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LSTM Networks and ARIMA Models for Financial Time Series Prediction

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Abstract: In this study, we evaluate the forecasting effectiveness of the classical ARIMA model and the deep learning-based LSTM model in the financial domain. An investment portfolio comprising equal shares of gold, the S&P 500, and 2-year U.S, is constructed to predict future trends, thereby accounting for market factors and risk-free interest rates. Various historical data are used to train the model and forecast the value of protfolio respectively. For the ARIMA model, predictions are made by segmenting the model into three groups based on the time span of the training data. The LSTM model utilizes 80% of the data as the training set and 20% as the test set. Furthermore, by employing diverse initial states for parallel training and averaging, errors are reasonably reduced. Key indicators, such as the portfolio's expected annual returns, daily logarithmic returns, volatility, and value at risk (VaR), are calculated. The findings suggest that both the forecasting models and the constructed portfolio are effective. Future research could focus on using prediction models to optimize and dynamically adjust portfolios, thereby enhancing returns.

Keywords: ARIMA model; LSTM network; financial time series; prediction

1. Introduction

In finance, prediction is a key research area, covering stock market trends and derivative pricing. The complexity of financial data characterized by nonlinear relationships, various factors and irrational behaviors, makes accurate forecasting challenging. Despite these difficulties, economists continue to develop methods to improve predictive accuracy and efficiency due to significant investment potential.

Traditional time series forecast models such as ARIMA are commonly used. These models provide good fit and reference value in time series processing, with applications even in fields like tourism forecasting[1]. However, their predictive accuracy declines sharply during significant events, and cumulative errors may increase over time.

In machine learning, numerous models like linear regression, decision trees, and ensemble methods like random forests have been applied effectively, for example in studies on oil options volatility[2]. These models are more effective at solving multicollinearity issues and complex functional relationships. The swift advancement of deep learning has propelled neural networks to the forefront, leading

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to the creation of convolutional neural networks (CNN) and recurrent neural networks (RNN), which are used for complex nonlinear predictive tasks, such as options pricing[3]. Moreover, neural networks have a broader range of applications, such as deep neural networks related to the Kyle single-period model[4]. However, due to the overly intricate relationships between variables, these models only uncover correlations within the data, though some scholars are working on methods to interpret them[5].

RNN performs well in fitting data with temporal dependencies because their feedback loops consider both current and past information. However, RNN faces training challenges like the ”vanishing gradient problem”. To address long-term dependencies and improve training, LSTM networks are introduced. The key innovation in LSTM is incorporating nonlinear, data-related control into RNN units[6]. This is achieved through a gating mechanism, which includes input, output, and forget gates, enabling the network to learn how to retain, transmit, or forget the information[7]. They have been widely applied in NLP[8], image identification and classification[9], etc. In finance, LSTM models are increasingly used, such as in studies on the SSE 500 index[10] and stock market jump detection[11].

In this paper, we study the prediction effect of ARIMI model and LSTM by constructing portfolio. After that, we use the predicted value to calculate the relevant indicators of the portfolio to verify the effect of the portfolio.

2. Methodology

2.1. Data

A portfolio is created with the S&P 500 index, gold, and 2-year U.S. Treasury bonds. The inclusion of gold and Treasury bonds is intended to mitigate prediction errors and hedge against stock market volatility by accounting for various market factors. Data from Yahoo Finance cover daily prices from 2000 to 2023 for these assets. The 2-year Treasury data is converted to daily prices using an initial amount of $1,000 and daily yields, while gold and S&P 500 data are daily closing prices. These datasets are then weighted and aggregated to compute the portfolio’s daily prices.

During data processing, the first step is to remove missing and outlier values. For the ARIMA model, it is crucial to apply differencing to achieve stationarity in the series. For the LSTM model, the steps of standardizing the data, subtracting the mean and dividing by the standard deviation are taken.

2.2. ARIMA model

The ARIMA (AutoRegressive Integrated Moving Average) model is a fundamental tool in time series analysis, designed to address the limitations of traditional regression methods, which often fail to accurately model the dynamic nature of time series data, resulting in significant prediction errors. These errors typically arise from the inability of direct regression to capture complex data structures and error correlations inherent in time series. As that data might not always be stationary, a differencing process is added, culminating in the ARIMA model[12].

The ARIMA model is composed of three primary elements: Autoregression (AR), Differencing (I), and Moving Average (MA). The autoregressive term describes how current values are related to its past values. Differencing is used to make a unsteady time sequence stationary. The moving average component captures the relationship between series values and past forecast errors.

Thus, an ARIMA model is typically denoted as ARIMA(p,d,q) and can be written as:

$$\Delta^d X_t = c + \sum_{i=1}^{p} \phi_i \Delta^d X_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \tag{1}$$

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Where $\Delta^d X_t$ represents the differenced time series after d operations.

We stabilize the data through differencing first, and then select the optimal ARIMA parameters (p, d, q) using the AIC criterion. The ARIMA is the model trained on the first five years of data to forecast the next five days. Using a rolling window approach, we re-fit the ARIMA model for each prediction, generating forecasts for one year, as illustrated in figure 1.

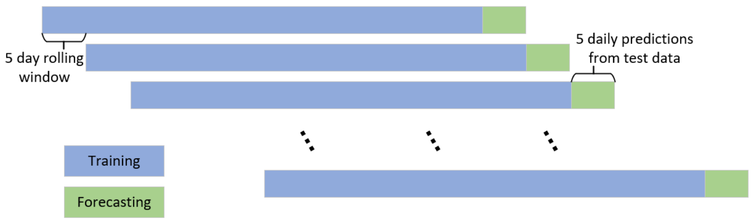

Figure 1: Blocks of forecast and training sets

2.3. LSTM

2.3.1. Introduction of LSTM

LSTM networks enhance traditional RNNs by using a memory cell to effectively learn long-term dependencies and address gradient issues. The figure 2 is the process of LSTM,

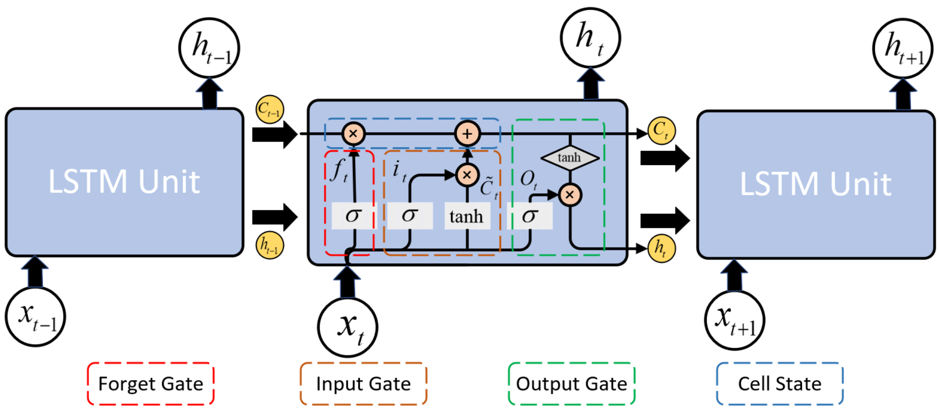

Figure 2: LSTM

LSTM networks use input, forget, and output gates to manage information flow within the memory cell, effectively balance the intake of new data, retention of past information, and output to enhance modeling of long-term dependencies.

$$f_t = \sigma(W_f \cdot [x_t, h_{t-1}] + b_f) \tag{2}$$

$$i_t = \sigma(W_i \cdot [x_t, h_{t-1}] + b_i) \tag{3}$$

$$o_t = \sigma(W_o \cdot [x_t, h_{t-1}] + b_o) \tag{4}$$

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where f_t is the output of forget gate, i_t represents the input gate value, and o_t denotes the output gate activation. And σ is the *sigmoid* activation function that make values range between 0 and 1.

At time step t, the cell state C_t is adjusted by merging the previous cell state C_{t-1} with the new candidate cell state $\tilde{C}_t$, as regulated by the forget gate f_t and the input gate i_t. The forget gate determines how much of C_{t-1} is retained, while the input gate controls the amount of $\tilde{C}_t$ to be added. The update rule for the cell state is given by,

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{5}$$

where

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

Finally, the output h_t is influenced by both the output gate o_t and the $\tanh$ function applied to the cell state C_t.

$$h_t = o_t \cdot tanh(C_t) \tag{6}$$

2.3.2. Training and Ensemble

The LSTM model are employed for time series forecasting, using 80% of the data for training and 20% for testing. The model is trained with a 12-day window size and a batch size of 64, and utilize 96 hidden units to balance complexity and long-term dependency capture.

Instead of using a single LSTM network, an ensemble of independently initialized LSTM networks are used. This approach improves prediction, enhances generalization and performance while reducing overfitting. In time series analysis, ensemble LSTM models capture diverse patterns and dependencies, leading to more reliable and accurate predictions.

Seven distinct weight initialization strategies are employed to enhance the performance and generalization capability of our LSTM networks. These initialization methods include:

Table 1: Different initializations for each LSTM

Initialization	Details	Parameters
Random Normal	Normal Distribution	μ = 0.0, σ = 0.05
Random Uniform	Uniform Distribution	min = -0.05, max = 0.05
Truncated Normal	Normal Distribution where $\sigma \geq 2$ are redrawn	μ = 0.0, σ = 0.05
Xavier Normal	Normal Distribution	μ = 0.0, $\sigma = \sqrt{\frac{2}{fan\_in+fan\_out}}$
Xavier Uniform	Uniform Distribution with [-$limit$,$limit$]	$limit = \sqrt{\frac{6}{fan\_in+fan\_out}}$
Identity	Identity matrix	
Orthogonal	Orthogonal matrix	

3. Result

3.1. Result of ARIMA

Figure 3 shows the relative error of ARIMA model predictions for portfolio prices with training periods of one year and 2 years. The average relative error is approximately 0.0063 for the 1-year model, and 0.0061 for the 2-year model. There are similar trends about notable errors in March and October 2023 likely due to random or seasonal factors.

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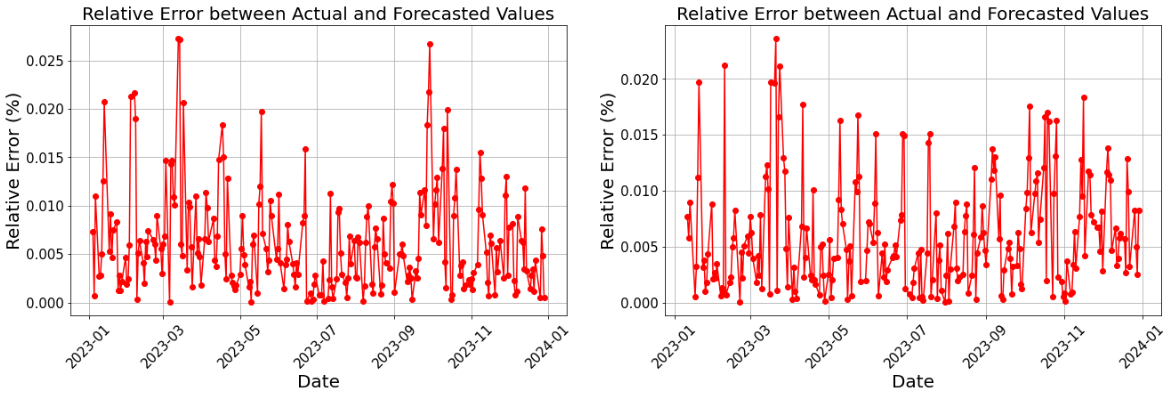
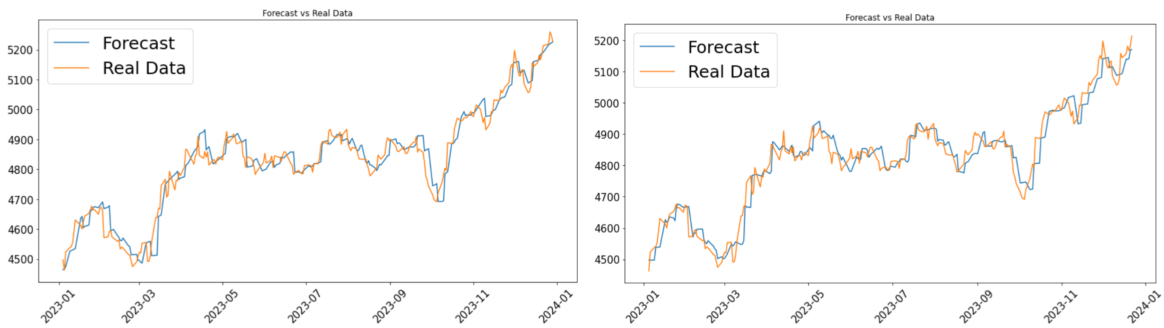


(a) 1-year Training Set (b) 2-year Training Set

Figure 3: Relative error between actual and forecast values of ARIMA

Further observation of the price trends, shown in figures 4 with the same sequence as the relative error plots, reveals that the predicted price trends lag behind the actual data. The predicted volatility is also slightly lower, but the overall trend remains consistent.



(a) 1-year Training Set (b) 2-year Training Set

Figure 4: Predictions of ARIMA

3.2. Result of LSTM

By using seven different LSTM networks, the prediction figures of some of these distinct initial weight LSTM networks are as followed.

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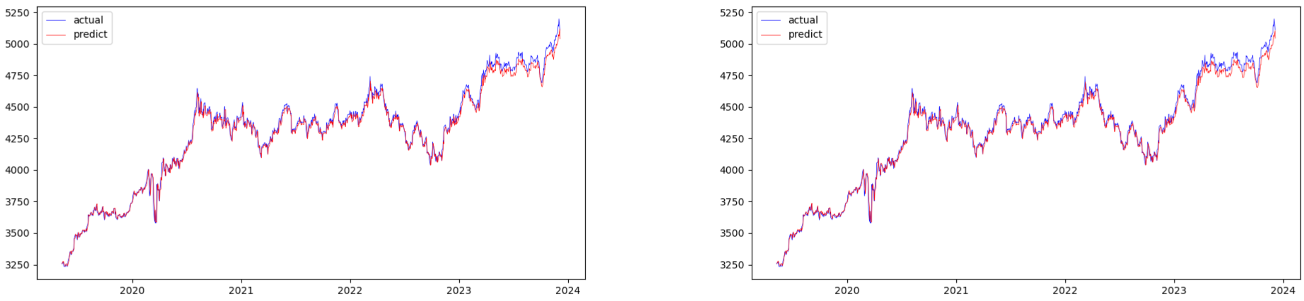

(a) Random Normal

(b) Random Uniform

Figure 5: Predictions of LSTM

Figure 5 illustrates the predictive performance of the LSTM model by comparing the actual observed data (depicted in blue) with the model's predictions (depicted in red) over time. The close alignment between the model's predictions and the actual values demonstrates the model's effectiveness in capturing overall trends and significant fluctuations. This indicates the successful learning of temporal dependencies inherent in the time series data.

Prediction errors are associated with major global disruptions. In early 2022, U.S. inflation prompted aggressive monetary tightening, which heightened market volatility and posed challenges to the LSTM model's predictive accuracy. Additionally, the Russia-Ukraine conflict and the ongoing effects of COVID-19, including supply chain disruptions, further complicated market conditions and predictions. These factors collectively contribute to the observed inaccuracies in the model's forecasts.

In the final prediction, the mean value of forecasting outcome of seven LSTM networks are taken with distinct initial weight configuration, and sketch the figure of relative errors as following.

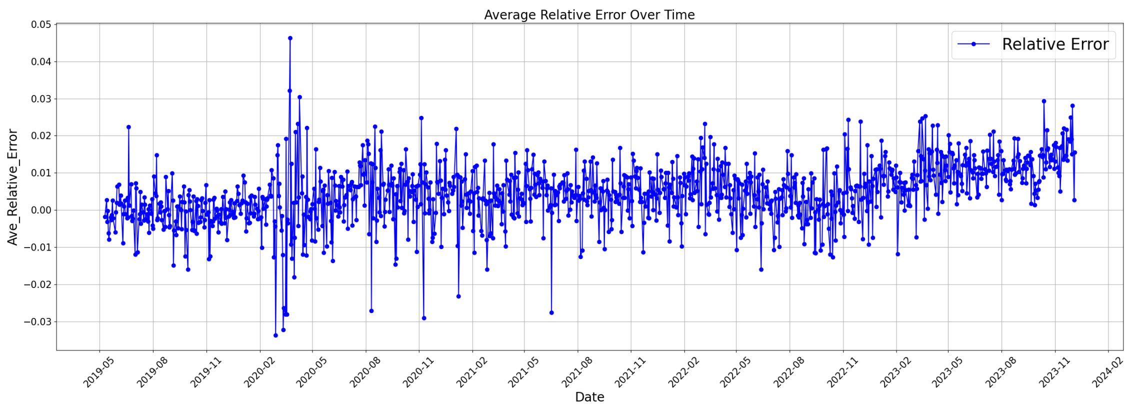

Figure 6: Average relative error of LSTM over time

Figure 6 shows the average relative error over time, with a mean of 0.45414%. The spikes in early 2020 and early 2022 are attributed to the COVID-19 pandemic and the Russia-Ukraine conflict, resulting in sudden market changes and challenged prediction accuracy. Overall, the model performs well but struggles during major market disruptions.

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3.3. Return, Volatility, and Value at Risk (VaR)

Using the LSTM model's predictions, we calculate these indicators.

Figure 7: Log Returns, Volatility

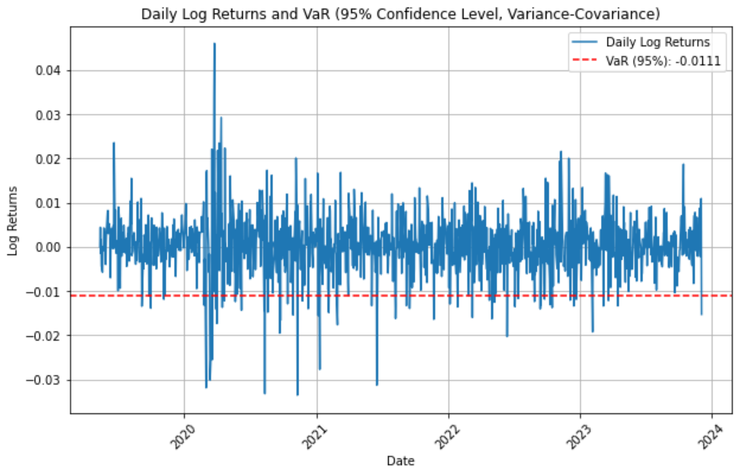

Figure 8: Daily Log Returns, VaR

Figure 7 and 8 show that log returns oscillate within a 0.02 range, with notable fluctuations in early 2020 due to the pandemic. Volatility exhibits cyclic patterns characterized by rapid increases followed by periods of stabilization, mirroring market cycles but with varying amplitudes. Post-2020, there is a slight increase in volatility, likely attributed to heightened uncertainty following the pandemic. The VaR value of about -0.01 suggests that with 95% confidence, daily returns will exceed this level. It is convinced that data below this threshold is affected by extreme events. The method of variance-covariance is adopted to calculate the value at risk at this point.

4. Conclusion

In conclusion, the use of LSTM networks and ARIMA models to forecast stock prices offers valuable insights for financial time series prediction. The LSTM model excels in its ability to analyze nonlinear relationships and large amounts of historical data which makes them particularly effective for stock price calculations. The strength of the ARIMA model lies in that it can analyze linear relationships with ease which makes them very suitable when analyzing simple markets.

In future research, a promising direction is to use the prediction model to optimize and dynamically adjust the portfolio to make our returns higher. In addition, no direct integration of models has not been completed, and integrating multiple models will also be a good research direction.

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Nan Zheng and Cuiyang Huang made equal contributions to this work and should both be regarded as co-first authors.

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