-2023 Group Project



01

Part one

Trade Data Processing and Re-publishing

02

Part two

Exchange Simulator

03

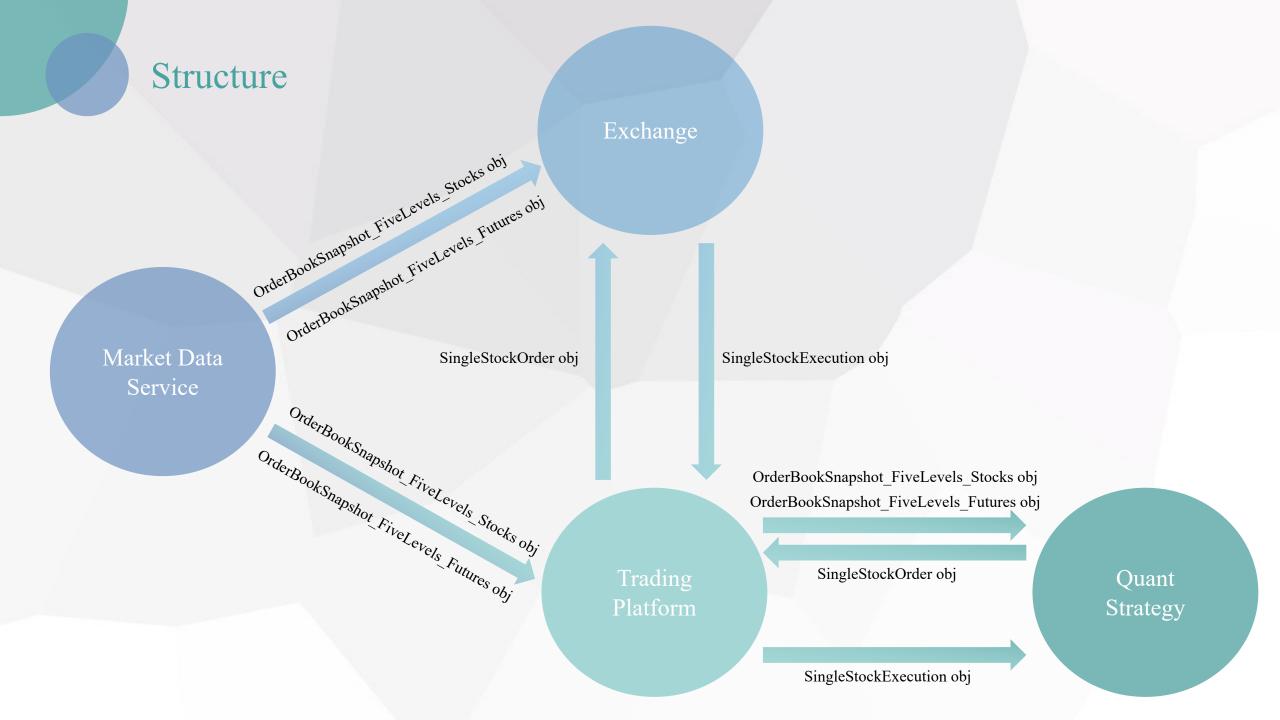
Part three

Quant Trading Platform

04

Part four

Single Stock and Single Stock Future HFT Strategies





LI Yangming
HE Xinyi
WANG Yishang
ZHENG Yadan

Stocks

1. Publish stock market data at the same speed as history

Start time: now

Time intervals: same as data used

```
self.next_time = data.at[0, 'time']
self.timegap = (self.next_time - self.this_time)/1000

for i in range(10): # data.shape[0]
    time.sleep(self.timegap)
    self.produce_quote(marketData_2_exchSim_q, marketData_2_platform_q, i, stock, data)
```

- 2. Simulate real market to show ten stocks together
- 3. Delay 15 min to print stocks to match with time of futures

Futures

1. Publish future market data at the same speed as history

```
self.timeStamps = np.unique(np.array(df.timeStamp))
self.timeIntervals = np.diff(self.timeStamps)
self.allTickerData = [group.values[:, 1:] for _, group in df.groupby('ticker')]
self.produce_quote(marketData_2_exchSim_q, marketData_2_platform_q)
time.sleep(self.timeIntervals[i]/10000000000)
```

*The timestamp is nanosecond: $1 \text{ ns}=10^{-9} \text{s}$

2. Simulate real market to show futures trading data

Stock Data Sample

[7 [7 [7 [7 [7 [7 [7	9296] < 9304] < 9298] < 9302] < 9299] < 9303] < 9300] < 9305] < 9305]Ma	<pre><<< call Ma <<<< call Ma call Ma <!--<-->< call Ma</pre>	rketDataS rketDataS rketDataS rketDataS rketDataS rketDataS rketDataS rketDataS rketDataS rketDataS rketDataS	ervice.ir ervice.ir ervice.ir ervice.ir ervice.ir ervice.ir ervice.ir ervice.ir volume	nit nit nit nit nit nit nit nit nit		askPrice5 9790.0	askPrice4 9780.0		askSize3 7	askSize2 6	askSize1 12	bidSize1 2	bidSize2 5	bidSize3 9	bidSize4 11	bidSize5 4
[7	9302]Ma ticker	26 columns] rketDataServ date	rice >>> p	roduce_qı volume		lastPx	askPrice5	askPrice4	4	askSize3	askSize2	askSize1	bidSize1	bidSize2	? bidSize3	bidSize4	bidSiz
0 64		2023-06-30	90001682	338	338.0	21100.0	21350.0	21300.0	· · · ·	62	2 82	44	37	81	L 54	22	
[7	9302]Ma ticker	26 columns] rketDataServ date 2023-06-30	rice >>> p time	volume	size	lastPx 21100.0	askPrice5 21350.0	askPrice4 21300.0		askSize3 62	askSize2 82	askSize1 44	bidSize1	bidSize2 81	bidSize3 54	bidSize4	bidSize 6
[7	9302]Ma ticker	26 columns] rketDataServ date 2023-06-30	vice >>> p time	volume	size	lastPx 21100.0	askPrice5	askPrice4 21300.0		askSize3 62	askSize2 82	askSize1 44	bidSize1 29	bidSize2	bidSize3 54	bidSize4 22	bidSize 6
[7	9302]Ma ticker	26 columns] rketDataServ date 2023-06-30	rice >>> p time	volume	size	lastPx 21100.0	askPrice5 21350.0	askPrice4 21300.0		askSize3	askSize2 82	askSize1 44	bidSize1 29	bidSize2 81	bidSize3	bidSize4 22	bidSize 6
[7	9302]Ma ticker	26 columns] rketDataServ date 2023-06-30	vice >>> p time	volume	size	lastPx 21100.0	askPrice5 21350.0	askPrice4 21300.0		askSize3 62	askSize2 82	askSize1 44	bidSize1 81	bidSize2 54	bidSize3 22	bidSize4 66	bidSize



LU Jiaqian
BIAN Yalan
FANG Hao
ZHENG Yuchang
GUO Chupeng

Save Data

Receive data from the first part and store it in the dictionary, update the data according to the stock name

```
md = marketData_2_exchSim_q.get()
self.current_orderbook_dict[md.ticker] = md

print('[%d]ExchSim.consume_md' % (os.getpid()))
print(md.outputAsDataFrame())
```

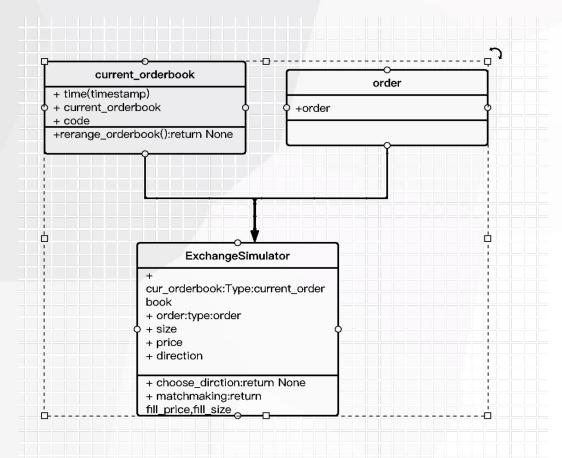
Save Order

Take stock orders from the part three

Transaction Judgment

1.Match the order sent by the third part with the saved stock data according to the stock code, and judge whether to trade

2.According to the direction of the order, and the corresponding price and transaction volume, judge the successful transaction volume and transaction price



Send Information

Send the calculated transaction price and transaction volume to the third group. If there is no transaction, a null value will be sent

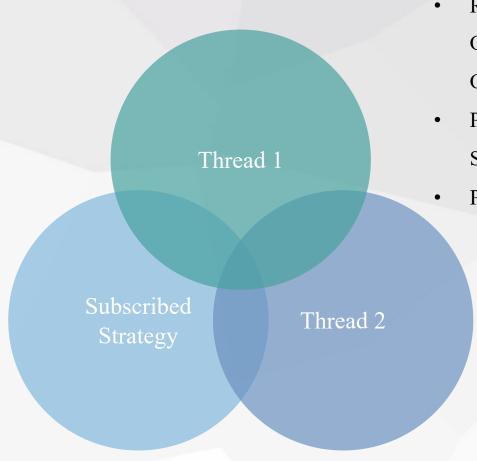
```
cur_orderbook is
                       askSize bidSize
   askPrice bidPrice
                                                         timestamp
                                                                    code
       8005
                 8000
                                    316 2023-07-23 13:33:42.215426
                                                                    0050
       8010
                 7995
                            30
                                    490 2023-07-23 13:33:42.215426
                                                                    0050
       8015
                            27
                                    477 2023-07-23 13:33:42.215426
                 7990
                                                                    0050
                            41
                                    236 2023-07-23 13:33:42.215426
       8020
                 7985
                                                                    0050
       8025
                 7980
                           250
                                    241 2023-07-23 13:33:42.215426 0050
order_submit_now is
    direction price size
                8010
                        34
01
fill_price:8007.5
fill_size:34
```



Trading Platform

YAO Shuochen TANG Sijia NI Jianle KANG Zhenqing

Structure



- Receive market data from Market Data Service as
 OrderBookSnapshot_FiveLevels_Stocks objects and
 OrderBookSnapshot_FiveLevels_Futures objects
- Pass orderbook snapshots to Quant Strategy and receive order back as SingleStockOrder object
- Pass order to Exchange
 - Receive execution from Exchange as SingleStockExecution object
 - Pass execution to Quant Strategy to calculate PnL

Details

Pass orderbook snapshot to Quant Strategy

- Dictionary of tickers as keys and OrderBookSnapshot_FiveLevels_Stocks objects and OrderBookSnapshot_FiveLevels_Futures objects as values
- Ignore empty queue of orderbook snapshots in specific ticker to avoid blocking queues

```
data_dic = {}
# fTicker_lis = ['EHF1', 'QWF1']
# sTicker_lis = ['1319','2388']
fTicker_lis = ['JBF1', 'QWF1', 'HCF1', 'DBF1', 'EHF1', 'IPF1', 'IIF1', 'QXF1', 'PEF1', 'NAF1']
sTicker_lis = ['3443','2388', '2498', '2610', '1319', '3035', '3006', '2615', '5425', '3105']
for i in range(len(fTicker_lis)):
    string = '''
    if marketData_2_platform_q_{}.empty() == False:
        data_dic[sTicker_lis[{}]] = marketData_2_platform_q_{}.get()
    else:
        pass
    if marketData_2_platform_q_{}.empty() == False:
        data_dic[fTicker_lis[{}]] = marketData_2_platform_q_{}.get()
    else:
        pass
    '''.format[sTicker_lis[i], i, sTicker_lis[i], fTicker_lis[i], i, fTicker_lis[i])
    exec(string)
```

Details

Receive orders back from strategy and pass them to Exchange separately for each stock and futures

```
if len(data_dic) > 0:
    new_order = self.quantStrat.run(data_dic, None)
else:
    new_order = None
if new_order is None:
    pass
else:
    # do something with the new order
    for key in new_order.keys():
        platform_2_exchSim_order_q.put(new_order[key])
```



Single Stock and Single Stock Future HFT Strategies

XIAO Li ZHANG Guangyu ZHENG Zixin WONG Chun Ho



How to build and back-testing a forecasting model

Steps to build our forecasting model



Part one Model Assumption



Pari one Model Assumption



Part three Model Selection



Part four Model building



Part one Model Assumption

- History can predict future
- More recent data play more important part in predicting the future.
- There are leading lagging effects between selected pairs of single futures and single stocks.
- In this project, we specifically look into how futures' lagging return leads the stocks' forward return.



Pari two
Data Preparation

- Sample dataset choosing:
 - Loading stocks and futures data using most recent 6 days
 - ["2023-06-29", "2023-06-28", "2023-06-27", "2023-06-26", "2023-06-26", "2023-06-20"]





Pari two

Data Preparation

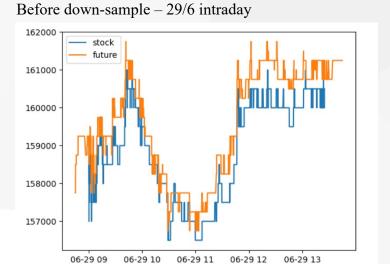
- Data cleaning:
 - Handling NaN INF ...
 - Synchronize time series of stock and future pairs (1)

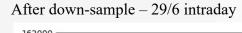
```
#Handle NA
stockData['lastPx'] = stockData.groupby('date')['lastPx'].fillna(method='ffill')
stockData['size'] = stockData.groupby('date')['size'].fillna(0)
futuresData['midQ'] = (futuresData['bidPrice1'] + futuresData['askPrice1']) / 2
# SYNCHRONIZE the two time series
# First, we want to get the common trading days from the two time series
                                                                               ##In order to synchronize trade time, too, we create indexes for both dataframes that have the same format
##We first get the trading days from the stock data
                                                                               stockData DateTime = pd.to datetime(stockData.date.astype(str) + ' ' + stockData.time.astype(str),
stockData dates = np.unique(stockData.date)
                                                                                                              format="%Y-%m-%d %H%M%S%f")
stoD = pd.to datetime(stockData dates, format="%Y-%m-%d")
                                                                               futuresData DateTime = pd.to datetime(futuresData.date.astype(str) + ' ' + futuresData.time.astype(str),
qqqq = stoD.year * 10000 + stoD.month * 100 + stoD.day
                                                                                                                format="%Y-%m-%d %H%M%S%f")
##Next, we get the trading days from the futures data
                                                                               ##Now, we create indexes of the same format for both the stock data and the index futures data
indexData dates = np.unique(futuresData.date)
                                                                                stockData.index = stockData DateTime
indD = pd.to datetime(indexData dates, format="%Y-%m-%d")
                                                                               stockData = stockData[~stockData.index.duplicated(keep='last')]
pppp = indD.year * 10000 + indD.month * 100 + indD.day
                                                                               futuresData.index = futuresData DateTime
##Now, we can get the common days of the two time series
                                                                               futuresData = futuresData[~futuresData.index.duplicated(keep='last')]
commonDays = pd.to datetime(pppp.intersection(qqqq), format="%Y%m%d")
```

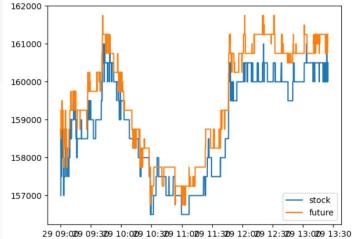


Data Preparation

- Data cleaning:
 - Synchronize time series of stock and future pairs (2)
 - Down-sample the time series with more time stamps









Parí two
Data Preparation

- Sample dataset choosing:
- Feature and Label Preparation:
 - Features: calculate x ticks lagging return on futures
 - Formula: return = (MidQ[t]-MidQ[t-x])/MidQ[t-x]
 - [fLaggingRtn_10', 'fLaggingRtn_20', ..., 'fLaggingRtn_90', 'fLaggingRtn_100']
 - Labels: calculate x ticks forward return on stocks
 - Formula: return = (MidQ[t+x]-MidQ[t])/MidQ[t]
 - [sForwardRtn_10', 'sForwardRtn_20', ..., 'sForwardRtn_90', 'sForwardRtn_100']



Pari two
Data Preparation

- Data splitting:
 - Training data: one day's whole tick data
 - ["2023-06-28", "2023-06-27", "2023-06-26", "2023-06-21", "2023-06-20"]
 - Testing data: the next day's whole day tick data
 - ["2023-06-29", "2023-06-28", "2023-06-27", "2023-06-26", "2023-06-21"]



Part three Model Selection

- Linear regression
 - Linear regression is a statistical method used to model the relationship between a dependent variable and one or more independent or predictor variables.
- Gradient Boosted Regression Trees (GBRT)
 - GBRT is a machine learning algorithm that combines multiple decision trees to make predictions.
 - GBRT is particularly effective for regression problems where the goal is to predict a continuous numerical value, such as predicting housing prices or stock prices.



• Training process:

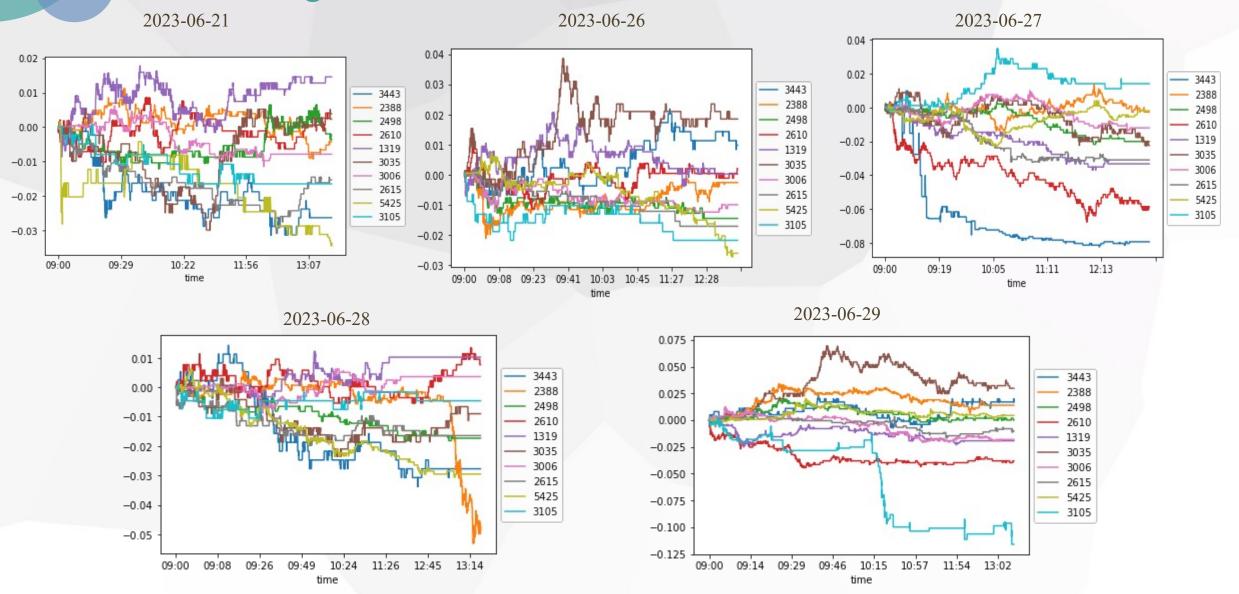
- Applying GBRT on features above to predict different labels
- Feature selection: select 5 most important features
- Model evaluation: In sample R^2

• Testing process:

- Evaluation: calculate the mean out of sample R^2 for each label in each day, and select the label with the highest mean R2 as the label for the best model.
- Backtesting: to be finished

- Back testing for the last 5 days (assume 06-21, 06-26, 06-27, 06-28 and 06-29 as the last trading day respectively and do the processes in previous part with corresponding days pushed back.)
- Consider single stock as a portfolio and see the performance to determine which stocks we will choose in the final simulated trading with our model.

Figure and data from different "GBRT_' + date" folders



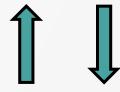
Information from 'Mean and std for single stock.ipynb'

```
In [19]: df
 Out[19]:
                               3443
                                         2388
                                                   2498
                                                             2610
                                                                       1319
                                                                                 3035
                                                                                           3006
                                                                                                     2615
                                                                                                               5425
                                                                                                                         3105
            13:24:56.566000 -0.02625
                                      -0.00417
                                                -0.00364
                                                          0.002345 0.014585
                                                                               0.0039
                                                                                        -0.00784
                                                                                                  -0.01529
                                                                                                           -0.03357
                                                                                                                      -0.01645
                                                                                                                      -0.02185
            13:23:03.336000
                            0.00975
                                      -0.00266
                                                -0.01456
                                                           0.00198
                                                                   0.000135
                                                                               0.01845
                                                                                       -0.010015
                                                                                                -0.017175
                                                                                                           -0.02616
                                                                   -0.03335
                                                                                                  -0.03103
                                                                                                            -0.0019
                                                                                                                       0.0141
            13:24:01.890000
                             -0.0795
                                     -0.002655
                                               -0.020105 -0.058705
                                                                              -0.02245
                                                                                      -0.012065
            13:21:10.018000
                                     -0.047005
                                               -0.017345
                                                          0.007642
                                                                    0.01021
                                                                             -0.009025
                                                                                         0.00358
                                                                                                 -0.016465
                                                                                                            -0.02954
                                                                                                                     -0.004625
            13:24:18.715000
                                     0.013965
                                               0.000075
                                                         -0.037997
                                                                   -0.01924
                                                                               0.02975
                                                                                        -0.01802 -0.010285 0.004435
          df. mean(). sort_values(ascending = False)
 Out[20]: 3035
                   0.004125
           1319
                  -0.005532
                  -0.008505
           2388
           3006
                  -0.008872
                  -0.011115
           2498
           2610
                  -0.016947
           5425
                 -0.017347
                 -0.018049
           2615
                 -0.021350
           3443
           3105 -0.028930
           dtype: float64
In [21]: df. std(). sort_values()
 Out[21]: 2615
                   0.007741
                   0.007926
           3006
           2498
                   0.008840
           5425
                   0.017339
           1319
                   0.020288
           3035
                   0.020863
                   0.022772
           2388
           2610
                   0.029673
                   0.038355
           3443
           3105
                   0.050495
           dtype: float64
```

- From the above information, we can find that our model does not perform well in this market, only one stock (3035) has got positive average return. So, in simulated trading we would trade that one.
- However, we can also find that 3035 has relatively high standard deviation. As a result, we would like to add several stocks to reduce the risk, then it comes to the stocks got negative return but not go too far from 0 (here we consider stocks have return higher than -0.01). Based on our condition, 1319, 2388 and 3006 could be take into consideration.
- Then we combine the information with the figure, we would find that 2388 once generated relatively big loss (on 0628) and has relatively high standard deviation. For this reason, we would not invest on it.
- Above all, our final invest pool would be 3035, 1319 and 3006.

How to communicate with trading platform

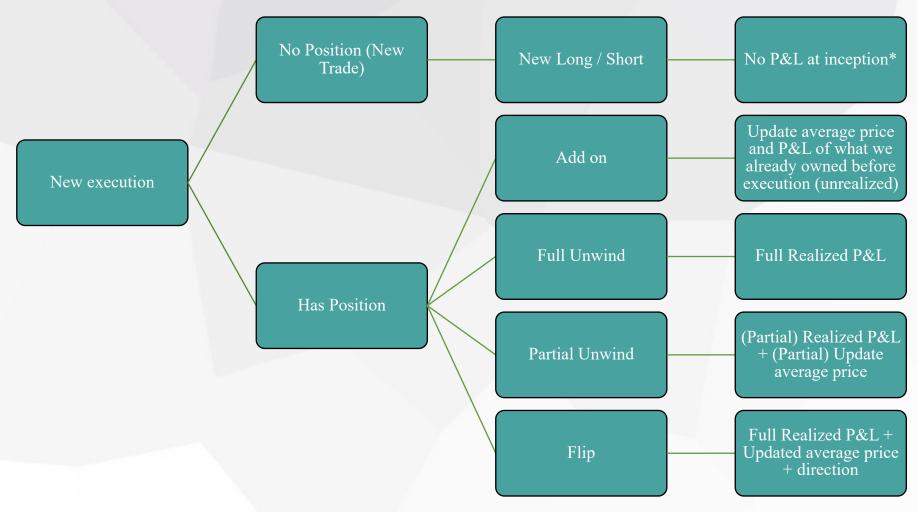
Trading Platform



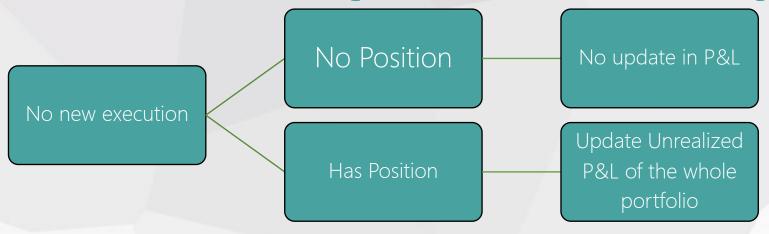
- Get snapshot data of stocks and futures from Trading platform:
- Generating order to Trading platform
- Receive execution information from Trading platform

Quant Strategy

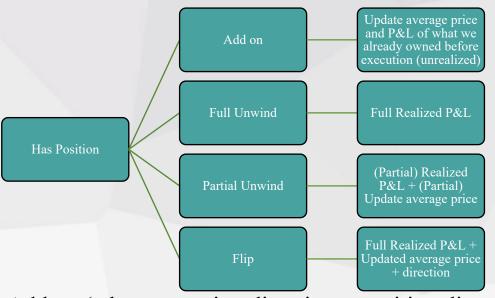
How to calculate and update P&L and other strategy metrics Position P&L for individual stocks:



^{*} We assume no trading cost (no levy, stamp, exchange fee and commission)



- Unrealized P&L
 - Long position:
 - P&L = Position x (latest Mid price average traded price)
 - Position is positive
 - Short position:
 - P&L = Position x (average traded price latest Mid price)
 - Position is negative



Position P&L for individual stocks

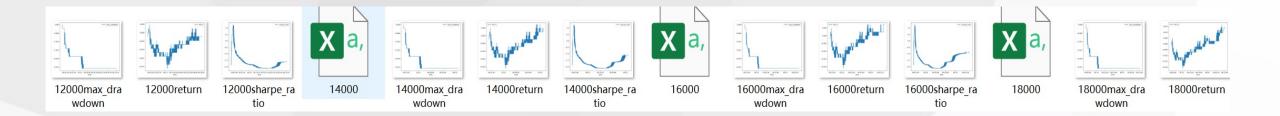
- Add on (when execution direction = position direction)
 - New Average price = (filled size x filled price + old average price x abs(position))/(filled size +abs(position))
 - Update P&L of what we already owned before execution (unrealized): position before execution x (average traded price filled price)
- Full Realized P&L (when filled size = position and opposite direction)
 - P&L = Position x (filled price average traded price)
 - Position = +ve when long and –ve when short
- Partial Realized P&L (when executed size < position and opposition direction)
 - $P\&L = \underline{Filled\ Size}\ x\ (filled\ price average\ traded\ price)$

Other potential strategy metrics:

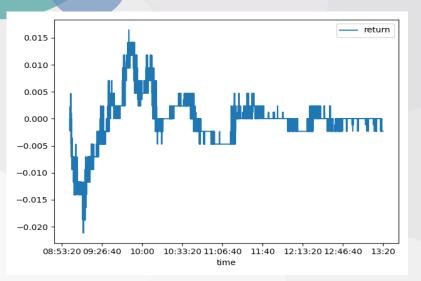
- Sharpe Ratio
 - measure the risk-adjusted return
 - to avoid overfocus on absolute P&L without consideration of risk
 - Sharpe Ratio = (Portfolio return risk free rate) / portfolio volatility
- Max Drawdown
 - Measure the drop in the value of a portfolio from peak to bottom
 - Max drawdown = (Trough value peak value) / Peak Value

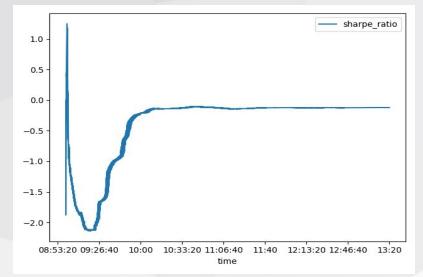
```
[24384] Strategy.marketdata: position of 3035: 47
[24384] Strategy.marketdata: current cash amount is 730.0
[24384] Strategy.marketdata: current asset amount is 1001655.0
[24384] Strategy.marketdata: current invest status of the portfolio:
 return
                        0.002385
sharpe_ratio
                       -1.07376
max_drawdown
                       -0.02583
total_pnl
                         2385.0
std
                       0.006102
time
                09:34:58.729000
```

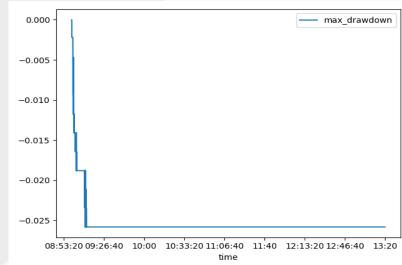
• Whenever we receive a new market data of stocks, we will print out our current 'position' (stands for the number of stocks we have here) of that stock, our current cash amount and asset amount, our current investment status (include return, sharpe ratio, max drawdown, total P&L, standard deviation of return and the time of that line of market data).



• For every 2000 lines of strategy metrics we calculated, we will create a csv file of them and create three figures (return, sharpe ratio and max drawdown (may have some fluctuations which might be due to multi-thread issue at the beginning)).







• Plot of return, sharpe ratio and max drawdown, after the last plot has generated (40000 lines of metrics here).

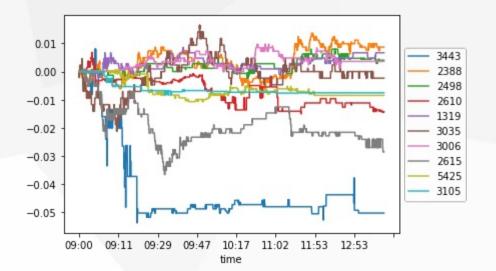
```
[27008] Strategy.marketdata: position of 3035: 47
[27008] Strategy.marketdata: current cash amount is 730.0
[27008] Strategy.marketdata: current asset amount is 999305.0
[27008] Strategy.marketdata: current invest status of the portfolio:
 return
                        0.000035
sharpe_ratio
                      -0.127908
max_drawdown
                      -0.025714
total_pnl
                           35.0
                       0.006649
std
time
                13:24:58.440000
Name: 0, dtype: object
```

• Final status of our portfolio after receiving the last market data.

More information

Trading stocks individually with our strategy (see it after getting the performance of our portfolio to see the relative performance of the stocks we selected to invest). Figure and data from 'GBRT_0630' folder, this is the information in simulated trading.

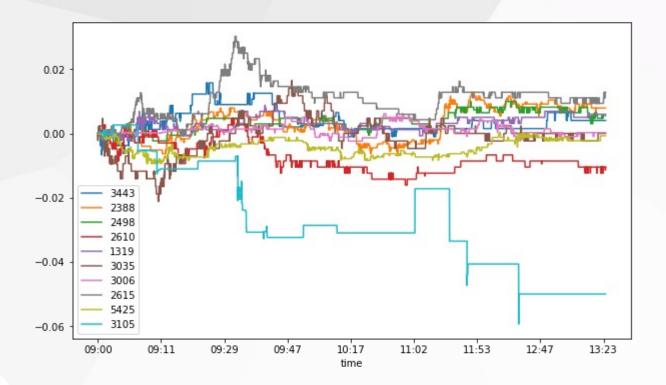
• As we can see, we have managed to select 3 of 5 stocks to trade that have the top 5 return when they are traded individually with our model. And have generated positive return while most of 10 stocks here have negative return (and some of them are much less than 0). As a result, we consider we have selected stocks that are suitable for our model.



More information

Performance of linear model for individually traded stocks Figure and data from 'linear' folder

• As we can see, linear model has got more stocks with return close or higher than 0, it may have better performance than GBRT strategy. In future work, we can try to do the similar process in previous part with linear regression.



Future improvement of Quant strategy

- Find more features to train the model, and take feature importance into consideration, using important features to predict.
- Add model selection process, try different models and find suitable models or strategies for different stocks.
- Consider more about when and how to submit order (here just simply submit order when predicted return larger than or less than and the submitted price is always askPrice1 or bidPrice1).
- Reasonably allocate investment amount on each stocks.

END THANKYOU