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Portfolio Optimization based on 10 US Stocks

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Abstract. Focusing on the U.S. market, this research selects ten high-capitalization U.S. stocks in different industries and uses stock price forecasting in machine learning as well as Monte Carlo simulation to explore the efficient frontier of assets. Besides, this paper builds a portfolio with equal weight, maximum Sharpe ratio, and minimum volatility criteria, respectively. The results show that the Exxon Mobil Corporation possesses the largest proportion of the maximum Sharpe ratio portfolio, and the UnitedHealth Group Inc. accounts largest weights for the portfolio with the minimum volatility. In addition, this paper also compares the cumulative returns of the three investment portfolios with the important index NASDAQ of the US stock market. The results indicate that that the above mentioned three portfolios are all better than the benchmark index and can obtain a higher return. The results may shed light on some investors' approach to portfolio management during this extraordinary time.

Keywords: stock forecasting, portfolio optimization, Sharpe ratio, US stock

1. Introduction

In recent years, the Covid-19 epidemic, Russia-Ukraine war and the raising of interest rate in US have led to a significant fluctuate in the U.S. stock market, leading investors to pay more attention to portfolio optimization in order to reduce investment risks [1]. Building investment portfolios has always been one of the mainstream ways for investors to avoid risks. However, owning an investment portfolio is not necessarily beneficial in itself. Investors need to allocate capital in a prudent way, reduce investment risk and maximize returns by creating a diversified investment portfolio [2].

Based on this, many scholars have analyzed financial time series data and portfolio optimization because the real financial market is full of uncertainty. Over time, scholars begin to introduce forecasting methods to portfolio optimization and achieve numerous investigations. Previous studies have mostly concentrated on using statistical methods to analyze financial historical data, which is a form of limited-outcome time series analysis. Deep learning algorithms have recently been developed for sequence prediction, particularly the recurrent neural network (RNN) [3]. Also, relevant research have shown that employing such a forecasting strategy can better improve portfolio performance.

This paper uses a variety of portfolio optimization techniques to build an effective portfolio. These techniques include Monte Carlo simulation, equal-weighted modeling, optimization modeling mean variant optimization (MVO), as well as LSTM network, which can forecast stock movement based on historical data. First, using LSTM to predict the closing price of the selected stock in the future

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and calculated the cumulative returns. Then, equally weighted portfolios along with two risk-based strategies, the maximum Sharpe ratio strategy, and the minimum variance strategy, will be applied. Calculate the weight of each share in each strategy, and observe that for the maximum Sharpe ratio portfolio, XOM accounts for the highest proportion, while in the minimum volatility portfolio, UNH takes up the most. Finally, by evaluating the weight performance, it is found that compared to other combinations in the same period, the portfolio with the largest Sharpe ratio obtained the highest return.

2. Data

This article selects the top 10 representative stocks of various industries based on the market capitalization of the constituent stocks of the NASDAQ stock exchange. They all have a relatively high market value to ensure that the stock price will not fluctuate greatly due to the special behavior of some individual investors or institutions. The codes of these 10 stocks are MSFT, APPL, GOOG, AMZN, BRK-B, UNH, NVDA, XOM, V and JPM.

Collect adjusted closing prices from January 4, 2021, to December 30, 2022, and split them into training and testing sets. This article assumes 252 trading days per year for consistency. In addition, the returns, covariance matrices, and Sharpe ratios involved in the process are annualized. All data and sources are from Yahoo Finance (https://finance.yahoo.com/lookup). After analyzing and calculating the relevant data of the 10 selected stocks, the basic information obtained in this paper is as follows in Table 1 and Table 2:

Table 1: Selected stocks.

Stock	Company
AAPL	Apple Inc.
AMZN	Amazon.com Inc.
BRK-B	Berkshire Hathaway Inc. Class B
GOOG	Alphabet Inc. Class C
JPM	JPMorgan Chase & Co
MSFT	Microsoft Corporation
NVDA	NVIDIA Corporation
UNH	UnitedHealth Group Inc.
V	Visa Inc.
XOM	Exxon Mobil Corporation

Table 2: Descriptive statistics of the daily return of the 10 stocks.

	Max	Min	Mean	Std Dev	Cumulative Return
APPL	0.2212	-0.2363	0.0012	0.0406	23.27%
AMZN	0.6971	-0.3007	0.0013	0.0595	-14.41%
BRK-B	0.1781	-0.1940	0.0009	0.0328	22.42%
GOOG	0.5102	-0.3581	0.0018	0.0530	26.54%
JPM	0.2431	-0.3560	0.0007	0.0414	-10.17%
MSFT	0.3250	-0.2865	0.0013	0.0422	23.42%
NVDA	0.5635	-0.5714	0.0042	0.0880	5.784%
UNH	0.1293	-0.3041	0.0014	0.0330	48.82%
V	0.1404	-0.1558	0.0006	0.0347	-2.504%
XOM	0.4800	-0.3241	0.0030	0.0545	125.55%

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As Table 2 illustrates, when it comes to the mean returns of these data, the highest is NVDA, the lowest is V and stock BRK-B has the least volatility in daily returns according to the variance of listed stocks. This paper also calculated their cumulative returns. Figure 1 reveals that the cumulative return rate of XOM is the highest, which is 125.55%, while the cumulative return rate of V decreases with fluctuations and reaches -2.504% in the end.

Figure 1: Cumulative returns of selected stocks.

3. Method

The method adopted in this paper is to firstly take the historical average return as the benchmark. Subsequently, based on historical data, uses machine learning models such as time series regression to train and predict future stock prices, and uses different calculation methods to obtain investment portfolios with different weights, as well as corresponding returns and volatility. The way to determine the best strategy is to compare the final calculated Sharpe ratios. The Sharpe ratio is the difference between the expected return and the risk-free return, divided by the volatility, in a betting strategy. Therefore, a higher Sharpe ratio always indicates that the investment is worthwhile.

3.1. LSTM Model

The financial industry has long been a hub for financial stock forecasting research. The linear prediction models among them are primarily ARIMA, GARCH, EGARCH and IGARCH [4-6]. However, it is still exceedingly challenging to correctly anticipate financial stock values using linear prediction models due to the significant noise and nonlinear properties of financial time series. The use of neural networks in the field of machine learning for stock forecasting has grown increasingly widespread, and has produced more accurate and efficient forecasting outcomes, thanks to the quick advancement of computer technology and the maturing of deep learning research.

One such unique RNN model is the long short-term memory model (LSTM). It is specifically utilized for time series forecasting because relational recurrent neural networks may learn long-term dependencies between data. The LSTM model's structure is depicted below (See Figure 2 and Figure 3):

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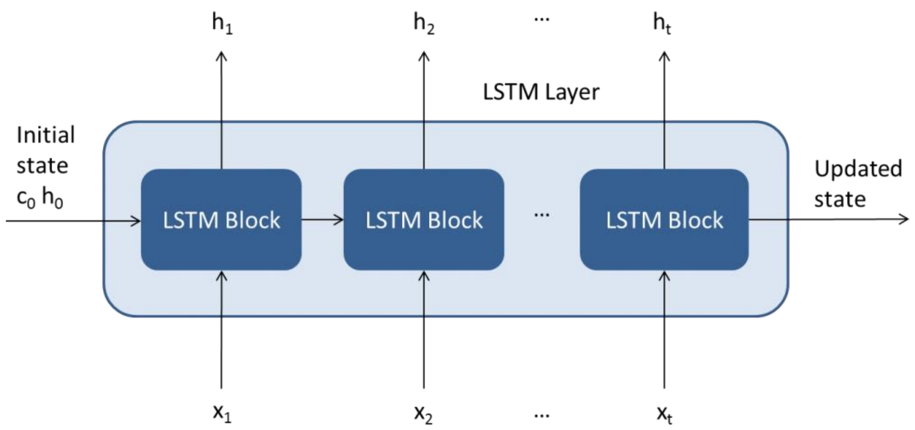

Figure 2: LSTM layer architecture.

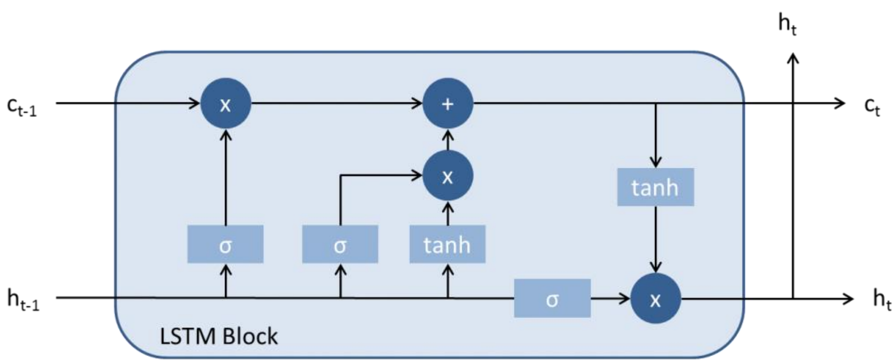

Figure 3: LSTM block architecture.

LSTM block structure consists of a recurring core module, as the figure shown above. This structure enables LSTM to learn long-term dependencies. The LSTM must be trained in order to discover the characteristics of a modeling assignment and develop prediction abilities. This procedure entails calculating the weights and biases of the LSTM by using optimization methods to minimize an objective function, often the RMSE.

3.2. Monte Carlo Simulations

Use Monte Carlo simulations to create different portfolios. This technique helps to simulate the operating process as a stochastic process with given parameters under specific conditions, where the average return and covariance matrix of stocks are used as parameters in this paper. By stochastically generating weights for each asset in the portfolio, the expected return and portfolio variance under the weights can be obtained. Then repeatedly simulating 100,000 portfolios in the same way, this pool of data will represent the most likely asset allocation and can be used to draw the efficient frontier.

3.3. Mean Variance Optimization

In this paper, three specific portfolios are considered: equal weight portfolio, maximum Sharpe ratio portfolio and minimum volatility portfolio. Various studies have shown that investors prefer to allocate funds evenly among various assets, thus simple equal-weight investment portfolios are

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widely used [7]. The Sharpe ratio is a widely used tool for measuring and evaluating risk-adjusted investment returns [8-10]. Calculated as follows:

$$SR = \frac{R_p - R_f}{\sigma_p} \tag{1}$$

Where Rf is the risk-free rate, Rp is the expected return on the portfolio, and σp is the standard deviation. Portfolios with the same expected return will have a higher Sharpe ratio if the standard deviation decreases. Therefore, the portfolio with the largest Sharpe ratio outperforms the other portfolios in terms of risk-adjusted performance. And the minimum variance strategy could help risk reversal investors minimize equity risk while maintaining market exposure, so the minimum volatility portfolio will provide investors with effective investment clues.

The strategies and models used in this paper can be used to predict future trends and prices of stocks based on past performance in data collected from Yahoo Finance. And they can be used to calculate the optimal portfolio, asset allocation weight, Sharpe ratio, volatility, and rate of return of assets under this strategy from the historical data of the stocks selected in this paper. However, it should be noted that due to the uniqueness and chance of the selected stocks, the volatility and Sharpe ratio calculated in this paper cannot be applied to other stocks; and if the strategy is used for subsequent research on other stocks, it needs to be recalculated.

4. Result

In a chart where each point represents a portfolio situation, the abscissa represents the standard deviation of risk, and the ordinate is the rate of return, the essence of investing is making a decision between risk and return. A rational investor always maximizes the expected return for a given level of risk or minimizes the expected risk for a given level of return, according to Markowitz portfolio theory.

This article first predicts and calculates the adjusted daily returns of 10 selected stocks from September 7, 2022, to December 30, 2022, based on the historical data from January 4, 2021, to September 6, 2022. Then combined with their historical data and forecast data, the results of 100,000 investment portfolios with different weights were simulated through the Monte Carlo method, and the expected returns and volatility of these investment portfolios were given, as shown in the figure below (See Figure 4):

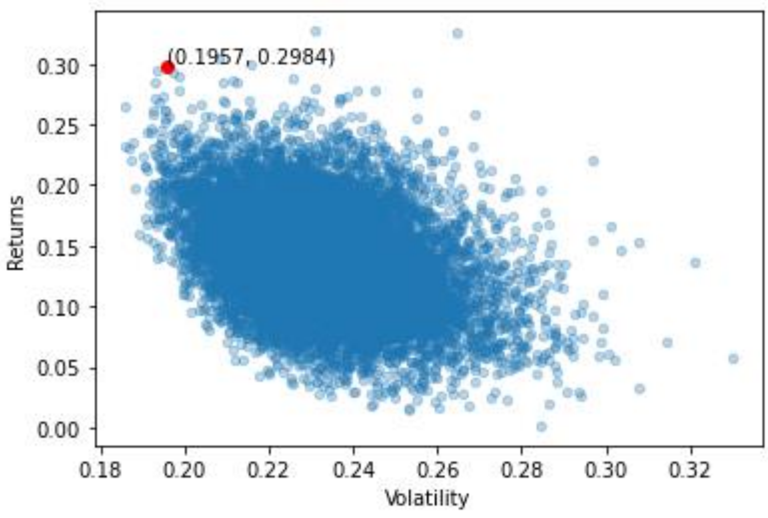

Figure 4: Efficient frontier: Portfolios with maximum Sharpe ratio.

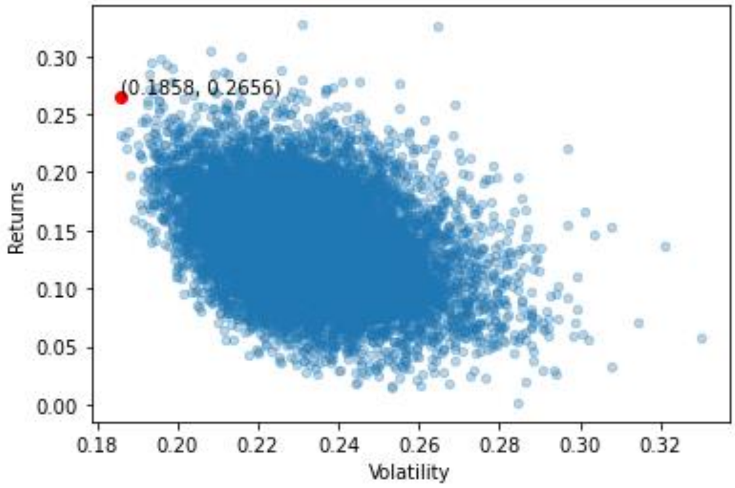

Figure 5: Efficient frontier: Portfolios with minimum volatility.

Then the best portfolios can be selected. The two targeted portfolios are calculated and labeled on Figure 4 and Figure 5. The weights of the chosen stocks in the maximum Sharpe ratio portfolio are APPL: 1.05%, AMZN: 2.24%, BRK-B: 6.01, GOOG: 14.74%, JPM:8.31%, MSFT: 0.01%, NVDA: 0.34, UNH: 20.29%, V: 15.83%, XOM: 31.18. The minimum volatility portfolio locates at the left limit of the frontier and the stock weights in the portfolio are: APPL: 1.46%, AMZN: 2.06%, BRK-B: 9.84%, GOOG: 11.66%, JPM:0.02%, MSFT: 0.90%, NVDA: 0.08, UNH: 32.02%, V: 19.75%, XOM: 22.21%, shown in Table 3. For the maximum Sharpe ratio portfolio, XOM accounts for more than a quarter, while in the minimum volatility portfolio, UNH takes up more than 25%. Besides, it should be noted that MSFT and NVDA possesses only a tiny fraction in both two portfolios.

Table 3: Weight of each stock in the two optimal portfolios (%).

	Max Sharpe Ratio	Min Volatility
APPL	1.05	1.46
AMZN	2.24	2.06
BRK-B	6.01	9.84
GOOG	14.74	11.66
JPM	8.31	0.02
MSFT	0.01	0.90
NVDA	0.34	0.08
UNH	20.29	32.02
V	15.83	19.75
XOM	31.18	22.21

Based on the two asset allocations, the next step will be calculating the portfolio return. Using test set data and stock weights, daily portfolio returns as well as cumulative returns can be obtained. For comparison, the return data for the NASDAQ index was collected over the same period. As can be seen from Figure 6, the results of this study are better than the broader market. The cumulative return of the largest Sharpe ratio portfolio was 0.32%, the cumulative return of the smallest volatility portfolio was 0.17%, the cumulative return of the equal weighted portfolio was 0.09%, and the return of the NASDAQ index was -0.11% (shown in Table 4). Figure 6 also shows that the three portfolios with different weights outperform the NASDAQ index most of the time.

Figure 6: Comparison between NASDAQ index return and the portfolio returns.

Table 4: Cumulative return comparison.

Portfolio Type	Cumulative Return
Max Sharpe Ratio	0.32%
Min Volatility	0.17%
Equal-Weight Portfolio	0.09%
NASDAQ Index	-0.11%

For cogency, a robustness check will be conducted. First, remove MSFT and NVDA, which account for the smallest proportion, from the portfolio components. Second, repeat the Monte Carlo simulation and calculation of cumulative returns. The changed weights for the two optimal portfolios are shown in Table 5, from which it can be seen that the largest components of the two portfolios remain unchanged: XOM for the portfolio with the largest Sharpe ratio and UNH for the portfolio with the smallest risk. Finally, calculate cumulative returns for each strategy, compare them to the NASDAQ index and it shows similar results to previous data. Therefore, the method and results are valid and effective (See Table 6).

Table 5: Weight of the remaining 8 stocks in the two optimal portfolios (%).

	Max Sharpe Ratio	Min Volatility
APPL	1.05	1.46
AMZN	2.24	2.06
BRK-B	6.05	9.84
GOOG	14.84	11.72
JPM	8.31	0.02
UNH	20.39	32.63
V	15.93	19.85
XOM	31.19	22.42

Table 6: Adjusted cumulative return comparison.

Portfolio Type	Cumulative Return
Max Sharpe Ratio	0.33%
Min Volatility	0.17%
Equal-Weight Portfolio	0.12%
NASDAQ Index	-0.11%

5. Conclusion

Portfolio construction is always a research interest in the financial area. Currently, most relevant research is analysis of general market conditions or specific industries, based on stock historical data. In this paper, we use machine learning and time series analysis to predict the future prices of leading stocks in different industries; then, apply mean-variance analysis for portfolio optimization, and construct equal-weighted portfolios, maximum Sharpe ratio portfolios and minimum volatility portfolios. In summary, this paper studies three portfolios (equal-weighted, minimum variance, and maximum Sharpe ratio) of 10 selected high-cap US stocks. According to the data of yahoo finance, it is possible to calculate and predict the cumulative return of stocks within a specific period of time. Afterwards, 100,000 random investment portfolios were simulated using Monte Carlo, and the returns and volatility of each investment portfolio were calculated. Visualize the data and point out the efficient frontier by plotting the relationship between portfolio return and volatility. All three portfolios beat the stock index when their cumulative returns were compared to those of the NASDAQ index over the same time period, with the portfolio with the highest Sharpe ratio achieving the highest return.

However, deficiencies also exist. The results of the optimal investment portfolio analyzed in this paper are all based on idealized data in a specific period. In the actual market, due to various factors, the asset returns and risk conditions in the asset portfolio may change at any time. Therefore, investors need to think dynamically when choosing a portfolio.

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