# Quant Strategy Report

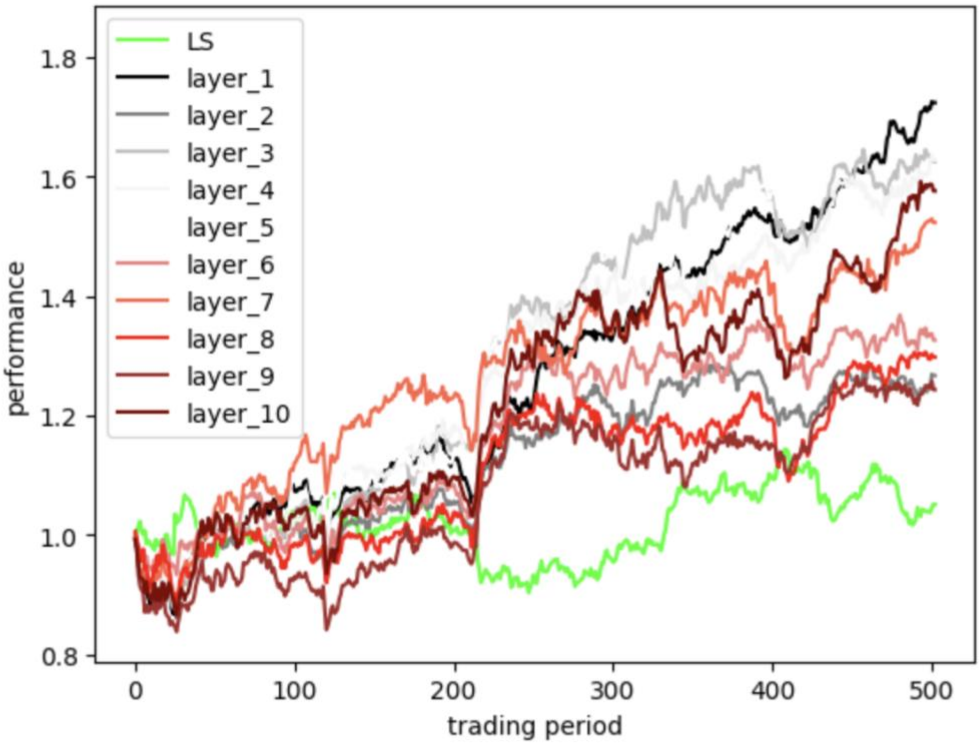
I choose the year 2010-2015 as the training set and year 2016 and 2017 as the test set and the out sample performance in 2016 and 2017 will be the final result of our trading strategy.

At first, I notice that there are 11 datasets containing 11 different features, the former 7 features basically updates every quarter and the last 4 features updates daily. So I think I can select the stock quarterly or monthly according to the quarterly features and trade stocks daily based on daily features.

After that I test the feature classification ability by classifying the stock into 10 groups with feature value from high to low. To make the calculation easier, I use the log return to substitute the daily return, in this way it is easier to calculate the return of the next several days with the rolling function of the dataframe. For feature 1-7 I calculate the future 66 trading days' return(almost a quarter) and calculate the average return of 10 group each quarter(notice that the quarterly features are not released on the same day and as a result it is a rough estimate). For feature 8-11 I calculate the future 1 trading day's return and calculate the average return of 10 group each day. Finally I find several feature has great ability to classify the different groups' return.

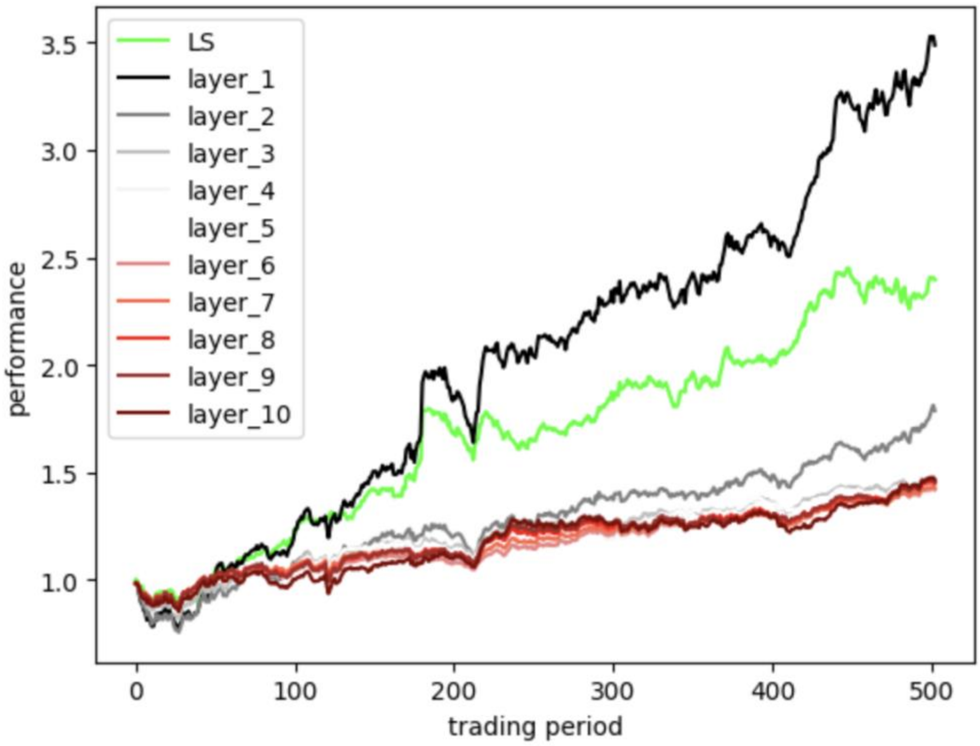
Then I try to find out how to gather several features to synthesize a better feature. Unluckily, I do not find significant improvement in the process. So I decide to focus on the feature 3 and feature 9 which performs best on the training set.

The next step is to construct the trading strategy based on feature 3 and feature 9. There are two options for feature 3, we can change the portfolio each quarter or each month based on groups classified by feature 3(the value of feature 3 will serve as the indicator for next month and next quarter). After that I can add feature 9 and see whether there is an improvement in the portfolio performance. To sum up, there are 4 kinds of strategy to test. After that I compare 4 different strategies and reach the conclusion that quarterly changed portfolio based on feature3 with daily changed portfolio based on feature9 has the best performance. I test it in the year 2016 and 2017.



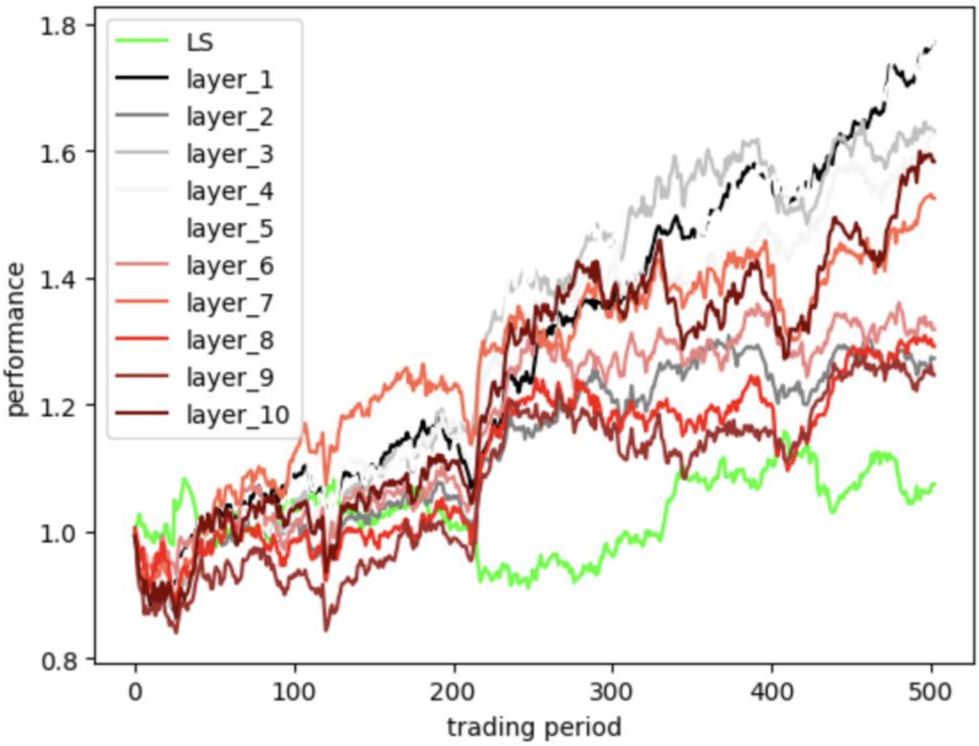

```
max drawdown:  -0.1245660488285053
annual return 0.3198939532404299
Sharpe ratio 2.491866388113577
volatility 0.12837524305731332
wining rate 0.5685884691848907
annual turnover: 1873%
```

While after that I find some stocks can not be included in the trading universe. So I adjust the portfolio to exclude the stock which is not in the trading universe and find quarterly changed portfolio based on feature3 has the best performance and test it in 2016 and 2017.

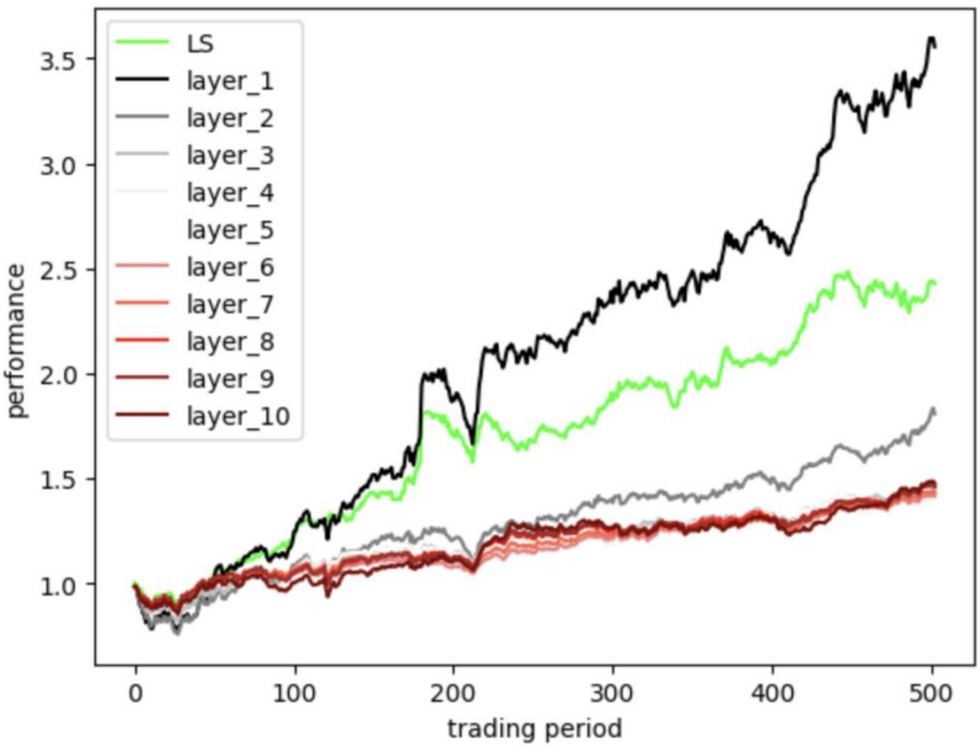



```
max drawdown:  -0.21180219120629173
annual return 0.882953166548879
Sharpe ratio 3.2385938392199978
volatility 0.2726347329684091
wining rate 0.5725646123260437
annual turnover: 800%
```

At last, I calculate the correlation between risk factor and future return and find risk factor 4 has strong relationship with the future return, so when risk factor4 is low, we will avoid this stock.




```
max drawdown:  -0.11590748802519046
annual return 0.3365075777206341
Sharpe ratio 2.5978413356034156
volatility 0.12953353736765896
wining rate 0.5745526838966203
annual turnover: 1873%
```




```
max drawdown:  -0.21243785420611627
annual return 0.9006818354586972
Sharpe ratio 3.2899207758319746
volatility 0.27377006828710865
wining rate 0.5745526838966203
annual turnover: 800%
```

A slight improvement is observed.

The trading fee has little impact on the performance. Sometimes the feature value is not separated enough to classify them into different groups , so some function can be created to make them more separated.