Evaluation and Analysis of an LSTM and GRU Based Stock Investment Strategy

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Abstract. Confronted with an extremely complicated and volatile external environment, it is such a tremendous challenge for researchers and investors to predict the stock market prices. To address the challenge, this paper proposes three steps for stock investment. The stock selection is based on a special ratio which is forward PE divided by trailing PE. This ratio can better evaluate the growth of individual stocks. The research found that stocks that have low PE ratios show strong growth in the price prediction part. Two deep learning-based stock market prediction models are proposed to predict the tendency. LSTM and GRU models are separately adopted to predict future trends of stock prices based on the price history. The experimental results show that the GRU model can improve prediction accuracy and reduce time delay, compared to the consequences of the LSTM model. After determining the scope of investment, to reduce the risk of investment in the stock market, get a higher or more stable rate of return, and achieve a good investment, this study calculated the correlation between these stocks' changes and then optimize the asset allocation. Monte Carlo model and SLSQP model are used to get the correlation between stocks and both of them to give the respective optimal portfolio. From the latter's results, the diversity of portfolios decreases with the optimization of asset allocation.

Keywords: component · Stock Selection · Price Prediction · Investment Strategy · Machine Learning

1 Introduction

Predicting the stock market is a very challenging subject [1], which attracts many researchers [2]. Particularly, the trading price of the stock market often serves as an indicator for the price and quantity of the stock, which can reflect the supply and demand

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relationship of the market [3]. However, the various factors and individual behavior factors make the stock price variation very complicated. Therefore, stock price (or trend) prediction is a great challenge due to its characteristics of noise and volatility [4]. And using advanced technology to maximize the profit of the option purchase while keeping the low risk has a great significance [5].

Many researchers have tried to investigate stock selection strategies. For example, I. Shittu, A. Masud, Y. M. Alkali argued that growth stocks yield more investment returns to investors compared to value stock counterparts [6]. Truong C found that low PE stocks outperform high PE stocks in New Zealand [7]. Easton P D used the PEG ratio, the PE ratio divided by the short-term earnings growth rate for stock selection, and found that the expected rate of return is shown higher for firms with higher PEG ratios [8]. Anderson K, Brooks C explored relationships between long-term PE ratio and short-term PE ratio. Their results suggested that a PE calculated from multiple years of earnings is a better predictor of returns than the traditional one-year PE [9].

Recently, many researchers tried to solve the above problems, which aim to obtain the maximum profits. For example, Donald C. Wunsch et al. [10] exploited time delay, recurrent, and probabilistic neural networks (TDNN, RNN, and PNN, respectively), utilizing conjugate gradient and multi-stream extended Kalman filter training for TDNN and RNN. They also discussed different predictability analysis techniques and perform an analysis of predictability based on a history of the daily closing price. Rather A M et al. proposed a robust and novel hybrid model for predicting stock returns, and their model is constituted of two linear models: autoregressive moving average model, exponential smoothing model, and a non-linear model: recurrent neural network [11].

The high risks and uncertainty of return obtained making investments in the capital market became a major obstacle. One of the ways that investors can do is to manage and diversify risk and return from investment products to obtain maximum investment results. Investors can optimize return and minimize the risk of the portfolio they have [12]. The Modern theory of Portfolio Management discovered by Harry Markowitz will be used to calculate the proportion of the portfolio assets to minimize risk and optimize the return of portfolio formed [13].

Recently, the rampant bull market after the blow of COVID-19 sent stocks prohibitively expensive. This trend made people doubt whether markets reflect the health of the economy or are just in a stock market bubble. We found one signal that PE is growing much faster than EPS may help explain the phenomenon. The stock over-evaluation led to stock bubbles. What's more, few studies investigate stock selection and price prediction under this circumstance. Therefore, in our research, the ratio of forward PE and trailing PE as a benchmark is used to select stocks. A three-layer LSTM model and a three-layer GRU model are then used to predict the price trend. Finally, the portfolios can be generated using the Monte Carlo and SLSQP, and the best return strategy can be obtained.

The most contributions of our research include 1) a novel ratio calculated by forwardPE/trailingPE is proposed to select the stocks; 2) comparing the performs of different machine-learning-based methods in the application of stock price; 3) Monte Carlo method and Sequential Least SQuares Programming algorithm (SLSQP) [14] are compared in this paper to analyze the performance of Sharpe Ratio and Volatility simulation.

The rest parts of this paper include that Sect. 2 introduces the Methods; Sect. 3 introduces the Results and Discussion of the proposed method, which could evaluate the performance of the proposed method; Sect. 4 introduces the conclusion of this paper.

2 Methods

In this paper, three steps are processed in the application of exploring the best investment strategy, stock price predicting, and stock selection. Especially, the stock selection is the basis of the others. After stock selection, different machine-learning methods are compared to find the most suitable method in stock price prediction. Finally, the Monte Carlo method and SLSQP method are compared in the application of stock price simulation. The overview of our work can be found in Fig. 1.

2.1 Data Preparation

500 individual stocks chosen are members of S&P500 listed in Wikipedia. For this article, data of individual stocks (forward PE, trailing PE) was collected from Yahoo Finance. 241 individual stocks were eliminated for data missing.

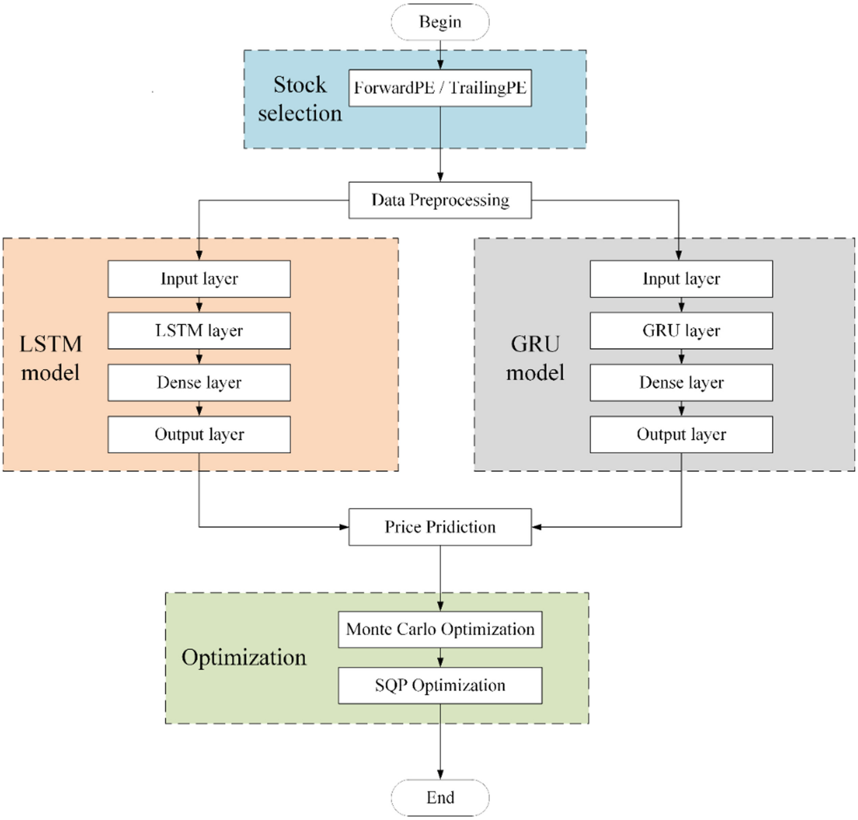

Fig. 1. The overflow of the investment strategy processing

After the stock selection, the historical price data of the targeted stock is gained from Yahoo Finance. In a bid to reflect the actual trends of the stock price and guarantee the accuracy of price prediction, the adjusted closing price is used to be the main research object, rather than the closing price. It has 12590 daily records of 10 targeted stocks from 2015/1/1 to 2019/12/31.

The entire data set is divided into a train set and a test set. The train set is the daily price data from 2015/1/1 to 2018/12/31, while the test set is the daily price data from 2019/1/1 to 2019/12/31, which contains 20% of the whole data set. And in our LSTM model for price prediction, the length of one sequence is 60.

We have two steps from preprocessing the data: 1) Normalization: MinMaxScaler estimator from sklearn scales is used to translate the feature into the given range between zero and one. 2) Data cleaning: Impute missing values.

2.2 Stock Selection and Portfolio Allocation

2.2.1 ForwardPE/TrailingPE

Our key step for selecting stocks is to use forward PE divided by trailing PE as a benchmark. Trailing PE uses earnings per share of the company over the previous 12 months, whereas forward PE uses the forecasted earnings over the next 12 months. Using the ratio of the two and evaluating the gap between the Price-Earning (PE) ratio now and the one in the future can better assess the growth of the stocks that we need to choose. The lower the ratio is, means that the stock is more likely to be underestimated.

$$PE = \frac{P_t}{EPS} \tag{1}$$

$$PE\ ratio = \frac{forward\ PE}{trailing\ PE} \tag{2}$$

where P_t represents stock price at time t and EPS represents earnings per share.

After calculating PE ratios of 500 individual stocks from S&P 500, stocks are ranked by the ratio from the lowest to the highest. 16 individual stocks are eliminated for extremely low ratios.

2.2.2 Monte Carlo Method

Consider the generic question of estimating the expected value of a function of some random variable X:

A plain Monte Carlo simulation scheme can be roughly divided into two steps:

(1) Generate samples, or independent identically distributed (iid) random variables X1, X2,…, Xn, that have the same distribution as X.
(2) The estimate of the expected value μ is defined to be the sample average

$$\mu = \frac{1}{n}[h(X_1) + h(X_2) + \cdots + h(X_n)] \tag{3}$$

2.3 Machine Learning-Based Methods for Predicting Price of Stocks

2.3.1 LSTM-Based Method

Long Short-Term Memory (LSTM) is a special version of Recurrent Neural Network (RNN). By changing the mechanisms of information processing, including how to keep the data and transmit the data, the LSTM model can avoid the long-term dependencies during the train of long-term time series.

LSTM model consists of many LSTM cells composed of cell state, input gate, output gate, and forget gate. The functions of the above parts are as follows:

- Cell State: It acts as a bond and transfers throughout the neural network and changes more slowly than the hidden state, processing the information with the aid of gates.
- Input gate: Via the pointwise operations of 'sigmoid' and 'tanh', it consists of the information flow to the current cell state.
- Output gate: Decides the information that can transmit to the next hidden state with the help of the 'sigmoid' operation.
- Forget gate: Controls which parts of the information from the previous cell state should be forgotten.

By the process of the three gates, the information in the cell state can be updated [15].

With respect to the mathematical equations, at time t, the input vector x_t and the hidden state h_{t-1} from the previous cell state go through the input gate i_t, forget gate f_t and output gates o_t, generating long-term memory c_t (cell state) and short-term memory h_t (hidden state):

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{4}$$

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \tag{5}$$

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \tag{6}$$

$$c_t = tanh\left(W_c \cdot \left[h_{t-1}, x_t\right] + b_c\right) \tag{7}$$

$$h_t = o_t * \tanh(c_t) \tag{8}$$

where $\left\{W_i, W_f, W_o, W_c\right\}$: weight matrix of certain gates, $\left\{b_i, b_f, b_o, b_c\right\}$: offset term of certain gates.

Our LSTM model contains a sequential input layer followed by three LSTM layers and a single dense layer in this paper. To reduce overfitting, we drop out 20% of the units after each layer.

2.3.2 GRU-Based Method

Gated Recurrent Unit (GRU) is a less complex edition of the Long Short-Term Memory (LSTM) model because the GRU model only owns two gates: update and reset, lacking an output gate. In the GRU model, the amount of previous state data used with current input data is considered as a reset gate, while the amount of data transfer to the next state is regarded as an update gate.

Our GRU model contains a sequential input layer followed by two GRU layers and a single dense layer in this paper. To reduce overfitting, we drop out 20% of the units after each layer.

3 Results and Discussion

3.1 Results of Stock Price Prediction Based on Machine Learning

3.1.1 LSTM Based Results

A comparison of targeted stocks price prediction using the LSTM model is shown in Fig. 2.

In Fig. 2, subfigure (a) shows the result of stock price prediction for ABT; subfigure (b) shows the result of stock price prediction for EA; subfigure (c) shows the result of stock price prediction for EL; subfigure (d) shows the result of stock price prediction

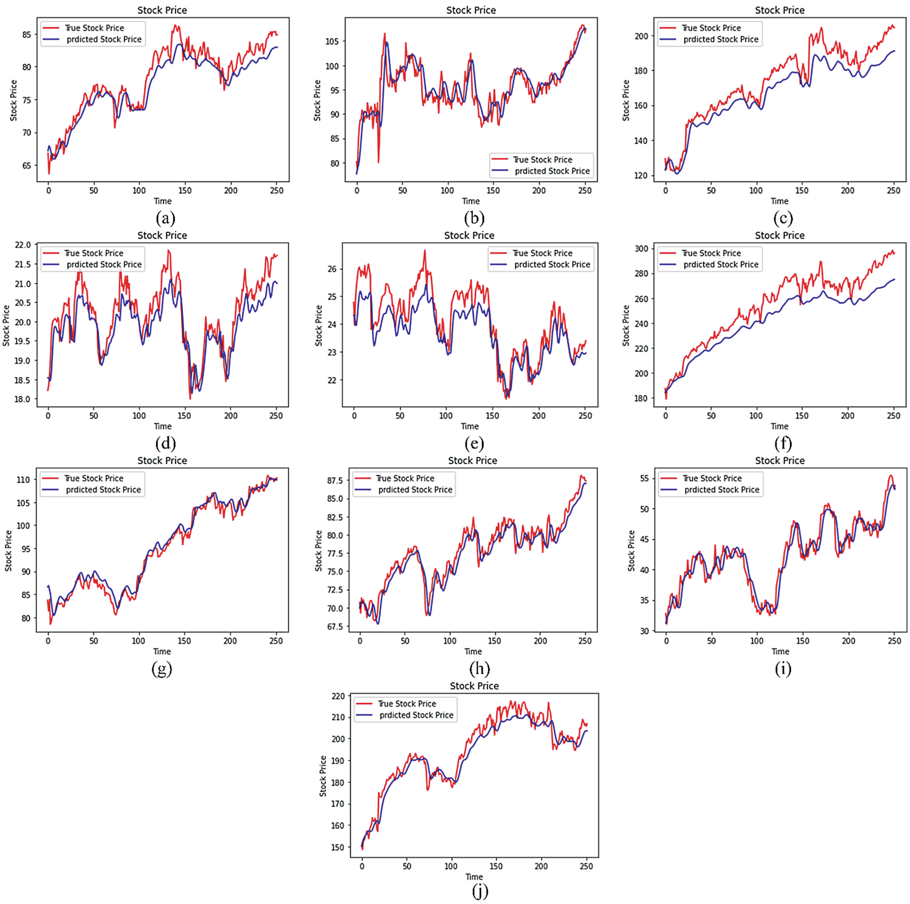

Fig. 2. Stock price prediction based on LSTM

for IPG; subfigure (e) shows the result of stock price prediction for JNPR; subfigure (f) shows the result of stock price prediction for MA; subfigure (g) shows the result of stock price prediction for MDT; subfigure (h) shows the result of stock price prediction for MKR; subfigure (i) shows the result of stock price prediction for MU; subfigure (j) shows the result of stock price prediction for SYK.

Figure 2 shows that the LSTM-based method can effectively fit the price variation trend of the above-selected stocks. However, the EL and MA have bad accuracy. The EL represents the Estee Lauder Corporation; the MA represents the Mastercard Corporation. The results show that the LSTM-based method is weak to fit the linear variation of stock price.

3.1.2 GRU-Based Results

The results of selected stocks price prediction using the GRU model are shown in Fig. 3.

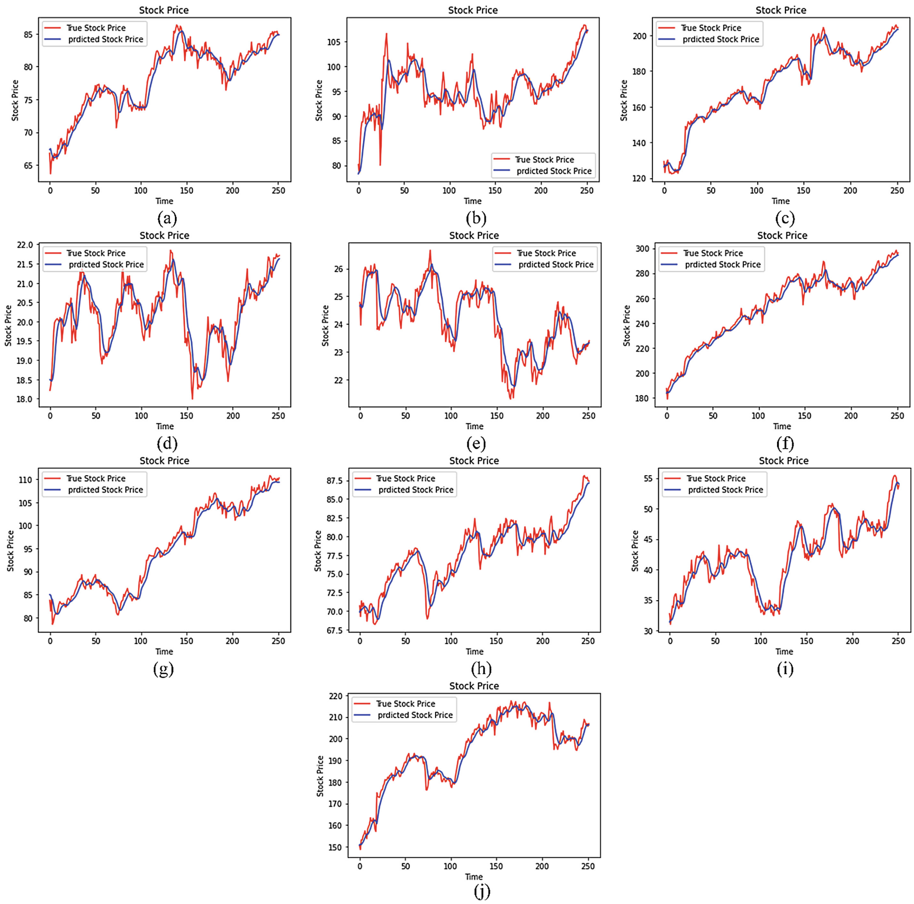

Fig. 3. Stock price prediction based on GRU

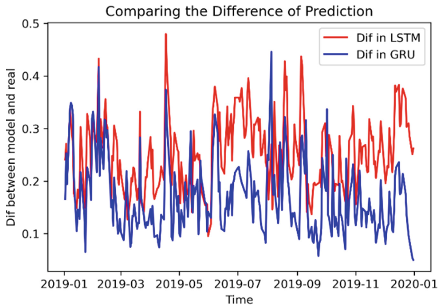

Fig. 4. The comparison of LSTM and GRU in stock price prediction

In Fig. 3, subfigure (a) shows the result of stock price prediction based on GRU for ABT; subfigure (b) shows the result of stock price prediction based on GRU for EA; subfigure (c) shows the result of stock price prediction based on GRU for EL; subfigure (d) shows the result of stock price prediction based on GRU for IPG; subfigure (e) shows the result of stock price prediction based on GRU for JNPR; subfigure (f) shows the result of stock price prediction based on GRU for MA; subfigure (g) shows the result of stock price prediction based on GRU for MDT; subfigure (h) shows the result of stock price prediction based on GRU for MKR; subfigure (i) shows the result of stock price prediction based on GRU for MU; subfigure (j) shows the result of stock price prediction based on GRU for SYK.

Figure 3 shows that the GRU-based machine learning method can effectively predict the price of the selected stocks with high accuracy. Compared to the LSTM-based method, the GRU method has a higher performance in processing the data with the linear variation characteristic. The comparison result of LSTM and GRU in the application of stock price prediction is shown in Fig. 4.

Obviously, from Fig. 4, the GRU-based method performs better than the LSTM-based method in applying the stock price prediction task.

3.2 Results of Investment Strategy Optimization

The results of the PE ratio can be found in Table 1.

Sharpe ratio can be used to measure the performance of investment returns under specific risks. This ratio adjusts the return of investment to compare different investment performances under a certain scale of risk. The investors with the most serious risk aversion will choose the minimum variance portfolio. The results of Table 1 show that the expected return is 21.02%, and the expected volatility is 12.74%. Investors pursuing the maximum risk-adjusted return will build a portfolio with the largest Sharpe ratio, with an expected return of 41.29% and expected volatility of 16.41%.

We also use Scipy's optimization function 'SLSQP' to get the asset allocation results. The result we get is almost the same as that in the randomly generated portfolio. The biggest difference is that the 'SLSQP' function does not allocate assets to some stocks in the portfolio. The diversity of the portfolio is decreasing with the optimization of asset allocation. The expected return corresponding to the highest risk is 44.43%, and

Table 1. Allocating portfolio using Sharpe Ratio and volatility

Ticker	PE ratio	Monte Carlo		SLSQP	
		Weights Sharpe	Weights Volatility	Weights Sharpe	Weights Volatility
ABT	0.5900	0.45%	1.29%	0.00%	0.00%
EA	0.4042	1.12%	2.15%	0.04%	0.00%
EL	0.5283	27.64%	5.41%	25.91%	0.27%
IPG	0.4739	2.06%	18.75%	1.96%	22.76%
JNPR	0.3265	0.10%	15.80%	0.00%	14.20%
MA	0.6243	26.24%	0.88%	44.10%	0.81%
MDT	0.3949	27.41%	27.77%	21.80%	32.68%
MRK	0.3819	3.59%	23.93%	0.00%	23.21%
MU	0.2628	7.43%	1.22%	6.19%	0.00%
SYK	0.3576	3.79%	2.80%	0.00%	6.07%

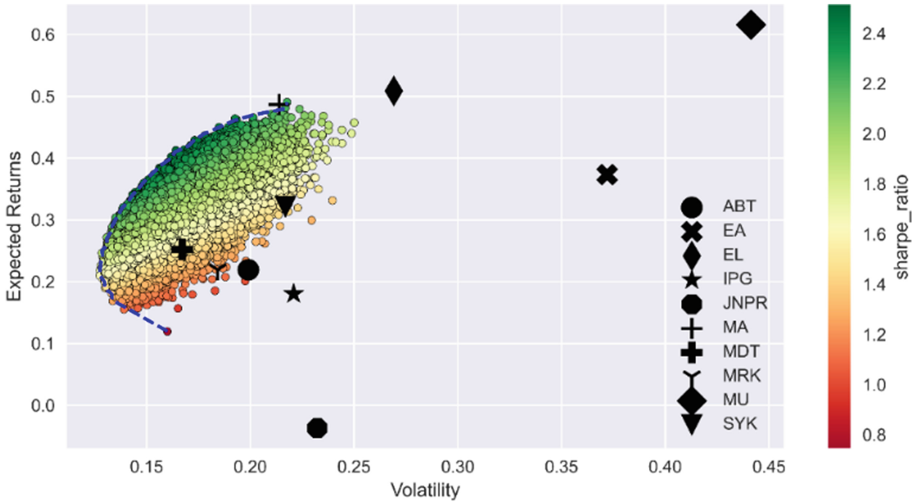

Fig. 5. The Efficient Frontier based on Monte Carlo simulations

the volatility is 17.36%. The expected return selected by the investors with the most serious risk aversion is 19.45%, and the expected volatility is 12.54%.

We use Monte Carlo simulations to find an effective frontier. We generate 100,000 portfolios and randomly assign weights to each stock in each portfolio to calculate the annual return and volatility of the portfolio. Ten stocks appear in the chart with different symbols. Each point on the line represents an optimal portfolio of stocks, which maximizes the expected return under a specific risk level. The process can be found in Figs. 5, 6, and 7.

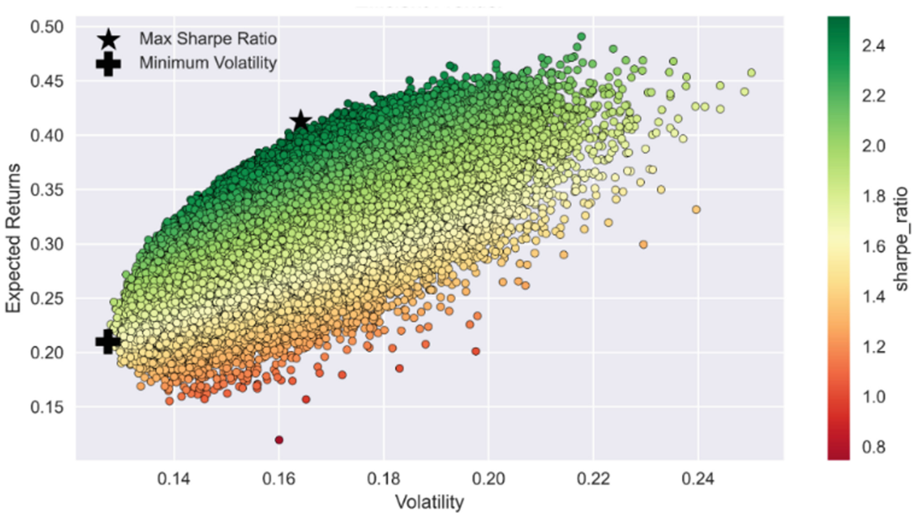

Fig. 6. Maximum Sharpe Ratio portfolio and Minimum Volatility portfolio

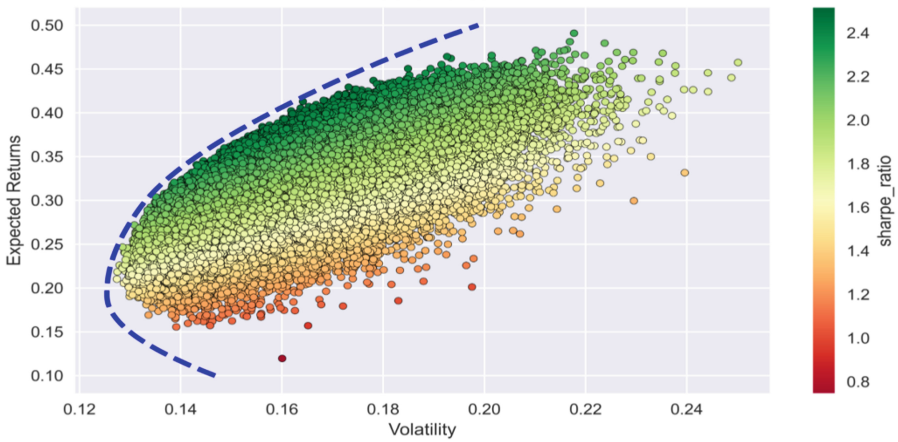

Fig. 7. The Efficient Frontier based on SLSQP

4 Conclusion

The ratio of forward PE and trailing PE has been shown to be useful to the problem of stock selection. After eliminating 16 stocks with an extremely low PE ratio, the individual rest stocks with low PE ratios show strong growth in the price prediction part.

According to our prediction results on selected stocks price, both of the machine learning models, including the Long Short-Term Memory Unit and the Gated Recurrent Unit model, are capable of yielding promising forecasting outcomes. However, in terms of certain stocks with violent volatility, the prediction results of the LSTM model have hysteresis phenomenon seriously and lower accuracy compared to the results of the GRU model.

In the process of realizing the optimal portfolio allocation, the Monte Carlo model and slsqp model well show the correlation between stocks to researchers. By choosing different optimal portfolios, different returns and risks can be obtained, from which diversified profits can be made, and the portfolio's risk can also be reduced.

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