Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 44 No. 12
December 2023

Forecasting the stock price value using Gated Recurrent Units (GRU) Neural Networks model

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Abstract: Forecastingstock price movements is a complex challenging task in the financial domain due to inherent volatility and unpredictability of the stock market.In this study we propose a novel approach to predict stock value using Gated Recurrent Units(GRU) Neural Networks, a variant or Recurrent Neural Network(RNN) known for their ability to capture long term dependencies in sequential data.The proposed GRU NN model showcases significant potential in forecasting stock price values, empowering investors, financial analysis and traders with valuable insights for informed-making. Its application can aid in minimizing risks and maximizing of returns in the ever-evolving stock market landscape. The findings of this study contribute to the growing body of research in financial forecasting using machine learning techniquesand provide a strong foundation for future advancements in the domain. The GRU Neural Network Model involves collecting historical stock price data trading volumes and relevant market indicators.After preprocessing the data to handle missing values and outliers,we engineer informative features,including technical indicators and sentiment scores derived for external sources to enrich the models understanding of the market dynamics. The GRU Model is then trained on prepared dataset to learn complex relationships between historical stock price patterns and other features.Then the proposed architecture model is evaluated using accuracy measure obtained from the loss function Mean Absolute Eror(MAE),Mean Absolute Scaled Error(MASE),Accuracy Percent ,Root Mean Squared Error(RMSE),Mean Absolute Percent Error(MAPE) the accuracy measurements represent lower accuracy, true accuracy and higher accuracy in using the model.

Keywords: Forecasting, Recurrent Neural Network, Gated Recurrent Units,Forecasting Accuracy,Machine Learning

Introduction:

The financial market is quite volatile and experiences periods of contraction as well as expansion. The stock market, as a major financial market, is likewise highly volatile. The stock market has the characteristics of high return which has attracted the majority of investors and high risk which puts pressure on investors to sell out at the wrong time. In order to reduce unnecessary losses and obtain higher trading profits, the investors usually except to predict the stock price trend. As a result, stock market forecasting has been a major research topic in the financial area and attracts the attention of investors. In the stock market, the factors affecting the rise and fall of stock prices are complex and diverse. It includes not only the impact of economic factors such as price indicator, circulation indicator, activity degree, and economic uncertainty but also the impact of noneconomic factors such as traders' expectations, traders' psychological factors, and political environment. Therefore, the prediction of stock price has always been a challenging task

Stock price forecasting has long been a focal point in the financial world, essential for making informed investment decisions, managing risk, and optimizing portfolio performance. Accurate and timely predictions of stock prices are of great interest to investors, financial analysts, and traders, as they provide valuable insights into potential market trends and opportunities. In recent years, advancements in deep learning and neural network architectures have revolutionized the field of time series prediction, offering more sophisticated tools to model the intricate dynamics of financial markets

One such neural network model that has gained prominence in the realm of sequential data analysis is the Gated Recurrent Units (GRU) neural network. GRUs are a type of recurrent neural network (RNN) that address the vanishing gradient problem, making them well-suited for capturing long-term dependencies in sequential data. The adaptability and effectiveness of GRUs have made them an attractive option for stock price forecasting.

This study delves into the application of GRU neural networks for forecasting stock price values. It aims to explore the architecture of the GRU model, the preprocessing of historical stock price data, and the evaluation metrics used to assess the model's predictive performance. In addition, it investigates the impact of hyperparameter tuning, the selection of relevant input features, and the influence of varying time horizons on the quality of predictions.

There are various methods for predicting stocks, which can be broadly classified into fundamental analysis and technical analysis. Currently, technical analysis methods commonly used in China and abroad can be roughly divided into two categories: econometric methods and machine learning (ML) methods. The mainstream econometric models, such as the autoregressive moving average (ARMA) model, the autoregressive integrated moving average (ARIMA) model, the generalized autoregressive conditional heteroscedasticity (GARCH) model, the vector auto regression (VAR) model, and so on, have been proven effective in predicting the stock market according to the literature. Although econometric methods are more objective in nature and supported by appropriate theories, their effectiveness with regard to stock market prediction relies on the strictness of their underlying assumptions, and they are only applicable to linearly structured data. However, given that the stock market is a dynamic system influenced by various factors and often characterized by a series of complex and nonlinear features, traditional econometric prediction methods are restricted by certain limitations and are not well suited to the analysis of complex, high-dimensional, and noisy financial time series.

Literature Survey:

Related Work:

Introduction to RNN:

Recurrent Neural Networks (RNNs) are a class of artificial neural networks designed for processing sequences of data. They are particularly well-suited for tasks involving time series data, natural language processing, speech recognition, and more. RNNs have an internal state or memory that allows them to maintain information about previous elements in a sequence, making them capable of capturing temporal dependencies.

The fundamental idea behind RNNs is to use the output from the previous step as input to the current step, allowing the network to maintain a form of memory about the past. This concept is often represented by a simple formula:

$$h_t = f(h_{t-1}, x_t)$$

Where:

- h_t is the hidden state at time step t.
- f is the activation function applied to combine the previous hidden state h_{t-1and input x_t at the current time step t.
- x_t represents the input at time step t

However, traditional RNNs have some limitations, such as the vanishing gradient problem, which makes it challenging for them to capture long-term dependencies. To address these issues, more advanced RNN variants have been developed, including:

Gated Recurrent Unit (GRU): GRUs are another variant of RNNs that use gating mechanisms to control the flow of information through the network. They are somewhat simpler than LSTMs but have shown similar capabilities in practice.

RNNs and their variants have been widely used in various applications, including:

Natural Language Processing (NLP): RNNs are used for tasks like text generation, sentiment analysis, machine translation, and named entity recognition.

Speech Recognition: RNNs are employed in automatic speech recognition systems to convert audio input into text.

Time Series Analysis: RNNs can be used for tasks like stock price prediction, weather forecasting, and anomaly detection in sensor data.

Video Analysis: RNNs can be used for action recognition, video captioning, and tracking in video data.

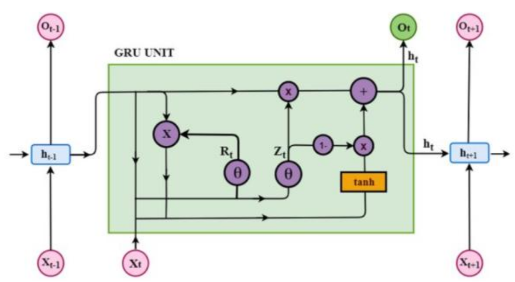
Recommendation Systems: RNNs can be applied in personalized recommendation systems to model user preferences over time.

It's worth noting that while RNNs and their variants have been powerful tools, more recent developments, such as Transformer-based models (e.g., BERT, GPT), have become popular in NLP and other sequence-to-sequence tasks due to their superior performance on many benchmarks. However, RNNs are still relevant and find applications in scenarios where capturing sequential information is crucial.

GRU (Gated Recurrent Unit):

A Gated Recurrent Unit (GRU) is a type of Recurrent Neural Network architecture that was designed to address some of the limitations of traditional RNNs while retaining the ability to capture and model sequential patters in data. It is a significant improvement in terms of simplicity and efficiency while offering competitive performance with more complex RNN Variants like Long Short Term Memory Networks. The GRU Model was introduced as a way to overcome the vanishing gradient problem and facilitate the training of deep recurrent networks.

Simplifying the architecture of a Gated Recurrent Network (GRU) while retaining its ability to capture sequential patterns can be achieved by reducing the number of parameters and simplifying the gating mechanism



Update Gate: Update gate decides if the cell state should be updated with the candidate state or not

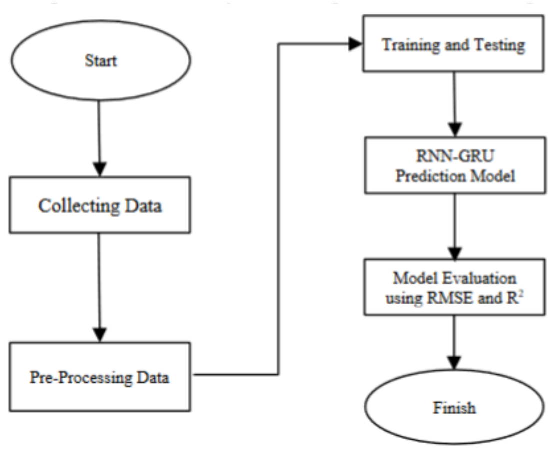
$$Z_t = \sigma\left(W^{(z)}x_t + U^{(z)}x_{t-1}\right)$$

Reset Gate: The Reset gate is used to decide whether the previous cell state is important or not.

$$R = \sigma\left(W^{(r)}x_t + U^{(r)}x_{t-1}\right)$$

Current Memory Gate: It is just simply same as the hidden state of RNN

$$h_t = tanh(Wx_t + r_t \Theta U h_{t-1})$$



System Architecture to Predict Stock Price Using GRU RNN Model

Model Architecture:

- Build a GRU Based RNN for time-series prediction
- Define the input shape , which typically includes historical price and feature data for a specified window.
- Design the GRU layers with the following parameters:

I Number of GRU units or neurons in each layer.

Ii Dropout layers to prevent overfitting

- Optionally you can add convolutional layers before the GRU layers to capture patterns the data
- The output layer can be a single neuron for predicting the next stock price

Methodology:

Evaluation Parameter:

To evaluate the model prediction results, this article selected the following evaluation metrics, the calculation methods of each evaluation metric are as follows

RMSE: RMSE is commonly utilized to assess the extent of deviation between predicted outcomes and actual data. A smaller RMSE Value indicate a high accuracy of the prediction model. The RMSE is mathematically defined as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i-1}^{N}(y_i - y_i^{'})^2}$$

MAE: MAE refers to the average absolute deviation between the arithemetic mean and individual observed values.A smaller MAE value indicates higher prediction accuracy. The MAE is mathematically defined as follows:

$$MAE = \frac{1}{N}\sum_{i-1}^{N}(|y_i - y_i^{'}|)$$

MAPE: MAPE is utilized to quantify the average deviation between the predicted value and the actual value .A lower MAPE value implies a higher level of prediction accuracy.The MAPE is mathematically defined as follows:

$$MAPE = \sum_{i=1}^{N}\left|\frac{y_i - y_i^{'}}{y_i}\right| X \frac{100}{N}$$

AMAPE:AMAPE is variation of the Mean Absolute Percentage Error(MAPE) the adjusts for cases where the actual values are close to zero .AMAPE is particulary useful when dealing with time series data

$$AMAPE = \frac{1}{N} * \sum \lfloor abs(y_{actual} - y_{pred})/(abs(y_{actual}) + abs(y_{pred})) \rfloor$$

Results:

The results of a Gated Recurrent Unit (GRU) Recurrent Neural Network (RNN) for stock price prediction can vary widely depending on the quality of data, model architecture, hyperparameters, and the inherent uncertainty of financial markets. Here are some possible outcomes you might observe when using a GRU RNN for stock price prediction:

1.Accurate Predictions: In some cases, a well-tuned GRU RNN may provide accurate predictions, closely following the actual stock price movements. The model may capture trends, patterns, and important factors affecting stock prices, making it a valuable tool for investors and traders.

2. Noisy Predictions: Stock prices are affected by numerous factors, including market sentiment, news events, and external economic conditions. This can introduce significant noise into the data, making it challenging for the model to make precise predictions. In such cases, the model might generate predictions that are somewhat erratic and sensitive to noise.

3.Overfitting: If the GRU RNN is too complex or overfit to the training data, it might perform exceptionally well on the training data but fail to generalize to unseen data, leading to poor performance on the validation or test datasets.

4.Underfitting: On the contrary, if the model is too simple or the training duration is insufficient, it might underfit the data, resulting in poor predictions due to a lack of capacity to capture complex patterns.

5.Short-Term Predictions: Some GRU RNN models may perform better at short-term predictions (e.g., daily or weekly) compared to long-term forecasts. Short-term predictions tend to be more accurate because they are less influenced by external factors and market noise.

6.Long-Term Predictions: Long-term predictions (e.g., monthly or yearly) can be more challenging due to the increased influence of external economic factors and market trends. Accurate long-term predictions are often more elusive and require a deep understanding of economic fundamentals.

7.Volatility Handling: Stock markets can be highly volatile, and the model's performance may vary depending on its ability to handle this volatility. Robust models can adapt to changing market conditions, while less robust models may struggle.

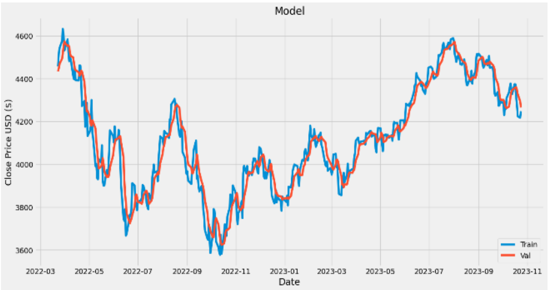
8.Interpretability: Understanding why the model makes specific predictions can be challenging with complex neural networks like GRUs. Implementing interpretability techniques can help gain insights into model decisions.

9.Continuous Updating: Financial markets are dynamic, and models may require regular updates to adapt to changing market conditions and data distributions.

It's important to note that stock price prediction is inherently uncertain, and no model can consistently provide perfect predictions. The goal is to develop models that offer insights and assist in decision-making rather than guaranteeing accurate forecasts. Thorough testing, evaluation, and continuous monitoring are essential when applying machine learning models to financial forecasting. Additionally, ensembling methods or combining various models and data sources can enhance prediction accuracy and robustness.

rmse= 64.84185583685039
mae= 51.03244959817441
mape= 1.2596267546800128
amape= 1.239708138936346
Optimal learning rate: 0.001
Optimal epochs: 100
Optimal batch size: 64
Optimal dropout rate: 0.2
Optimal activation function: relu
Optimal optimizer: RMSprop
Optimal neurons for the first GRU layer: 100
Optimal Dense neuron 1: 30
Optimal Dense neuron 2: 5
L2 regularization lambda: 0.0005

In the below figure shows red curve shows estimation and blue curve shows actual values.As the model approaches the blue curve its predictive power increase(The Actual price trend)



Conclusion:

In conclusion, the study underscores the potential of GRU Neural Networks in stock priceprediction, offering valuable insights into market trends. It emphasizes the need for ongoing model monitoring and adaptation to ensure relevance and accuracy in the ever-changing landscape of financial markets. This research contributes to the growing body of knowledgeon machine learning applications in finance, opening doors for further exploration and improvement in the field of stock price forecasting.

Future scope:

The future of stock price forecasting using GRU Neural Networks and similar AI models holds significant potential. As machine learning techniques continue to advance and more data becomes available, the accuracy and reliability of stock price predictions are likely to improve, providing valuable insights for investors and financial professionals. However, it is essential to stay vigilant about the challenges of market noise, model interpretability, and continuous adaptation to changing market conditions.

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