# Trading Strategy with Time Series and Reinforcement Learning

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## Introduction

With the trend of neural network, more and more people want to use deep learning with big data to predict the stock market. However, even if the accuracy of their model is good, those meaningless weights, ratios, and other combinations of numbers in neural networks cannot help to understand the market. And models come from meaningless combinations can stand for long term and represent the market. Therefore, I want to use combination of different linear regression model to simulate the neural networks. And take some useful skills in machine learning for time series to improve my model to predict the stock prices.

## Literature Review

Forecasting Time Series by SOFNN with Reinforcement Learning

*--by Takashi Kuremoto, Masanao Obayashi, and Kunikazu Kobayashi*

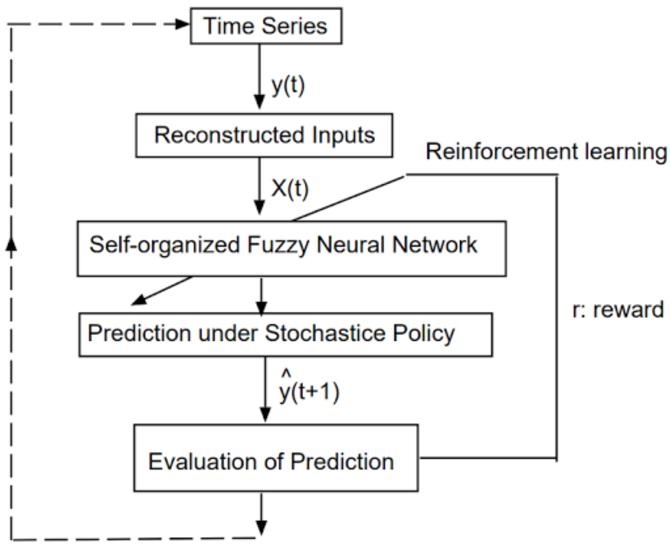



Fig. 1. Flow chart of training and forecasting.

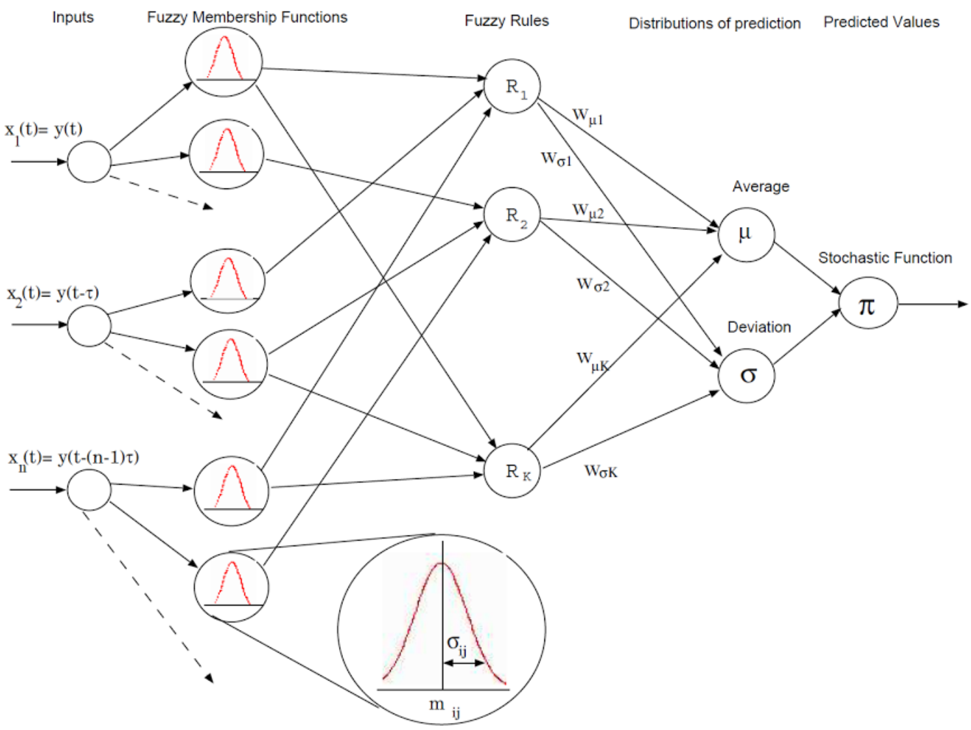
In this paper, it only uses stock prices

$$X(t) = (x1(t), x2(t), \cdots, xn(t)) = (y(t), y(t - \tau), \cdots, y(t - (n - 1)\tau)$$

And use a simple neural network with kernel functions

$$\mu(X(t), \omega_{\mu k}) = \frac{\sum_{k=1}^{K} \lambda_k \omega_{\mu k}}{\sum_{k=1}^{K} \lambda_k}$$

$$\sigma(X(t), \omega_{\sigma k}) = \frac{\sum_{k=1}^{K} \lambda_k \omega_{\sigma k}}{\sum_{k=1}^{K} \lambda_k}$$




The creative skills are in later steps.
After getting predictions from this model, it takes the errors as time series of rewards and change the weights in every time t, according to the reward in time t. Since this is the kernel function, so it is needed to use derivatives to know how much weight should be changed to modify the error, that is add or minus these rewards. And in the process of computing rewards and modifying the error, the weight would be improved to make the prediction more accurate.

## Methodology

There are 4 steps
And in to get the results, just follow read.me in the file.

1)
Use linear regression on stock prices of the past 50 days for predicting the stock price of next week (the $5^{th}$ day from now). Since linear regression must be a good fit for the stock prices in the period which we trained, it has to be applied on following days for testing( I choose test_days=40 in OLS_TS for testing )
And then, without loss generality, I can choose the stocks which is suitable for using linear regression to predict stock prices. Now, the stocks in portfolio has been selected.

2)
On rolling windows, construct weekly returns data and Sharpe Ratio with the stock prices, interest rates, variances in the period. Again use linear regression on past 50 days weekly returns (or Shape Ratio) to predict the weekly returns(or Shape Ratio) of the $5^{th}$ day from now. Then, the predicted returns and Sharpe Ratios are transformed to predicted stock prices, using their formula and stock price each day. Now there are 3 predicted stock prices got from different way.

3)
Using gradient descent from the initial weight (1/3, 1/3, 1/3) for the 3 predicted stock prices to fit the true stock prices. Since it is a linear combination, it is convenient to get the gradient.

$$S_{i,pred} - S_{i,true} = F(weight_i) = weight_i \times [\text{3 predicted stock prices}] - S_{i,true}$$

$$\nabla F(weight_i) = [\text{3 predicted stock prices}]$$

$$weight_{i+1} = weight_i - \mathrm{sign}(S_{i,pred} - S_{i,true}) \times \alpha \times \nabla F(weight_i)$$

$\alpha$ is the learning rate, and it should be tried to get the best one.

In the process, $weight_{i+1}$is modified from $weight_i$ in the direction of making $S_{i,pred}$ closed $S_{i,true}$. This way works without loss of generality.

4)

Finally, the last step is optimization.

$$\max_{w_A} \; w_A'\alpha - \frac{\lambda}{2} w_A'\Sigma w_A$$

$$\Rightarrow \min_{w_A} \; -w_A'\alpha + \frac{\lambda}{2} w_A'\Sigma w_A$$

With

$$\begin{gathered} -0.3 \le w_A'\beta \le 0.3 \\ -w_B \le w_A \le 1 - w_B \\ w_A' 1 = 0 \end{gathered}$$

The first term is to make activate investment can get more access return by the alpha predicted in the model. The latter term is to ensure active risk would not be too high when we pursue higher access return. So the lambda here should be tried with different value to a get suitable vale for the portfolio and the model. These constraints are to limit the beta, and make sure there is no short and beta bet. $\beta$ can be computed by returns of stocks in portfolio with the benchmark returns (calculate by the stocks' returns with market capital weighted).

## Data

Same as the paper inspired me, I only use the stock prices to predict stock prices and alpha. In the first step, I get the stock prices of Top 200 stocks in NASDAQ in the period 31/12/2008 to 31/12/2016. And all the stock prices are retrieved from Yahoo Finance with the API in MATLAB.

After the first filter, these are 46 stocks have been selected. And for testing and improve accuracy, some data of the beginning and the end has to be abandoned. For example, I give 100 days data in step3. Because the learning rate is small, and the initial data is given intuitively, the weights need some time to converge to the better values.

| | mean | STD | min | max |
|---|---|---|---|---|
| MSFT | 31.71487 | 11.09298 | 15.44419 | 59.26732 |
| AMZN | 305.4595 | 182.4409 | 73.6 | 844.36 |
| NVDA | 18.76827 | 11.26848 | 7.787691 | 71.77251 |
| TXN | 35.09213 | 13.54153 | 13.74392 | 69.43372 |
| MDLZ | 27.43853 | 9.495235 | 11.94942 | 45.32643 |
| ADI | 39.13249 | 12.48692 | 15.26203 | 64.49027 |
| LRCX | 51.38313 | 18.19862 | 22.52643 | 100.489 |
| AAL | 20.90747 | 15.3581 | 1.973181 | 54.31586 |
| MCHP | 33.969 | 10.1513 | 14.45877 | 61.34662 |
| WLTW | 97.02566 | 18.17544 | 57.48243 | 130.7977 |
| MYL | 33.71855 | 15.57392 | 12.1 | 76.06 |
| SBAC | 70.66005 | 32.48693 | 22.2 | 128.01 |
| MXIM | 24.18294 | 7.231275 | 9.839958 | 39.69069 |
| MELI | 90.22229 | 34.47454 | 19.72838 | 190.562 |
| ACGL | 46.5328 | 17.38918 | 18.38667 | 83.15 |
| HAS | 44.32045 | 17.60829 | 17.67942 | 84.22901 |
| SNPS | 34.68753 | 10.44979 | 18.2 | 60.56 |
| AMD | 4.893758 | 2.247129 | 1.62 | 10.16 |
| RYAAY | 44.36844 | 20.56426 | 19.17966 | 87.64 |
| ASML | 60.21291 | 32.3938 | 13.61188 | 111.3574 |
| SHY | 81.86581 | 1.447705 | 77.79339 | 84.29572 |
| JBHT | 57.35327 | 19.57358 | 23.37973 | 89.43139 |
| TTWO | 19.02788 | 9.508263 | 7.52 | 46.34 |
| CDNS | 13.69034 | 5.647197 | 4.59 | 26.25 |
| QVCB | 18.41137 | 6.915321 | 3.878069 | 31.4 |
| VRSN | 46.73896 | 20.21598 | 15.22528 | 93.12 |
| EXPD | 40.00323 | 5.904301 | 26.64289 | 51.55796 |
| TRMB | 23.28326 | 6.970922 | 9.25 | 39.96 |
| GRMN | 32.46389 | 9.11254 | 13.50025 | 52.49079 |
| CGNX | 12.40318 | 6.765853 | 2.896751 | 27.17946 |
| MRVL | 12.58512 | 2.813313 | 6.506254 | 20.21112 |
| SGEN | 28.0673 | 12.97981 | 8.19 | 57.25 |
| UHAL | 176.0112 | 118.3107 | 28.44403 | 431.4254 |
| IONS | 25.58668 | 18.61745 | 6.47 | 77.08 |
| SBNY | 83.73813 | 39.52471 | 24.98 | 160.73 |
| NDSN | 56.19683 | 19.72497 | 16.01019 | 100.9993 |
| ERIE | 61.70572 | 19.29414 | 24.47529 | 102.006 |

| | | | | |
|---|---|---|---|---|
| LAMR | 36.10596 | 13.22581 | 12.16004 | 65.10173 |
| COHR | 54.67894 | 19.18976 | 17.25146 | 113.37 |
| ICLR | 39.27683 | 20.16632 | 14.83 | 85.04 |
| LECO | 45.11188 | 16.57304 | 14.32194 | 70.75474 |
| ESLT | 52.43271 | 18.56687 | 26.12317 | 100.5177 |
| PBCT | 11.60999 | 1.940888 | 7.960409 | 15.56285 |
| FIZZ | 18.39187 | 11.8753 | 5.997961 | 60.09102 |
| OZRK | 21.61082 | 13.24042 | 4.352711 | 53.0877 |
| CBSH | 32.88676 | 7.381951 | 18.64336 | 49.79721 |

Totally 46 stocks in 1892 days.

And after the last abandon, and transformation. It becomes 46 stocks in 358 weeks.

## Empirical session

The key point of my alpha model is the skill to combine different predicted prices to get a better prediction. And take the advantage of the change from prices to different ratio to make prices data can be used in many ways.

Before the combination, mean $l^1 - error$ of predicted returns of by prices, returns and Sharpe ratio are 0.0432  0.0313  0.0320

After the combination it decrease to 0.277

After abandon of first 100 days, it decrease to 0.268

Another strength of my model is that I replace R-square value with my new

R-square_pred. Since the in the 8 years of the period I chosed, the stock price increased a lot. Almost all average prices of past 50 days are much lower than the price of 5 days after. So, it is trivial that using today’s price to predict the 5 days later is much better. And using todays price multiplied by average weekly return is even better. Hence, in my first step I use $\text{Rsqure}_{\text{pre}} = 1 - \frac{SSres}{SSpre}$

$$SSpre = \sum (Y_i - S_{i,today} \times \mu_{5daysreturn})^2$$

And I select the stock by using $\text{Rsqure}_{\text{pre\_test}} > 0.05$ in the test data.

| | Rsquare | Rsquare_pre | Rsquare_pre_test |
|---|---|---|---|
| AAPL | 0.992848 | 0.031169 | -0.02576 |
| GOOGL | 0.993108 | 0.086919 | -0.1774 |
| GOOG | 0.992807 | 0.084755 | -0.08607 |
| MSFT | 0.991104 | 0.067887 | 0.093632 |
| AMZN | 0.994047 | 0.06509 | 0.0789 |
| CMCSA | 0.996491 | 0.063019 | -0.65975 |
| INTC | 0.986752 | 0.030827 | -0.03758 |
| CSCO | 0.976564 | 0.044465 | -0.03031 |
| AMGN | 0.993981 | 0.064292 | -0.34806 |
| CELG | 0.993334 | 0.086183 | -0.0471 |
| GILD | 0.994615 | 0.046365 | 0.019906 |
| NVDA | 0.991686 | 0.072687 | 0.17811 |
| PCLN | 0.992953 | 0.074306 | -0.02981 |
| WBA | 0.993363 | 0.039559 | -0.01408 |
| TXN | 0.993432 | 0.034132 | 0.108755 |
| NFLX | 0.988364 | 0.061427 | -0.12356 |
| SBUX | 0.996749 | 0.095269 | -0.42755 |
| ADBE | 0.993705 | 0.069811 | 0.031918 |
| QCOM | 0.977778 | 0.042438 | -0.15759 |
| COST | 0.99646 | 0.03722 | -0.28984 |
| BIIB | 0.991518 | 0.051294 | 0.046831 |
| BIDU | 0.983039 | 0.068395 | -0.03968 |
| MDLZ | 0.993469 | 0.051723 | 0.125206 |
| AMOV | 0.955066 | 0.046487 | -0.11441 |
| AABA | 0.990179 | 0.062111 | -0.10673 |
| QQQ | 0.996009 | 0.088988 | -0.02268 |
| TMUS | 0.983478 | 0.048015 | -0.0705 |
| ATVI | 0.993699 | 0.036459 | -0.01852 |

| | | | |
|---|---|---|---|
| AMAT | 0.98556 | 0.020525 | -0.04448 |
| FOX | 0.992109 | 0.040883 | -0.1958 |
| ADP | 0.996037 | 0.036934 | -0.48977 |
| CSX | 0.984883 | 0.053686 | -0.40202 |
| REGN | 0.994244 | 0.102085 | -0.13653 |
| CME | 0.990951 | 0.034324 | -0.37914 |
| CTSH | 0.988302 | 0.057891 | -0.11845 |
| EBAY | 0.988072 | 0.044534 | -0.42937 |
| MAR | 0.993097 | 0.051681 | -0.05227 |
| VRTX | 0.978364 | 0.045601 | -1.10333 |
| ISRG | 0.980591 | 0.043522 | 0.028364 |
| MU | 0.987481 | 0.061528 | 0.006591 |
| EA | 0.993969 | 0.052751 | 0.001372 |
| ESRX | 0.983745 | 0.022002 | -0.21705 |
| INTU | 0.993722 | 0.04973 | -0.55092 |
| EQIX | 0.994984 | 0.045126 | 0.002388 |
| ALXN | 0.990767 | 0.059624 | -0.00686 |
| FOXA | 0.992834 | 0.050142 | -0.27004 |
| MNST | 0.994402 | 0.04598 | -0.04695 |
| ILMN | 0.98933 | 0.048493 | -0.06713 |
| ADI | 0.989226 | 0.038151 | 0.116945 |
| LRCX | 0.986681 | 0.033343 | 0.08284 |
| LBTYA | 0.990673 | 0.075401 | -0.02039 |
| LBTYK | 0.991603 | 0.077526 | -0.10901 |
| FISV | 0.997629 | 0.097564 | -0.46375 |
| ADSK | 0.978938 | 0.075666 | -0.13147 |
| INCY | 0.990048 | 0.145062 | 0.001173 |
| WDC | 0.988272 | 0.052718 | -0.12169 |
| DISH | 0.992216 | 0.042854 | -0.89279 |
| SIRI | 0.994128 | 0.073984 | 0.021005 |
| PCAR | 0.979668 | 0.035953 | -0.06744 |
| ROST | 0.996073 | 0.058772 | 0.007701 |
| CTRP | 0.980763 | 0.056305 | -0.00311 |
| CERN | 0.992351 | 0.036027 | -0.79534 |
| AMTD | 0.987949 | 0.036286 | -0.12279 |
| AAL | 0.991298 | 0.078706 | 0.251116 |
| EXPE | 0.989215 | 0.065566 | -0.09079 |
| PAYX | 0.994441 | 0.047816 | -0.54195 |

| | | | |
|---|---|---|---|
| NTES | 0.992342 | 0.053741 | 0.003165 |
| MCHP | 0.987122 | 0.038213 | 0.253752 |
| WLTW | 0.98068 | 0.04141 | 0.082254 |
| SYMC | 0.972511 | 0.012087 | 0.046488 |
| TROW | 0.98444 | 0.052428 | -0.0813 |
| NTRS | 0.978803 | 0.052276 | -0.09007 |
| DLTR | 0.993523 | 0.054593 | -0.0851 |
| SWKS | 0.992157 | 0.080512 | -0.21899 |
| FITB | 0.983832 | 0.06382 | -0.21493 |
| CHKP | 0.990839 | 0.071304 | -0.19129 |
| PFF | 0.995403 | 0.094342 | -0.00396 |
| ORLY | 0.997285 | 0.083177 | -0.23946 |
| MYL | 0.987611 | 0.049349 | 0.15953 |
| SBAC | 0.994962 | 0.110562 | 0.228102 |
| IBKR | 0.991305 | 0.053692 | -0.19985 |
| DVY | 0.996797 | 0.064561 | -0.27537 |
| XLNX | 0.985447 | 0.028673 | -0.08004 |
| BMRN | 0.989596 | 0.088508 | -0.38069 |
| VIA | 0.987874 | 0.03765 | -0.12257 |
| KLAC | 0.990633 | 0.030668 | -0.15979 |
| WYNN | 0.985355 | 0.093016 | -0.2087 |
| ALGN | 0.991659 | 0.051469 | -0.43524 |
| CTAS | 0.99714 | 0.067857 | -0.83333 |
| CA | 0.982389 | 0.042217 | -0.19365 |
| HBAN | 0.985598 | 0.054782 | -0.01395 |
| ULTA | 0.993769 | 0.044421 | -0.06309 |
| IDXX | 0.991314 | 0.032938 | -0.09768 |
| XRAY | 0.986387 | 0.077334 | -0.54294 |
| HSIC | 0.995856 | 0.045355 | -0.35848 |
| MXIM | 0.98558 | 0.046111 | 0.135659 |
| MELI | 0.978378 | 0.044912 | 0.155126 |
| ACGL | 0.996842 | 0.045438 | 0.106829 |
| FAST | 0.986071 | 0.04716 | -0.08191 |
| VOD | 0.987324 | 0.042615 | -0.95134 |
| SHPG | 0.989659 | 0.046033 | -0.05394 |
| NDAQ | 0.995337 | 0.057388 | -0.67204 |
| CINF | 0.996783 | 0.036486 | -0.58786 |
| EMB | 0.993425 | 0.02898 | -0.03019 |

| | | | |
|---|---|---|---|
| HAS | 0.993224 | 0.055435 | 0.251353 |
| SNPS | 0.992756 | 0.047696 | 0.086186 |
| CSJ | 0.997793 | 0.087166 | -0.44934 |
| CTXS | 0.959488 | 0.04394 | -0.24918 |
| AMD | 0.969835 | 0.054995 | 0.182114 |
| RYAAY | 0.992496 | 0.049318 | 0.103462 |
| ASML | 0.993883 | 0.069681 | 0.17573 |
| ETFC | 0.970142 | 0.082532 | -0.35319 |
| ANSS | 0.988728 | 0.051008 | -0.6924 |
| SHY | 0.995733 | 0.090376 | 0.060801 |
| SNI | 0.984778 | 0.066878 | -0.02583 |
| JBHT | 0.992165 | 0.041901 | 0.179651 |
| LKQ | 0.991277 | 0.03019 | -0.52515 |
| MBB | 0.997171 | 0.04249 | -0.1107 |
| NTAP | 0.96094 | 0.028617 | -0.29334 |
| HOLX | 0.987611 | 0.034769 | -0.16589 |
| TTWO | 0.99188 | 0.056006 | 0.149261 |
| CDNS | 0.993318 | 0.087912 | 0.220636 |
| QVCB | 0.988666 | 0.088475 | 0.23212 |
| QVCA | 0.98962 | 0.054038 | -0.17787 |
| VRSN | 0.9935 | 0.054283 | 0.234905 |
| EXPD | 0.952285 | 0.038167 | 0.056152 |
| CHRW | 0.952613 | 0.045286 | -0.01592 |
| TRMB | 0.97811 | 0.054565 | 0.165838 |
| GRMN | 0.979681 | 0.020631 | 0.190363 |
| IBB | 0.994485 | 0.076935 | 0.02038 |
| VIAB | 0.989447 | 0.043132 | -0.18541 |
| IPGP | 0.983254 | 0.045469 | 0.034794 |
| CGNX | 0.992027 | 0.054722 | 0.112165 |
| STX | 0.988741 | 0.055904 | -0.02886 |
| IAC | 0.989704 | 0.037273 | 0.022849 |
| DOX | 0.994474 | 0.080163 | -0.42336 |
| JAZZ | 0.993574 | 0.148738 | -0.0549 |
| SCZ | 0.987473 | 0.046898 | -0.0505 |
| DISCB | 0.973473 | 0.224398 | -0.26464 |
| CSGP | 0.993352 | 0.04167 | -0.11681 |
| SIVB | 0.987525 | 0.053139 | -0.10244 |
| SEIC | 0.992641 | 0.076856 | -0.64952 |

| | | | |
|---|---|---|---|
| IEP | 0.985284 | 0.050976 | -0.38102 |
| FLEX | 0.981081 | 0.028366 | -0.26156 |
| MRVL | 0.949665 | 0.025207 | 0.215464 |
| ZION | 0.955882 | 0.034816 | -0.07539 |
| OTEX | 0.989916 | 0.039267 | -0.04158 |
| LULU | 0.980509 | 0.048018 | -0.67754 |
| ODFL | 0.995204 | 0.051019 | -0.00328 |
| TLT | 0.988744 | 0.038158 | 0.02068 |
| EWBC | 0.990439 | 0.055412 | -0.04675 |
| GT | 0.982702 | 0.037714 | -0.03098 |
| STLD | 0.965623 | 0.035049 | 0.006991 |
| ALKS | 0.983971 | 0.08544 | 0.005214 |
| DISCA | 0.987047 | 0.038986 | -0.05012 |
| AKAM | 0.976214 | 0.035776 | -0.36222 |
| EXEL | 0.947228 | 0.049352 | 0.020648 |
| JKHY | 0.997581 | 0.060259 | -0.87936 |
| TSCO | 0.994369 | 0.061535 | -0.51658 |
| IEI | 0.995017 | 0.040836 | 0.041935 |
| ACWI | 0.988206 | 0.060217 | -0.03818 |
| SGEN | 0.979449 | 0.045703 | 0.104105 |
| IEF | 0.993653 | 0.032643 | 0.041261 |
| UHAL | 0.996326 | 0.058442 | 0.095587 |
| DISCK | 0.987554 | 0.049211 | 0.000993 |
| CPRT | 0.990918 | 0.027426 | 0.043096 |
| AGNC | 0.989722 | 0.071827 | -0.04613 |
| FFIV | 0.963921 | 0.024038 | -0.01014 |
| ALNY | 0.983221 | 0.083232 | -0.11856 |
| QGEN | 0.957274 | 0.027963 | 0.021485 |
| CIU | 0.998056 | 0.043389 | -0.02976 |
| PPC | 0.990953 | 0.09445 | -0.03181 |
| IONS | 0.980693 | 0.036735 | 0.083538 |
| MIDD | 0.994574 | 0.060497 | -0.73885 |
| ON | 0.929552 | 0.030984 | 0.012784 |
| ABMD | 0.99228 | 0.064175 | -0.10005 |
| ARCC | 0.991862 | 0.066967 | -0.00499 |
| MKTX | 0.996975 | 0.061188 | -1.54888 |
| SBNY | 0.994287 | 0.083636 | 0.216527 |
| NDSN | 0.988161 | 0.067638 | 0.278976 |

| | | | |
|---|---|---|---|
| DXCM | 0.993037 | 0.062953 | -0.60558 |
| PTC | 0.985985 | 0.066489 | 0.017047 |
| JBLU | 0.991788 | 0.070681 | -0.12466 |
| ERIE | 0.993786 | 0.054961 | 0.138226 |
| LAMR | 0.990111 | 0.066167 | 0.09653 |
| COHR | 0.983564 | 0.047608 | 0.123062 |
| OLED | 0.960953 | 0.042918 | -0.14333 |
| SRCL | 0.986246 | 0.029547 | -0.31518 |
| ICLR | 0.992023 | 0.047759 | 0.105326 |
| LOGI | 0.974826 | 0.023847 | -0.05617 |
| SHV | 0.986574 | 0.176708 | -0.00213 |
| RGLD | 0.945459 | 0.042518 | -0.17375 |
| LECO | 0.99078 | 0.056235 | 0.053474 |
| ESLT | 0.990827 | 0.049522 | 0.185215 |
| PBCT | 0.977587 | 0.067022 | 0.168452 |
| VEON | 0.97339 | 0.043087 | -0.25614 |
| MSCC | 0.978873 | 0.032969 | -0.03106 |
| FIZZ | 0.992082 | 0.062387 | 0.201807 |
| OZRK | 0.994848 | 0.085994 | 0.108636 |
| CBSH | 0.986977 | 0.069297 | 0.149388 |
| | 0.986825 | 0.056395 | -0.11697 |

The last row is the mean of these 3 scores. The mean of $\mathrm{Rsqure}_{\mathrm{pre\_test}}$ is negative, but we can still find 46 stocks with $\mathrm{Rsqure}_{\mathrm{pre\_test}} > 0.05$ closed to the mean of $\mathrm{Rsqure}_{\mathrm{pre}} = 0.056$. Selecting the stocks suitable for linear regression is important for continuing to work on more linear method.

Although it is not a very good prediction, it has been proved that it is better than using average return to predict on the test data. Hence, the linear regression works in the stocks of my portfolio.

Interestingly, in step2, it is found that using regression on returns and Sharpe ration can get better prediction (showed by $l^1 - error$ before), although I choose them by the performance of regression on prices. It proves my selection of stocks is right.

## Final Results

TE = 0.0289

IR = 1.9068

IC = 0.2644

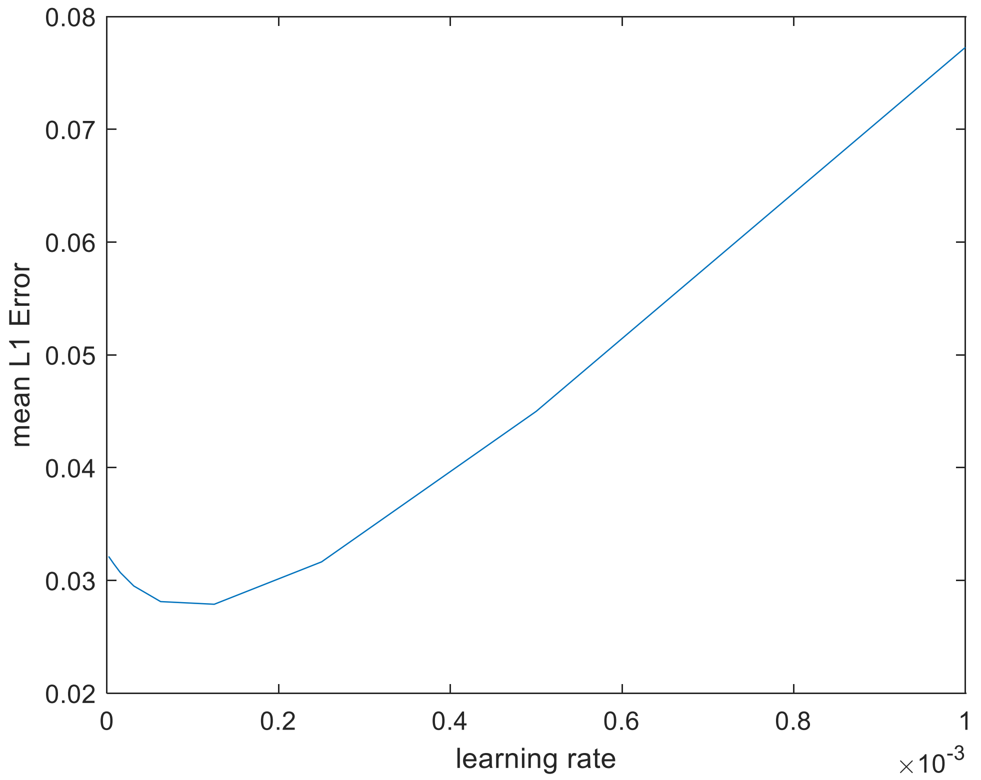
The result is surprising. The return of the portfolio is really high, and it can earn much more if there is no constraint of Tracking Error. When I knew that the $l^1 - error$ of return is about o.o27, I don't think is really good because if the prediction of a stock return is 1% this week, it may be negative with not low possibility. However, in the process of optimization of the portfolio. It can distribute more weights in 1 to 5 stocks of 46 stocks, and distribute negative weights in others. That makes my portfolio can get access return even if my alpha model doesn't has really high winning rate.

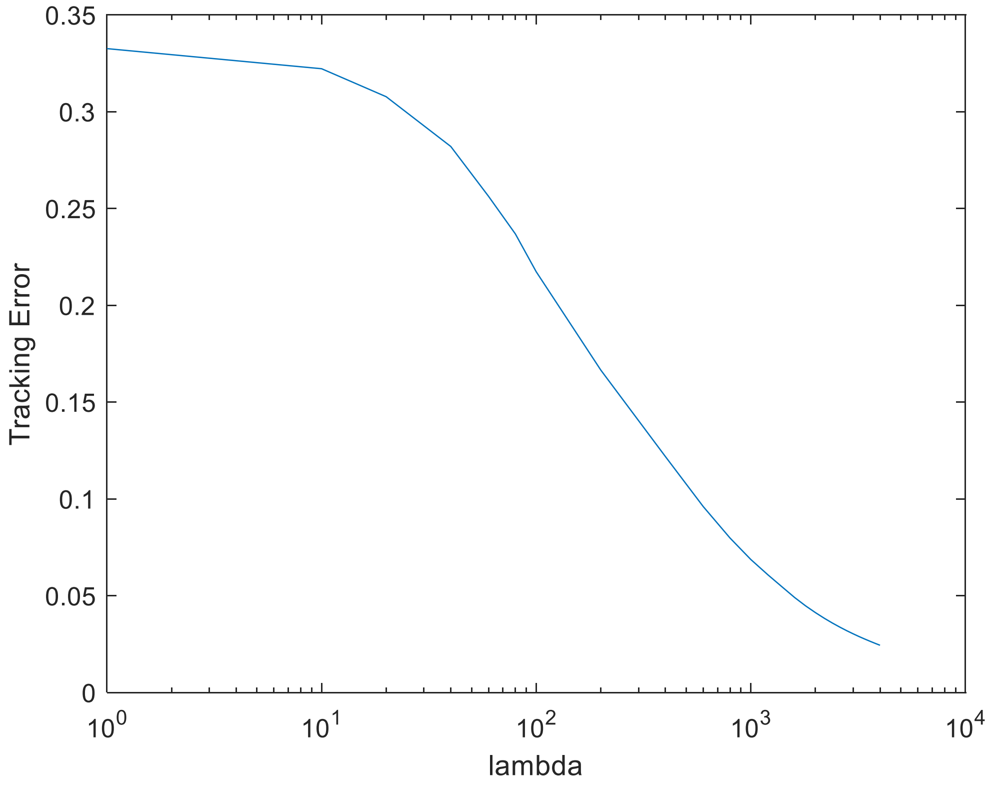
## Summary

For time series model, if I continue working on linear model, I should not add data other than stock prices. Since the coefficient of them would be much different than parameter made from prices. It probably needs other ratios, multiplication, and even kernel functions to deal with them. My step3 may not still work.

Therefore, I would try to add more ratios made from stock prices to get more predicted prices. For example, $\frac{\mathrm{R}_{i,t}-R_{M,t}}{\sigma_i}$ may be good, since it is a modified Sharpe ratio and may be more related to alpha. Afterwards, in step3, there are more prediction, and more parameters in weights to control. I believe it would get better results.

## Appendix


0.08
0.07
0.06
0.05
0.04
0.03
0.02
mean L1 Error
0
0.2
0.4
0.6
0.8
1
learning rate
×10-3


0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
Tracking Error
10^0
10^1
10^2
10^3
10^4
lambda