.Order, trade_decision: qlib.backtest.decision.BaseTradeDecision, executor: qlib.backtest.executor.BaseExecutor, exchange: qlib.backtest.exchange.Exchange, ticks_per_step: int, backtest_data: qlib.rl.data.native.IntradayBacktestData*)

Maintain states of the environment. SAOEStateAdapter accepts execution results and update its internal state according to the execution results with additional information acquired from executors & exchange. For example, it gets the dealt order amount from execution results, and get the corresponding market price / volume from exchange.

Example usage:

```
adapter = SAOEStateAdapter(...)
adapter.update(...)
state = adapter.saoe_state
```

__init__(*order: qlib.backtest.decision.Order, trade_decision: qlib.backtest.decision.BaseTradeDecision, executor: qlib.backtest.executor.BaseExecutor, exchange: qlib.backtest.exchange.Exchange, ticks_per_step: int, backtest_data: qlib.rl.data.native.IntradayBacktestData*) → None

Initialize self. See help(type(self)) for accurate signature.

generate_metrics_after_done() → None

Generate metrics once the upper level execution is done

class qlib.rl.order_execution.**SAOEMetrics**

Metrics for SAOE accumulated for a "period". It could be accumulated for a day, or a period of time (e.g., 30min), or calculated separately for every minute.

> **Warning:** The type hints are for single elements. In lots of times, they can be vectorized. For example, `market_volume` could be a list of float (or ndarray) rather tahn a single float.

stock_id = None

Stock ID of this record.

datetime = None

Datetime of this record (this is index in the dataframe).

direction = None

Direction of the order. 0 for sell, 1 for buy.

market_volume = None

(total) market volume traded in the period.

market_price = None

Deal price. If it's a period of time, this is the average market deal price.

amount = None

Total amount (volume) strategy intends to trade.

inner_amount = None

Total amount that the lower-level strategy intends to trade (might be larger than amount, e.g., to ensure ffr).

deal_amount = None
Amount that successfully takes effect (must be less than inner_amount).

trade_price = None
The average deal price for this strategy.

trade_value = None
Total worth of trading. In the simple simulation, trade_value = deal_amount * price.

position = None
Position left after this "period".

ffr = None
Completed how much percent of the daily order.

pa = None
Price advantage compared to baseline (i.e., trade with baseline market price). The baseline is trade price when using TWAP strategy to execute this order. Please note that there could be data leak here). Unit is BP (basis point, 1/10000).

class `qlib.rl.order_execution.`**SAOEState**
Data structure holding a state for SAOE simulator.

order
The order we are dealing with.

cur_time
30.

Type Current time, e.g., 9

cur_step
Current step, e.g., 0.

position
Current remaining volume to execute.

history_exec
See `SingleAssetOrderExecution.history_exec`.

history_steps
See `SingleAssetOrderExecution.history_steps`.

metrics
Daily metric, only available when the trading is in "done" state.

backtest_data
Backtest data is included in the state. Actually, only the time index of this data is needed, at this moment. I include the full data so that algorithms (e.g., VWAP) that relies on the raw data can be implemented. Interpreter can use this as they wish, but they should be careful not to leak future data.

ticks_per_step
How many ticks for each step.

ticks_index
31, …, 14:59].

Type Trading ticks in all day, NOT sliced by order (defined in data) e.g., [9

Type 30, 9

ticks_for_order
46, …, 14:44].

Type Trading ticks sliced by order, e.g., [9

Type 45, 9

class qlib.rl.order_execution.**SAOEStrategy**(*policy: tianshou.policy.base.BasePolicy, outer_trade_decision: Optional[qlib.backtest.decision.BaseTradeDecision] = None, level_infra: Optional[qlib.backtest.utils.LevelInfrastructure] = None, common_infra: Optional[qlib.backtest.utils.CommonInfrastructure] = None, **kwargs*)

RL-based strategies that use SAOEState as state.

__init__(*policy: tianshou.policy.base.BasePolicy, outer_trade_decision: Optional[qlib.backtest.decision.BaseTradeDecision] = None, level_infra: Optional[qlib.backtest.utils.LevelInfrastructure] = None, common_infra: Optional[qlib.backtest.utils.CommonInfrastructure] = None, **kwargs*) → None

Parameters **policy** – RL policy for generate action

reset(*outer_trade_decision: Optional[qlib.backtest.decision.BaseTradeDecision] = None, **kwargs*) → None

- reset *level_infra*, used to reset trade calendar, .etc
- reset *common_infra*, used to reset *trade_account*, *trade_exchange*, .etc
- reset *outer_trade_decision*, used to make split decision

NOTE: split this function into *reset* and *_reset* will make following cases more convenient 1. Users want to initialize his strategy by overriding *reset*, but they don't want to affect the *_reset* called when initialization

post_upper_level_exe_step() → None

A hook for doing sth after the upper level executor finished its execution (for example, finalize the metrics collection).

post_exe_step(*execute_result: Optional[list]*) → None

A hook for doing sth after the corresponding executor finished its execution.

Parameters **execute_result** – the execution result

generate_trade_decision(*execute_result: Optional[list] = None*) → Union[qlib.backtest.decision.BaseTradeDecision, Generator[Any, Any, qlib.backtest.decision.BaseTradeDecision]]

For SAOEStrategy, we need to update the *self._last_step_range* every time a decision is generated. This operation should be invisible to developers, so we implement it in *generate_trade_decision()* The concrete logic to generate decisions should be implemented in *_generate_trade_decision()*. In other words, all subclass of *SAOEStrategy* should overwrite *_generate_trade_decision()* instead of *generate_trade_decision()*.

class qlib.rl.order_execution.**ProxySAOEStrategy**(*outer_trade_decision: Optional[qlib.backtest.decision.BaseTradeDecision] = None, level_infra: Optional[qlib.backtest.utils.LevelInfrastructure] = None, common_infra: Optional[qlib.backtest.utils.CommonInfrastructure] = None, **kwargs*)

Proxy strategy that uses SAOEState. It is called a 'proxy' strategy because it does not make any decisions by itself. Instead, when the strategy is required to generate a decision, it will yield the environment's information and let the outside agents to make the decision. Please refer to *_generate_trade_decision* for more details.

__init__(*outer_trade_decision: Optional[qlib.backtest.decision.BaseTradeDecision] = None, level_infra: Optional[qlib.backtest.utils.LevelInfrastructure] = None, common_infra: Optional[qlib.backtest.utils.CommonInfrastructure] = None, **kwargs*) → None

Parameters **policy** – RL policy for generate action

reset(*outer_trade_decision: Optional[qlib.backtest.decision.BaseTradeDecision] = None*, ***kwargs*) → None

- reset *level_infra*, used to reset trade calendar, .etc
- reset *common_infra*, used to reset *trade_account*, *trade_exchange*, .etc
- reset *outer_trade_decision*, used to make split decision

NOTE: split this function into *reset* and *_reset* will make following cases more convenient 1. Users want to initialize his strategy by overriding *reset*, but they don't want to affect the *_reset* called when initialization

class qlib.rl.order_execution.**SAOEIntStrategy**(*policy: dict | BasePolicy*, *state_interpreter: dict | StateInterpreter*, *action_interpreter: dict | ActionInterpreter*, *network: dict | torch.nn.Module | None = None*, *outer_trade_decision: BaseTradeDecision = None*, *level_infra: LevelInfrastructure = None*, *common_infra: CommonInfrastructure = None*, ***kwargs*)

(SAOE)state based strategy with (Int)preters.

__init__(*policy: dict | BasePolicy*, *state_interpreter: dict | StateInterpreter*, *action_interpreter: dict | ActionInterpreter*, *network: dict | torch.nn.Module | None = None*, *outer_trade_decision: BaseTradeDecision = None*, *level_infra: LevelInfrastructure = None*, *common_infra: CommonInfrastructure = None*, ***kwargs*) → None

Parameters **policy** – RL policy for generate action

reset(*outer_trade_decision: Optional[qlib.backtest.decision.BaseTradeDecision] = None*, ***kwargs*) → None

- reset *level_infra*, used to reset trade calendar, .etc
- reset *common_infra*, used to reset *trade_account*, *trade_exchange*, .etc
- reset *outer_trade_decision*, used to make split decision

NOTE: split this function into *reset* and *_reset* will make following cases more convenient 1. Users want to initialize his strategy by overriding *reset*, but they don't want to affect the *_reset* called when initialization

Utils

class qlib.rl.utils.**LogLevel**

Log-levels for RL training. The behavior of handling each log level depends on the implementation of `LogWriter`.

DEBUG = 10

If you only want to see the metric in debug mode.

PERIODIC = 20

If you want to see the metric periodically.

INFO = 30

Important log messages.

CRITICAL = 40

LogWriter should always handle CRITICAL messages

class qlib.rl.utils.**DataQueue**(*dataset: Sequence[T], repeat: int = 1, shuffle: bool = True, producer_num_workers: int = 0, queue_maxsize: int = 0*)

Main process (producer) produces data and stores them in a queue. Sub-processes (consumers) can retrieve the data-points from the queue. Data-points are generated via reading items from `dataset`.

`DataQueue` is ephemeral. You must create a new DataQueue when the `repeat` is exhausted.

See the documents of `qlib.rl.utils.FiniteVectorEnv` for more background.

Parameters

- **dataset** – The dataset to read data from. Must implement `__len__` and `__getitem__`.
- **repeat** – Iterate over the data-points for how many times. Use `-1` to iterate forever.
- **shuffle** – If `shuffle` is true, the items will be read in random order.
- **producer_num_workers** – Concurrent workers for data-loading.
- **queue_maxsize** – Maximum items to put into queue before it jams.

Examples

```
>>> data_queue = DataQueue(my_dataset)
>>> with data_queue:
...     ...
```

In worker:

```
>>> for data in data_queue:
...     print(data)
```

__init__(*dataset: Sequence[T], repeat: int = 1, shuffle: bool = True, producer_num_workers: int = 0, queue_maxsize: int = 0*) → None

Initialize self. See help(type(self)) for accurate signature.

class `qlib.rl.utils.`**EnvWrapper**(*simulator_fn: Callable[[...], qlib.rl.simulator.Simulator[~InitialStateType, ~StateType, ~ActType][InitialStateType, StateType, ActType]], state_interpreter: qlib.rl.interpreter.StateInterpreter[~StateType, ~ObsType][StateType, ObsType], action_interpreter: qlib.rl.interpreter.ActionInterpreter[~StateType, ~PolicyActType, ~ActType][StateType, PolicyActType, ActType], seed_iterator: Optional[Iterable[InitialStateType]], reward_fn: Optional[qlib.rl.reward.Reward] = None, aux_info_collector: Optional[qlib.rl.aux_info.AuxiliaryInfoCollector[~StateType, typing.Any][StateType, Any]] = None, logger: Optional[qlib.rl.utils.log.LogCollector] = None*)

Qlib-based RL environment, subclassing `gym.Env`. A wrapper of components, including simulator, state-interpreter, action-interpreter, reward.

This is what the framework of simulator - interpreter - policy looks like in RL training. All the components other than policy needs to be assembled into a single object called "environment". The "environment" are replicated into multiple workers, and (at least in tianshou's implementation), one single policy (agent) plays against a batch of environments.

Parameters

- **simulator_fn** – A callable that is the simulator factory. When `seed_iterator` is present, the factory should take one argument, that is the seed (aka initial state). Otherwise, it should take zero argument.
- **state_interpreter** – State-observation converter.
- **action_interpreter** – Policy-simulator action converter.
- **seed_iterator** – An iterable of seed. With the help of `qlib.rl.utils.DataQueue`, environment workers in different processes can share one `seed_iterator`.

- **reward_fn** – A callable that accepts the StateType and returns a float (at least in single-agent case).
- **aux_info_collector** – Collect auxiliary information. Could be useful in MARL.
- **logger** – Log collector that collects the logs. The collected logs are sent back to main process, via the return value of `env.step()`.

status

Status indicator. All terms are in *RL language*. It can be used if users care about data on the RL side. Can be none when no trajectory is available.

Type *EnvWrapperStatus*

__init__(*simulator_fn: Callable[[...], qlib.rl.simulator.Simulator[~InitialStateType, ~StateType, ~ActType][InitialStateType, StateType, ActType]], state_interpreter: qlib.rl.interpreter.StateInterpreter[~StateType, ~ObsType][StateType, ObsType], action_interpreter: qlib.rl.interpreter.ActionInterpreter[~StateType, ~PolicyActType, ~ActType][StateType, PolicyActType, ActType], seed_iterator: Optional[Iterable[InitialStateType]], reward_fn: Optional[qlib.rl.reward.Reward] = None, aux_info_collector: Optional[qlib.rl.aux_info.AuxiliaryInfoCollector[~StateType, typing.Any][StateType, Any]] = None, logger: Optional[qlib.rl.utils.log.LogCollector] = None*) → None

Initialize self. See help(type(self)) for accurate signature.

reset(***kwargs*) → ObsType

Try to get a state from state queue, and init the simulator with this state. If the queue is exhausted, generate an invalid (nan) observation.

step(*policy_action: PolicyActType*, ***kwargs*) → Tuple[ObsType, float, bool, qlib.rl.utils.env_wrapper.InfoDict]

Environment step.

See the code along with comments to get a sequence of things happening here.

render(*mode: str = 'human'*) → None

Compute the render frames as specified by render_mode attribute during initialization of the environment.

The set of supported modes varies per environment. (And some third-party environments may not support rendering at all.) By convention, if render_mode is:

- None (default): no render is computed.
- human: render return None. The environment is continuously rendered in the current display or terminal. Usually for human consumption.
- rgb_array: return a single frame representing the current state of the environment. A frame is a numpy.ndarray with shape (x, y, 3) representing RGB values for an x-by-y pixel image.
- rgb_array_list: return a list of frames representing the states of the environment since the last reset. Each frame is a numpy.ndarray with shape (x, y, 3), as with *rgb_array*.
- ansi: Return a strings (str) or StringIO.StringIO containing a terminal-style text representation for each time step. The text can include newlines and ANSI escape sequences (e.g. for colors).

Note: Make sure that your class's metadata 'render_modes' key includes the list of supported modes. It's recommended to call super() in implementations to use the functionality of this method.

class `qlib.rl.utils.`**LogCollector**(*min_loglevel: int | LogLevel = <LogLevel.PERIODIC: 20>*)

Logs are first collected in each environment worker, and then aggregated to stream at the central thread in vector env.

In *LogCollector*, every metric is added to a dict, which needs to be `reset()` at each step. The dict is sent via the `info` in `env.step()`, and decoded by the *LogWriter* at vector env.

`min_loglevel` is for optimization purposes: to avoid too much traffic on networks / in pipe.

__init__(*min_loglevel: int | LogLevel = <LogLevel.PERIODIC: 20>*) → None
Initialize self. See help(type(self)) for accurate signature.

reset() → None
Clear all collected contents.

add_string(*name: str*, *string: str*, *loglevel: int | LogLevel = <LogLevel.PERIODIC: 20>*) → None
Add a string with name into logged contents.

add_scalar(*name: str*, *scalar: Any*, *loglevel: int | LogLevel = <LogLevel.PERIODIC: 20>*) → None
Add a scalar with name into logged contents. Scalar will be converted into a float.

add_array(*name: str*, *array: np.ndarray | pd.DataFrame | pd.Series*, *loglevel: int | LogLevel = <LogLevel.PERIODIC: 20>*) → None
Add an array with name into logging.

add_any(*name: str*, *obj: Any*, *loglevel: int | LogLevel = <LogLevel.PERIODIC: 20>*) → None
Log something with any type.

As it's an "any" object, the only LogWriter accepting it is pickle. Therefore, pickle must be able to serialize it.

class `qlib.rl.utils.`**LogWriter**(*loglevel: int | LogLevel = <LogLevel.PERIODIC: 20>*)
Base class for log writers, triggered at every reset and step by finite env.

What to do with a specific log depends on the implementation of subclassing `LogWriter`. The general principle is that, it should handle logs above its loglevel (inclusive), and discard logs that are not acceptable. For instance, console loggers obviously can't handle an image.

episode_count = None
Counter of episodes.

step_count = None
Counter of steps.

active_env_ids = None
Active environment ids in vector env.

__init__(*loglevel: int | LogLevel = <LogLevel.PERIODIC: 20>*) → None
Initialize self. See help(type(self)) for accurate signature.

global_step = None
Counter of steps. Won"t be cleared in `clear`.

global_episode = None
Counter of episodes. Won"t be cleared in `clear`.

episode_lengths = None
Map from environment id to episode length.

episode_rewards = None
Map from environment id to episode total reward.

episode_logs = None
Map from environment id to episode logs.

clear()
Clear all the metrics for a fresh start. To make the logger instance reusable.

state_dict() → dict
Save the states of the logger to a dict.

load_state_dict(*state_dict: dict*) → None
Load the states of current logger from a dict.

static aggregation(*array: Sequence[Any], name: str | None = None*) → Any
Aggregation function from step-wise to episode-wise.

If it's a sequence of float, take the mean. Otherwise, take the first element.

If a name is specified and,
- if it's `reward`, the reduction will be sum.

log_episode(*length: int, rewards: List[float], contents: List[Dict[str, Any]]*) → None
This is triggered at the end of each trajectory.

Parameters
- **length** – Length of this trajectory.
- **rewards** – A list of rewards at each step of this episode.
- **contents** – Logged contents for every step.

log_step(*reward: float, contents: Dict[str, Any]*) → None
This is triggered at each step.

Parameters
- **reward** – Reward for this step.
- **contents** – Logged contents for this step.

on_env_step(*env_id: int, obs: ObsType, rew: float, done: bool, info: InfoDict*) → None
Callback for finite env, on each step.

on_env_reset(*env_id: int, _: ObsType*) → None
Callback for finite env.

Reset episode statistics. Nothing task-specific is logged here because of a limitation of tianshou.

on_env_all_ready() → None
When all environments are ready to run. Usually, loggers should be reset here.

on_env_all_done() → None
All done. Time for cleanup.

qlib.rl.utils.**vectorize_env**(*env_factory: Callable[..., gym.Env], env_type: FiniteEnvType, concurrency: int, logger: LogWriter | List[LogWriter]*) → FiniteVectorEnv
Helper function to create a vector env. Can be used to replace usual VectorEnv.

For example, once you wrote:

```
DummyVectorEnv([lambda: gym.make(task) for _ in range(env_num)])
```

Now you can replace it with:

```
finite_env_factory(lambda: gym.make(task), "dummy", env_num, my_logger)
```

By doing such replacement, you have two additional features enabled (compared to normal VectorEnv):
1. The vector env will check for NaN observation and kill the worker when its found. See `FiniteVectorEnv` for why we need this.
2. A logger to explicit collect logs from environment workers.

Parameters
- **env_factory** – Callable to instantiate one single `gym.Env`. All concurrent workers will have the same `env_factory`.
- **env_type** – dummy or subproc or shmem. Corresponding to parallelism in tianshou.

- **concurrency** – Concurrent environment workers.
- **logger** – Log writers.

> **Warning:** Please do not use lambda expression here for `env_factory` as it may create incorrectly-shared instances.
>
> Don't do:
>
> ```
> vectorize_env(lambda: EnvWrapper(...), ...)
> ```
>
> Please do:
>
> ```
> def env_factory(): ...
> vectorize_env(env_factory, ...)
> ```

class qlib.rl.utils.**ConsoleWriter**(*log_every_n_episode: int = 20*, *total_episodes: int = None*, *float_format: str = ':.4f'*, *counter_format: str = ':4d'*, *loglevel: int | LogLevel = <LogLevel.PERIODIC: 20>*)

Write log messages to console periodically.

It tracks an average meter for each metric, which is the average value since last `clear()` till now. The display format for each metric is <name> <latest_value> (<average_value>).

Non-single-number metrics are auto skipped.

__init__(*log_every_n_episode: int = 20*, *total_episodes: int = None*, *float_format: str = ':.4f'*, *counter_format: str = ':4d'*, *loglevel: int | LogLevel = <LogLevel.PERIODIC: 20>*) → None

Initialize self. See help(type(self)) for accurate signature.

prefix = None

Prefix can be set via `writer.prefix`.

clear() → None

Clear all the metrics for a fresh start. To make the logger instance reusable.

log_episode(*length: int, rewards: List[float], contents: List[Dict[str, Any]]*) → None

This is triggered at the end of each trajectory.

Parameters

- **length** – Length of this trajectory.
- **rewards** – A list of rewards at each step of this episode.
- **contents** – Logged contents for every step.

class qlib.rl.utils.**CsvWriter**(*output_dir: Path*, *loglevel: int | LogLevel = <LogLevel.PERIODIC: 20>*)

Dump all episode metrics to a `result.csv`.

This is not the correct implementation. It's only used for first iteration.

__init__(*output_dir: Path*, *loglevel: int | LogLevel = <LogLevel.PERIODIC: 20>*) → None

Initialize self. See help(type(self)) for accurate signature.

clear() → None

Clear all the metrics for a fresh start. To make the logger instance reusable.

log_episode(*length: int, rewards: List[float], contents: List[Dict[str, Any]]*) → None

This is triggered at the end of each trajectory.

Parameters

- **length** – Length of this trajectory.
- **rewards** – A list of rewards at each step of this episode.
- **contents** – Logged contents for every step.

on_env_all_done() → None
All done. Time for cleanup.

class qlib.rl.utils.**EnvWrapperStatus**
This is the status data structure used in EnvWrapper. The fields here are in the semantics of RL. For example, `obs` means the observation fed into policy. `action` means the raw action returned by policy.

class qlib.rl.utils.**LogBuffer**(*callback: Callable[[bool, bool, LogBuffer], None], loglevel: int | LogLevel = <LogLevel.PERIODIC: 20>*)
Keep all numbers in memory.

Objects that can't be aggregated like strings, tensors, images can't be stored in the buffer. To persist them, please use `PickleWriter`.

Every time, Log buffer receives a new metric, the callback is triggered, which is useful when tracking metrics inside a trainer.

Parameters **callback** – A callback receiving three arguments:

- on_episode: Whether it's called at the end of an episode
- on_collect: Whether it's called at the end of a collect
- log_buffer: the `LogBbuffer` object

No return value is expected.

__init__(*callback: Callable[[bool, bool, LogBuffer], None], loglevel: int | LogLevel = <LogLevel.PERIODIC: 20>*)
Initialize self. See help(type(self)) for accurate signature.

state_dict() → dict
Save the states of the logger to a dict.

load_state_dict(*state_dict: dict*) → None
Load the states of current logger from a dict.

clear()
Clear all the metrics for a fresh start. To make the logger instance reusable.

log_episode(*length: int, rewards: list[float], contents: list[dict[str, Any]]*) → None
This is triggered at the end of each trajectory.

Parameters

- **length** – Length of this trajectory.
- **rewards** – A list of rewards at each step of this episode.
- **contents** – Logged contents for every step.

on_env_all_done() → None
All done. Time for cleanup.

episode_metrics() → dict[str, float]
Retrieve the numeric metrics of the latest episode.

collect_metrics() → dict[str, float]
Retrieve the aggregated metrics of the latest collect.

1.25 Qlib FAQ

1.25.1 Qlib Frequently Asked Questions

---

1. RuntimeError: An attempt has been made to start a new process before the current process has finished its bootstrapping phase...

```
RuntimeError:
        An attempt has been made to start a new process before the
        current process has finished its bootstrapping phase.

        This probably means that you are not using fork to start your
        child processes and you have forgotten to use the proper idiom
        in the main module:

            if __name__ == '__main__':
                freeze_support()
                ...

        The "freeze_support()" line can be omitted if the program
        is not going to be frozen to produce an executable.
```

This is caused by the limitation of multiprocessing under windows OS. Please refer to here for more info.

Solution: To select a start method you use the `D.features` in the if __name__ == '__main__' clause of the main module. For example:

```
import qlib
from qlib.data import D


if __name__ == "__main__":
    qlib.init()
    instruments = ["SH600000"]
    fields = ["$close", "$change"]
    df = D.features(instruments, fields, start_time='2010-01-01', end_time='2012-12-31
↪')
    print(df.head())
```

2. qlib.data.cache.QlibCacheException: It sees the key(...) of the redis lock has existed in your redis db now.

It sees the key of the redis lock has existed in your redis db now. You can use the following command to clear your redis keys and rerun your commands

```
$ redis-cli
> select 1
> flushdb
```

If the issue is not resolved, use `keys *` to find if multiple keys exist. If so, try using `flushall` to clear all the keys.

Note: `qlib.config.redis_task_db` defaults is `1`, users can use `qlib.init(redis_task_db=<other_db>)` settings.

Also, feel free to post a new issue in our GitHub repository. We always check each issue carefully and try our best to solve them.

3. ModuleNotFoundError: No module named 'qlib.data._libs.rolling'

```
#### Do not import qlib package in the repository directory in case of importing qlib␣
↪from . without compiling #####
Traceback (most recent call last):
File "<stdin>", line 1, in <module>
File "qlib/qlib/__init__.py", line 19, in init
    from .data.cache import H
File "qlib/qlib/data/__init__.py", line 8, in <module>
    from .data import (
File "qlib/qlib/data/data.py", line 20, in <module>
    from .cache import H
File "qlib/qlib/data/cache.py", line 36, in <module>
    from .ops import Operators
File "qlib/qlib/data/ops.py", line 19, in <module>
    from ._libs.rolling import rolling_slope, rolling_rsquare, rolling_resi
ModuleNotFoundError: No module named 'qlib.data._libs.rolling'
```

- If the error occurs when importing `qlib` package with `PyCharm` IDE, users can execute the following command in the project root folder to compile Cython files and generate executable files:

  ```
  python setup.py build_ext --inplace
  ```

- If the error occurs when importing `qlib` package with command `python` , users need to change the running directory to ensure that the script does not run in the project directory.

4. BadNamespaceError: / is not a connected namespace

```
File "qlib_online.py", line 35, in <module>
  cal = D.calendar()
File "e:\code\python\microsoft\qlib_latest\qlib\qlib\data\data.py", line 973, in␣
↪calendar
  return Cal.calendar(start_time, end_time, freq, future=future)
File "e:\code\python\microsoft\qlib_latest\qlib\qlib\data\data.py", line 798, in␣
↪calendar
```

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```
  self.conn.send_request(
File "e:\code\python\microsoft\qlib_latest\qlib\qlib\data\client.py", line 101, in␣
↪send_request
  self.sio.emit(request_type + "_request", request_content)
File "G:\apps\miniconda\envs\qlib\lib\site-packages\python_socketio-5.3.0-py3.8.
↪egg\socketio\client.py", line 369, in emit
  raise exceptions.BadNamespaceError(
BadNamespaceError: / is not a connected namespace.
```

- The version of `python-socketio` in qlib needs to be the same as the version of `python-socketio` in qlib-server:

```
pip install -U python-socketio==<qlib-server python-socketio version>
```

5. TypeError: send() got an unexpected keyword argument 'binary'

```
File "qlib_online.py", line 35, in <module>
  cal = D.calendar()
File "e:\code\python\microsoft\qlib_latest\qlib\qlib\data\data.py", line 973, in␣
↪calendar
  return Cal.calendar(start_time, end_time, freq, future=future)
File "e:\code\python\microsoft\qlib_latest\qlib\qlib\data\data.py", line 798, in␣
↪calendar
  self.conn.send_request(
File "e:\code\python\microsoft\qlib_latest\qlib\qlib\data\client.py", line 101, in␣
↪send_request
  self.sio.emit(request_type + "_request", request_content)
File "G:\apps\miniconda\envs\qlib\lib\site-packages\socketio\client.py", line 263, in␣
↪emit
  self._send_packet(packet.Packet(packet.EVENT, namespace=namespace,
File "G:\apps\miniconda\envs\qlib\lib\site-packages\socketio\client.py", line 339, in␣
↪_send_packet
  self.eio.send(ep, binary=binary)
TypeError: send() got an unexpected keyword argument 'binary'
```

- The `python-engineio` version needs to be compatible with the `python-socketio` version, reference: https://github.com/miguelgrinberg/python-socketio#version-compatibility

```
pip install -U python-engineio==<compatible python-socketio version>
# or
pip install -U python-socketio==3.1.2 python-engineio==3.13.2
```

1.26 Changelog

Here you can see the full list of changes between each QLib release.

1.26.1 Version 0.1.0

This is the initial release of QLib library.

1.26.2 Version 0.1.1

Performance optimize. Add more features and operators.

1.26.3 Version 0.1.2

- Support operator syntax. Now `High() - Low()` is equivalent to `Sub(High(), Low())`.
- Add more technical indicators.

1.26.4 Version 0.1.3

Bug fix and add instruments filtering mechanism.

1.26.5 Version 0.2.0

- Redesign `LocalProvider` database format for performance improvement.
- Support load features as string fields.
- Add scripts for database construction.
- More operators and technical indicators.

1.26.6 Version 0.2.1

- Support registering user-defined `Provider`.
- Support use operators in string format, e.g. `['Ref($close, 1)']` is valid field format.
- Support dynamic fields in `$some_field` format. And existing fields like `Close()` may be deprecated in the future.

1.26.7 Version 0.2.2

- Add `disk_cache` for reusing features (enabled by default).
- Add `qlib.contrib` for experimental model construction and evaluation.

1.26.8 Version 0.2.3

- Add `backtest` module
- Decoupling the Strategy, Account, Position, Exchange from the backtest module

1.26.9 Version 0.2.4

- Add `profit attribution` module
- Add `rick_control` and `cost_control` strategies

1.26.10 Version 0.3.0

- Add `estimator` module

1.26.11 Version 0.3.1

- Add `filter` module

1.26.12 Version 0.3.2

- Add real price trading, if the `factor` field in the data set is incomplete, use `adj_price` trading
- Refactor `handler` `launcher` `trainer` code
- Support `backtest` configuration parameters in the configuration file
- Fix bug in position `amount` is 0
- Fix bug of `filter` module

1.26.13 Version 0.3.3

- Fix bug of `filter` module

1.26.14 Version 0.3.4

- Support for `finetune model`
- Refactor `fetcher` code

1.26.15 Version 0.3.5

- Support multi-label training, you can provide multiple label in `handler`. (But LightGBM doesn't support due to the algorithm itself)
- Refactor `handler` code, dataset.py is no longer used, and you can deploy your own labels and features in `feature_label_config`
- Handler only offer DataFrame. Also, `trainer` and model.py only receive DataFrame
- Change `split_rolling_data`, we roll the data on market calendar now, not on normal date
- Move some date config from `handler` to `trainer`

1.26.16 Version 0.4.0

- Add *data* package that holds all data-related codes
- Reform the data provider structure
- Create a server for data centralized management qlib-server
- Add a *ClientProvider* to work with server
- Add a pluggable cache mechanism

- Add a recursive backtracking algorithm to inspect the furthest reference date for an expression

Note: The `D.instruments` function does not support `start_time`, `end_time`, and `as_list` parameters, if you want to get the results of previous versions of `D.instruments`, you can do this:

```
>>> from qlib.data import D
>>> instruments = D.instruments(market='csi500')
>>> D.list_instruments(instruments=instruments, start_time='2015-01-01', end_time=
↪'2016-02-15', as_list=True)
```

1.26.17 Version 0.4.1

- Add support Windows
- Fix `instruments` type bug
- Fix `features` is empty bug(It will cause failure in updating)
- Fix `cache` lock and update bug
- Fix use the same cache for the same field (the original space will add a new cache)
- Change "logger handler" from config
- Change model load support 0.4.0 later
- The default value of the `method` parameter of `risk_analysis` function is changed from **ci** to **si**

1.26.18 Version 0.4.2

- Refactor DataHandler
- Add `Alpha360` DataHandler

1.26.19 Version 0.4.3

- Implementing Online Inference and Trading Framework
- Refactoring The interfaces of backtest and strategy module.

1.26.20 Version 0.4.4

- Optimize cache generation performance
- Add report module
- Fix bug when using `ServerDatasetCache` offline.
- In the previous version of `long_short_backtest`, there is a case of `np.nan` in long_short. The current version `0.4.4` has been fixed, so `long_short_backtest` will be different from the previous version.
- In the `0.4.2` version of `risk_analysis` function, `N` is `250`, and `N` is `252` from `0.4.3`, so `0.4.2` is `0.002122` smaller than the `0.4.3` the backtest result is slightly different between `0.4.2` and `0.4.3`.
- **refactor the argument of backtest function.**

  - **NOTE**: - The default arguments of topk margin strategy is changed. Please pass the arguments explicitly if you want to get the same backtest result as previous version. - The TopkWeightStrategy is changed slightly. It will try to sell the stocks more than `topk`. (The backtest result of TopkAmountStrategy remains the same)

- The margin ratio mechanism is supported in the Topk Margin strategies.

1.26.21 Version 0.4.5

- **Add multi-kernel implementation for both client and server.**
  - Support a new way to load data from client which skips dataset cache.
  - Change the default dataset method from single kernel implementation to multi kernel implementation.
- Accelerate the high frequency data reading by optimizing the relative modules.
- Support a new method to write config file by using dict.

1.26.22 Version 0.4.6

- **Some bugs are fixed**
  - The default config in *Version 0.4.5* is not friendly to daily frequency data.
  - Backtest error in TopkWeightStrategy when *WithInteract=True*.

1.26.23 Version 0.5.0

- **First opensource version**
  - Refine the docs, code
  - Add baselines
  - public data crawler

1.26.24 Version 0.8.0

- **The backtest is greatly refactored.**
  - Nested decision execution framework is supported
  - **There are lots of changes for daily trading, it is hard to list all of them. But a few important changes could be r**
    - **The trading limitation is more accurate;**
      - In previous version, longing and shorting actions share the same action.
      - In current version, the trading limitation is different between logging and shorting action.
    - **The constant is different when calculating annualized metrics.**
      - Current version uses more accurate constant than previous version

* A new version of data is released. Due to the unstability of Yahoo data source, the data may be different after downloading data again.
* Users could check out the backtesting results between Current version and previous version

1.26.25 Other Versions

Please refer to Github release Notes

Python Module Index

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