Predicting Mutual Fund Performance based on LSTM Models

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Abstract. Accurate prediction of mutual fund performance is becoming crucial for investors and fund managers to make informed investment decisions and earn profits. This paper utilized Long Short-Term Memory (LSTM) models to forecast the future performance of mutual funds in this research paper. This paper began by collecting a comprehensive dataset comprising historical fund prices and relevant financial indicators from Yahoo Finance. The dataset is preprocessed to handle missing values and format errors. LSTM models are known for their ability to retain and utilize information from earlier time steps in a sequence to make predictions or decisions at later time steps. This capability enables them to capture and understand long-term dependencies or relationships between elements in the sequential data, which are employed to understand and model the changes and trends in the performance of a mutual fund over time. The models are trained on a subset of the dataset, and hyperparameters are optimized to enhance their predictive capabilities. Evaluation metrics such as Mean Squared Error (MSE), the mean absolute error (MAE), root mean square error (RMSE), and R^2 are employed to evaluate how accurately the models can predict future outcomes or events based on the available data. In conclusion, this research presents a robust methodology for predicting mutual fund performance using LSTM models. The findings highlight the potential of LSTM models as valuable tools for fund managers and investors, offering enhanced accuracy and providing valuable insights for informed decision-making in the dynamic and competitive mutual fund market.

Keywords: LSTM model; mutual fund; RMSE.

1. Introduction

Eendragt Maakt Magt, a trust and the first contemporary investment funds, was established by Amsterdam-based entrepreneur Abraham (or Adriaan) van Ketwich in the Dutch Republic. Due to the matter of fact that Financial crisis often leads to a sharp decline in stock prices and other assets, the trust was to minimalize the effect of financial crisis of 1772 to 1773 and considered as the precursor of mutual funds. The businessman's goal was to provide small investors or individuals a chance to diversify and benefit from it. The majority of the early mutual funds had a fixed number of shares available for investment during the 1890s, meaning that once all the shares are sold, new investors cannot buy into the fund. It was also the time when mutual funds were first offered in the US. There was a demand for these funds and investors were willing to pay a premium to invest in them learning from the traded prices higher than net asset value(NAV) of the portfolio. On March 21, 1924, the Massachusetts Investors Trust, which is still in operation today and is run by MFS Investment Management, became the first open-end mutual fund with redeemable shares. In 1929, only 5% of the total assets in the sector, which amounted to $27 billion, were held by open-end funds. This indicates that closed-end funds dominated the market during that time. Additionally, a mutual fund consists of a diversified portfolio of various assets such as stocks, bonds, and others. These portfolios are managed by professionals who possess relevant economic knowledge and expertise.

A sectionized of everything contained is what you receive when you purchase shares of a mutual fund. There are also inexpensive index mutual funds available that follow well-known indices like the S&P 500. In the case of actively managed funds, the professional responsible for managing the fund will carefully choose the investments within the mutual fund. The selection process is driven by various objectives, such as seeking growth (capital appreciation) or generating income (through dividends or interest payments). Over extended periods, actively managed funds have historically underperformed passive funds and charge higher fees. A range of US mutual funds, including income and bond funds, money market funds, and equity funds, with assets totaling more than $1 trillion by 1990 [1]. The industry accounts for 4% of all main securities and 9% of the GDP for the median country [2].

Fund predictions have become increasingly critical in the financial industry as investors and financial institutions put much effort into making informed investment decisions. Accurate predictions of fund performance and behavior can provide valuable insights into market trends, risk management, and portfolio optimization. The conventional method of analysis incorporates both fundamental analysis, which focuses on intrinsic value and regression techniques, and technical analysis, which uses historical price data and economic principles to predict future price movements. These methods are commonly employed in the field of economics and finance to analyze and evaluate investments and assets. In recent years, the use of Long Short-Term Memory (LSTM) models [3, 4], a type of recurrent neural network (RNN) [5, 6], has gained significant attention in predictions in the financial-economic field due to their ability to capture temporal dependencies and handle sequential data. LSTM excels in applications requiring long-term memory of a small amount of data [7]. Since mutual fund has the characteristics of random walk and can be considered as a time series, LSTM model is applied in this research work.

This paper aims to present the efficient result of mutual fund predictions using LSTM models, highlighting the methodologies and performance evaluation. In summary, this paper aims to provide a comprehensive review of the literature on fund predictions using LSTM models. It covers various applications, enhancements, and evaluation techniques, highlighting the effectiveness of LSTM models in capturing temporal dependencies and improving prediction accuracy. By synthesizing the findings of these studies, this review aims to contribute to a better result of LSTM-based fund predictions and assist investors and financial institutions in making informed decisions.

2. Methods

2.1. Data Sources and Description

The dataset used in this analysis is obtained from a website Kaggle, was scraped by Stefano Leone, and was updated in 2021. The dataset is provided in a CSV file format named 'fund_prices.csv'. It contains historical data on fund prices over a specific time period.

The dataset includes several columns, such as 'Date', 'Fund Name', 'Price', 'Volume', and 'Returns'. The 'Date' column represents the date of the fund price, while the 'Fund Name' column provides the name or identifier of the fund. The 'Price' column denotes the closing price of each fund on a given date. The 'Volume' column represents the trading volume of the fund on that particular date. Finally, the 'Returns' column indicates the daily returns of each fund. It was preprocessed to handle missing values and outliers, and feature engineering techniques were employed to extract meaningful features.

2.2. LSTM Model

The network model known as LSTM was developed by Schmidhuber et al. in 1997 to address the long-standing issues of gradient explosion and gradient disappearance in RNN [8]. In existing RNN architectures [9, 10], the backpropagated error, which is the mechanism used to update the weights of the network during training, either blows up (increases exponentially) or decays (decreases exponentially) when dealing with long-time lags. This means that the gradients used to update the weights become either too large or too small, making it challenging for the network to capture and learn from long-term dependencies. This limitation of existing RNNs served as the inspiration for the development of the LSTM architecture. The LSTM architecture was specifically designed to overcome this issue by introducing memory cells and gating mechanisms. It has a memory of its own and is capable of making forecasts that are reasonably accurate, making it a popular tool for converting spoken language into written text, identifying and understanding the emotions expressed in various kinds of forms of communication, and analyzing and interpreting textual data. There have been researchers applying LSTM to forecast stock market recently as well. The information flows through the RNN in a straightforward manner, without any specialized mechanisms for handling long-term dependencies. On the other hand, an LSTM network consists of multiple repeating modules, where four of these modules work in a distinct and interactive way. As depicted in Figure 1, the memory cell is made up of three components: the forget gate, which determines how much of the previously stored information in the memory cell should be discarded or forgotten, the input gate, a part to regulate how much new information should be stored in the memory cell, and the output gate, controlling how much information from the memory cell should be used to generate the output of the LSTM unit.

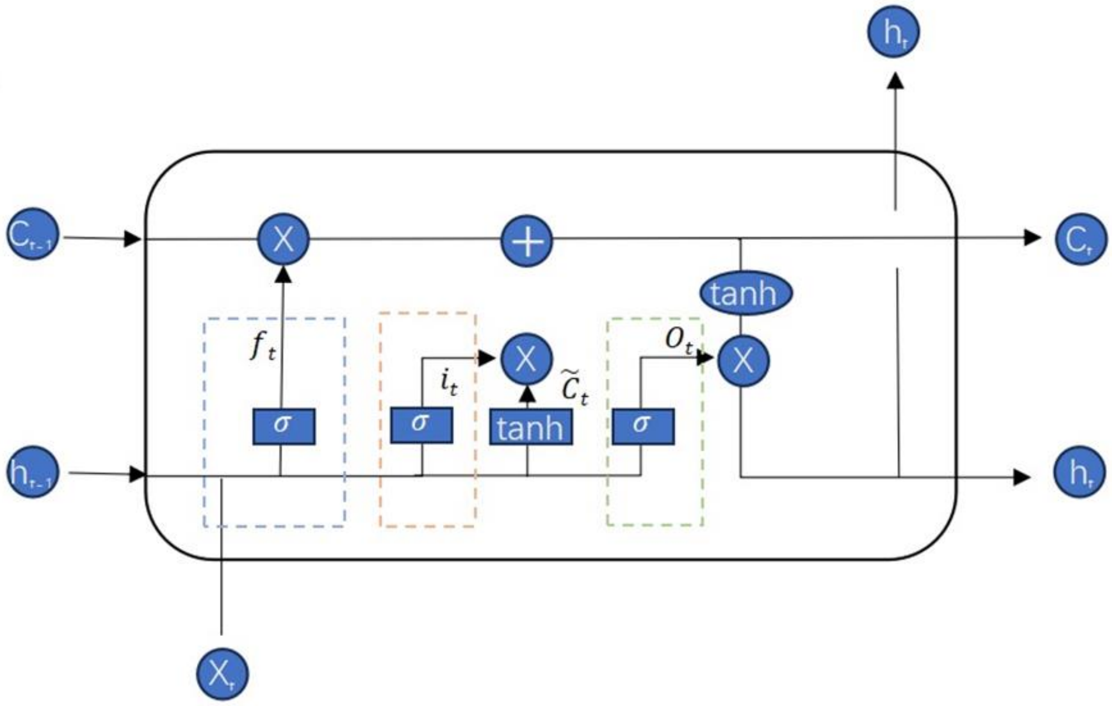

Fig. 1 LSTM structure

3. Results and Discussion

3.1. Implementation of LSTM

The LSTM models were compared with traditional machine learning algorithms to assess their superiority in predicting mutual fund performance. The results demonstrated the superior performance of LSTM models, outperforming traditional approaches in terms of prediction accuracy and capturing complex dynamics. Table 1 displays the LSTM's parameter settings for this experiment (Table 1).

Table 1. Parameter setting of LSTM

Parameters	Value
Number of hidden units in LSTM layer	32
LSTM layer activation function	tanh
Time_step	20
Batch_size	1
Learning rate	0.01
Optimizer	Adam
Loss function	Mean_square_error
Epochs	300

3.2. Model Results

When it comes to evaluating how mutual funds perform, most studies concentrated on how well mutual fund managers are able to predict the future price movements of the specific stocks they have chosen to invest in and forecast the general direction and trends of the broader stock market. Since they are both highly dependent on time information acquired from stock evaluation is valuable. We can learn that LSTM has outperformed MLP, CNN, and RNN from several perspectives in predicting stocks.

According to the efficient market hypothesis, the price of an asset will take into account all relevant information. In reality, prices may not always respond instantly to new information in an economically efficient market. There may be delays or inefficiencies due to various factors. Nonetheless, over the long term, the statement suggests that speculation cannot consistently generate profits if transaction costs, such as fees or taxes, are considered. This is because any potential gains from speculation would be offset by these costs. Many believe that markets generally incorporate and reflect available information in asset prices. However, this theory is regularly contested and occasionally challenged by earlier studies that may question its validity or provide alternative perspectives.

By monitoring and analyzing the price of the mutual fund, investors and analysts can gain insights into the performance and potential returns of the diversified portfolio as a whole. Figure 2 shows that LSTM has a relatively decent performance while data training which can also be known from Table 2. LSTM predicts precise trends of mutual funds while training loss is nearly zero, as shown in Figure 3, 4.

Fig. 2 Comparison of the training prediction and the real value

Table 2. Evaluation indices of LSTM.

Parameters	Value
MAE	25.582
RMSE	36.375
R^2	0.9955

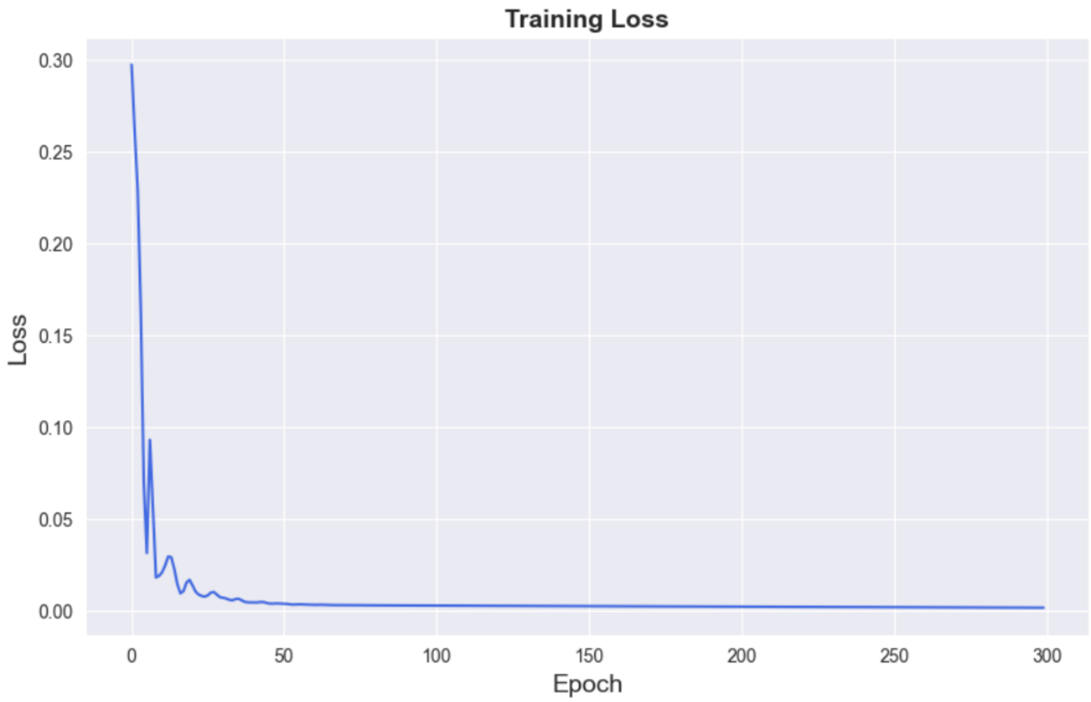

Fig. 3 Loss function

Fig. 4 Comparison of the test prediction and the real value

4. Conclusion

This study has explored the application of LSTM models for predicting mutual fund performance. The research has demonstrated the effectiveness and potential of LSTM models in forecasting the future performance of mutual funds. Through the analysis of a comprehensive dataset consisting of historical fund prices and relevant financial indicators, we were able to preprocess the data and extract meaningful features. This allowed us to train LSTM models that capture the temporal patterns and dynamics of fund performance. The experimental results have shown that LSTM models outperform traditional approaches in predicting mutual fund performance. The models exhibited strong predictive capabilities, as evidenced by their superior performance in terms of evaluation metrics. This indicates their potential as valuable tools for investors and fund managers.

Moreover, the comparative analysis with traditional machine learning algorithms highlighted the superiority of LSTM models in capturing the complex dynamics of fund performance. LSTM models, due to their architecture, are effective at capturing and understanding long-term dependencies. They can analyze the sequential nature of the data, identify patterns, and learn the intricate relationships between different time periods in mutual fund performance. By providing accurate predictions of fund performance, our LSTM models enable investors to estimate decisions thoroughly regarding fund selection and portfolio management. This can lead to improved investment outcomes and better risk management.

It is concluded that this study contributes to the field of finance by showcasing the potential of LSTM models in predicting mutual fund performance. The findings emphasize the importance of utilizing advanced machine learning techniques to enhance predictive accuracy in the dynamic and competitive mutual fund market. As future research, it would be valuable to explore the application of LSTM models in other financial domains and investigate any potential enhancements or refinements to further improve their performance.

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