BITCOIN TIME SERIES FORECASTING

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Abstract:

Cryptocurrencies, particularly Bitcoin, have gained significant attention as alternative investments. Accurate price forecasting is crucial for making informed investment decisions. In this project, we explore the use of recurrent neural networks (RNN), long short-term memory (LSTM), and gated recurrent unit (GRU) models to forecast Bitcoin prices. We evaluate the performance of these models to determine their suitability for predicting Bitcoin's future price trends.

Motivation:

We are driven to explore the exciting world of cryptocurrencies and blockchain technologies, which is why we are concentrating on Bitcoin time series forecasting. Precise estimation and forecasting of prices are crucial in the quickly changing realm of virtual currency. While financial forecasting, that is, estimating sales and making financial decisions is widespread in the business world, our goal is to address the difficulties presented by the minute-by-minute trade data of Bitcoin. We hope to realize the potential for accurate, real-time information in the bitcoin market by deciphering the intricacies of this high-frequency data.

Literature Review:

One of the forerunners in the peer-to-peer payment network's cryptocurrency space is Bitcoin. Bitcoin has changed over time to consistently satisfy consumer demand and support a healthy cryptocurrency ecosystem. Despite its lack of awareness, Bitcoin is not just a money but also a viable option for investments. As per its supporters, the ultimate objective of Bitcoin is to function as a substitute for current payment systems and facilitate international transactions and currency denominations without any intervention from central banks or sovereign entities, and without any purported exploitation by conventional financial intermediaries like banks. Unlike gold, which has inherent value, bitcoin cannot be used to create valuable physical goods like jewelry. Nevertheless, worth endures because of acceptance and trust.

LSTM (Long Short-Term Memory): LSTM is a form of recurrent neural network (RNN) architecture designed to manage long-range dependencies in sequential data. It resolves the problem of vanishing gradients that simpler RNNs have, allowing it to capture and remember information over longer sequences. LSTMs are important in time series forecasting because they can efficiently model complex patterns, trends, and seasonality, making them ideal for applications such as stock price prediction and climate forecasting. Their ability to keep a recollection of previous information and selectively update it makes them useful for capturing both short-term and long-term dependencies in time series data.

GRU (Gated Recurrent Unit): GRU is another RNN variation that, like LSTM, handles the issue of the vanishing gradient problem. It uses gating mechanisms to control the flow of information inside the network, although its architecture is simpler than that of LSTM. GRUs are useful in time series forecasting because of their efficiency in training and prediction. They excel in circumstances with limited computational resources and are well-suited for applications such as speech recognition, natural language processing, and traffic flow prediction.

Simple RNN (Recurrent Neural Network): A simple RNN is the most basic type of recurrent neural network. While conceptually straightforward, it encounters the vanishing gradient problem, limiting its ability to capture long-term dependencies. Simple RNNs can nevertheless be useful in time series forecasting for tasks with relatively short-term dependencies, such as predicting stock values over a short time horizon. However, when it comes to longer and more complex sequences, they fall short of LSTM and GRU. Simple RNNs are useful for teaching and learning about the fundamentals of recurrent networks.

Methodology:

Model Selection

The choice of LSTM, GRU, and Simple RNN deep learning models for Bitcoin time series forecasting is justified by their distinct features and benefits. In the raw data, these deep learning models capture sequential dependencies. LSTM models excel at capturing long-term dependencies and reducing the vanishing gradient problem, making them suited for forecasting Bitcoin prices with complicated and long-term patterns. GRU models provide computational efficiency and are adept at catching short- to medium-term trends, while also employing gating methods to control information. Simple RNNs can be used as educational aids and for short-term forecasting or benchmarking. We chose LSTM, GRU, and simple RNN models since they handle time series data well and can forecast data.

Data Source:

We utilized **yfinance** as our data source for Bitcoin price analysis, leveraging its reputation for accuracy and its widespread use in analyzing financial data, including stocks. With a user-friendly interface, **yfinance** offers extensive data coverage, making it reliable for historical and real-time Bitcoin price data. Its compatibility with data analysis tools further enhances its value for conducting in-depth price trend analyses and data-driven studies. In summary, **yfinance's** accuracy, accessibility, and integration capabilities make it a dependable choice for Bitcoin analysis.

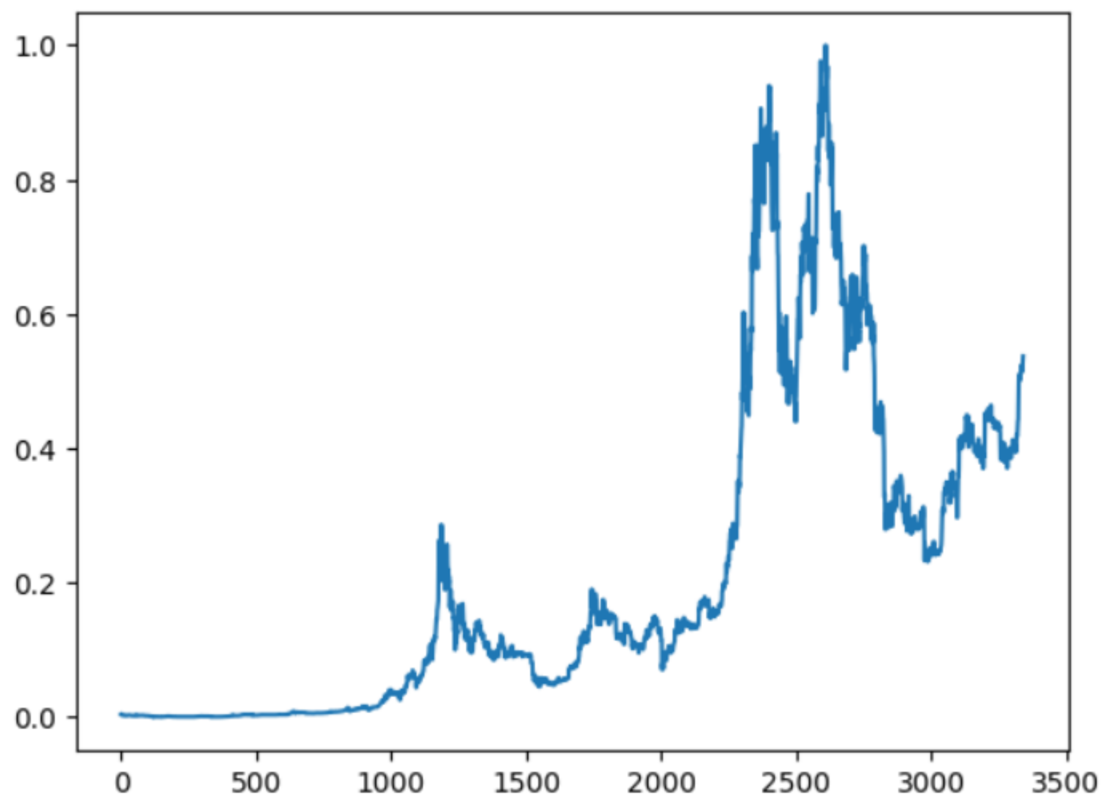
Data preprocessing:

Due to the substantial price variability in Bitcoin, forecasting its price without normalization can lead to significant errors. Normalization is applied to enhance predictability.

MinMaxScaler, utilized in Bitcoin time series analysis, serves the purpose of normalization. It facilitates data point comparison, elevates model performance, and upholds data stability. This process aligns data within a consistent and interpretable range, often [0, 1], making it more manageable and suitable for various analytical techniques.

The significance of MinMaxScaler extends to improving model convergence, mitigating gradient-related issues common in deep learning, and enhancing the overall effectiveness of forecasting models. This scaling technique ensures data compatibility and contributes to the accuracy and reliability of Bitcoin price predictions.

Plotting the timeseries bitcoin data



Choice of lookback size:

The lookback size, also known as the sequence length or window size. The selection of lookback size is an important parameter in Bitcoin time series forecasting utilizing LSTM, GRU, or Simple RNN models; the size of the lookback can have a substantial impact on the performance of these models. In this project, we have considered lookback size of 3 and size of 7.

A lookback size of 3 captures short-term patterns, making it excellent for making quick decisions and reacting to recent market movements. A lookback size of 7, on the other hand, broadens the historical background, providing insights into medium-term trends while minimizing sensitivity to short-term noise. The choice between the two is determined by the precise forecasting aims, with a lookback of 3 chosen for short-term trading strategies and a lookback of 7 favored for medium- to long-term investing and portfolio management methods.

Evaluation criteria:

The term "time series analysis" refers to "an ordered sequence of values of a variable at equally spaced time intervals." It is used to comprehend the influencing elements and structure of observed data, as well as to select a model to forecast, resulting in better decision making.
The basic purpose of Time Series Analysis is to develop an appropriate model to characterize a pattern or trend in data more accurately. Time series data forecasting, on the other hand, forecasts future events based on the recent past. Forecasting can be done for daily stock closing/opening rates, quarterly revenues of a corporation, and so forth.
The efficient market hypothesis supports financial market time series forecasting. Machine learning and deep learning technologies are intended to address prediction issues in which variables are linked in a layered hierarchical structure. Zhu 2020 proposes the use of Recurrent Neural Networks for stock price prediction.

The most prevalent form of information in the Financial and Financial domains is financial time series. Examining, anticipating, and controlling this type of data are important tasks for financial specialists and scientists. Securities, trade rates, loan fees, stock costs, and financial prospects costs are all included in financial time series. They can also include macroeconomic metrics such as investment, pay, and utilization from a macro perspective. The protections market is the primary body of the financial market and plays a vital role in it. The level of incorporation between our nation's economy and the global economy is increasing, particularly in terms of rising global financial joining, and the Financial industry is confronting more significant and newer advancement prospective open doors and difficulties. Understanding and mastering the fundamental laws of the financial market is essential to the strength, competency, and security of our country's financial system. Following a period of rapid change, our country's financial industry has framed a substantial scale. The financial market is a complex structure that is influenced by various factors. The law of its movement is difficult to predict, although financial time series data are positive. It is the trademark's exterior indicator. "Peculiarities mirror the embodiment, and the substance decides the peculiarity." As a result, there should be a wealth of information on financial rules hidden in the financial time series.

We chose Root Mean Squared Error (RMSE) to be one of the main evaluating parameters for our project. Root Mean Squared Error (RMSE) is a prominent metric for measuring the effectiveness of forecasting models in Bitcoin time series forecasting, including those based on LSTM, GRU, and Simple RNN. The RMSE provides an interpretable metric of forecast accuracy. It is the square root of the average squared difference between predicted and actual values. A lower RMSE indicates more accuracy. The mathematical features of RMSE are advantageous for model optimization. It is a differentiable function, making it excellent for use with optimization algorithms such as gradient descent, which is often used for training LSTM, GRU, and Simple RNN models. The major purpose of financial forecasting is frequently to minimize prediction errors and optimize investment decisions. RMSE fits nicely with this purpose since it quantifies total predictive performance in a way that is directly related to the forecasting goal.

Model Training and Evaluation

We divided the dataset into training and testing sets, using 67% of the data for training and the remainder for evaluation. The hyperparameters, including hidden size, number of epochs, and look-back window, were optimized for each model.

The models were trained on the training data and evaluated using appropriate evaluation metrics, such as Root Mean Squared Error (RMSE).

Summary of the model parameters used for analysis:

	Hidden Size	**Number of Epochs**	**Look Back Window**
RNN, LSTM, GRU	50	1000	3
RNN, LSTM, GRU	100	2000	3
RNN, LSTM, GRU	50	1000	7
RNN, LSTM, GRU	100	2000	7
RNN, LSTM, GRU	1000	2000	7

For evaluating the performance of models, we have used RMSE on test data set as metric.

RESULTS:

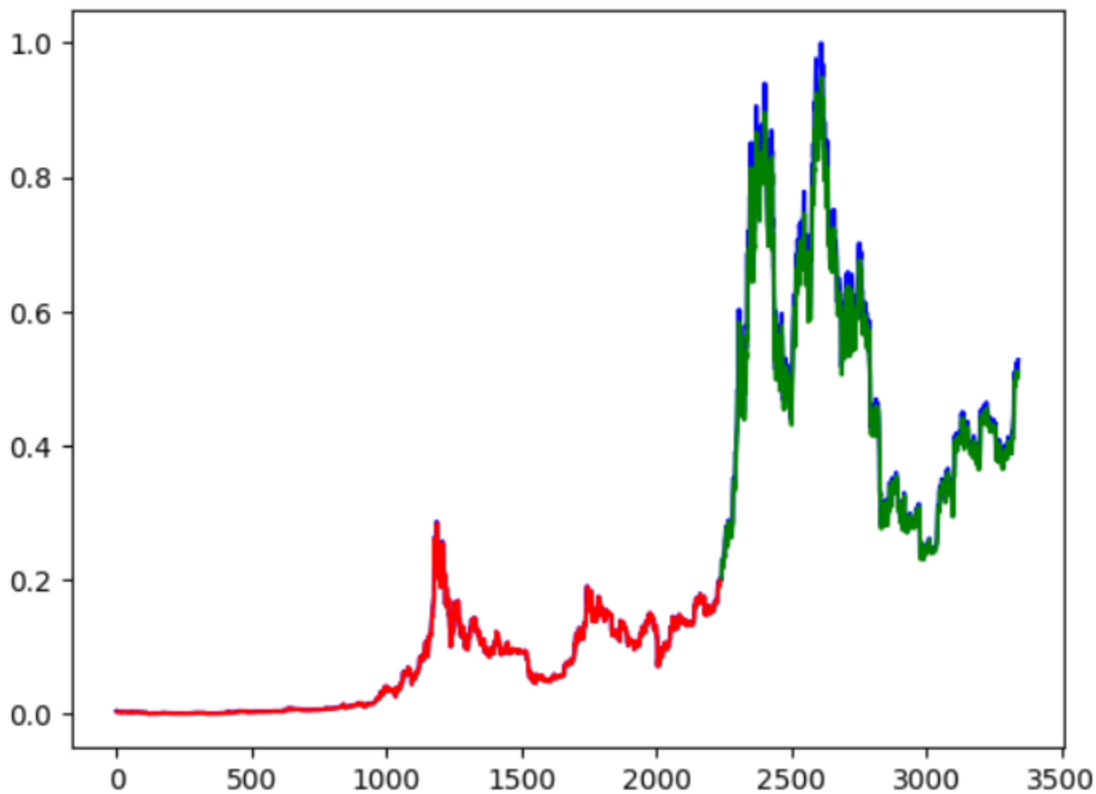
Foreach of the RNN, LSTM, GRU ran on bitcoin data with the different parameters used as mentioned in the table, the best models obtained has the test RMSE as

- `the best RNN model has the test RMSE score of 0.0708.`
- `the best LSTM model has the test RMSE score of 0.0282.`
- `the best GRU model has the test RMSE score of 0.0296.`

CONCLUSION:

Based on the RMSE scores obtained from the above test results, it is evident that LSTM achieved the lowest RMSE score. Therefore, among the defined set of deep learning models, LSTM outperforms the others.

Plotting the predictions vs actual values for the best model:



- Blue Color represents the original values in the dataset.
- Red Color represents the predicted values on training data set.
- Green Color represents the predicted values on test data set.

Source code Link: https://github.com/Niharred/Bitcoin-Time-series-Forecasting

Business Applications of Bitcoin Time series forecasting:

1. Investment Decision-Making: Bitcoin time series forecasting provides investment professionals with significant insights. It aids in price trend prediction, identifying entry and exit locations, and risk management in the highly volatile bitcoin market. Accurate predictions allow investors to make well-informed decisions and potentially profit from trade opportunities.
2. Risk management: Risk management is an essential component of financial management. Bitcoin time series forecasting enables risk managers to predict and plan for market fluctuations, thereby reducing potential losses. Forecasting models aid in the development of strong strategies for risk management by quantifying risk factors such as price volatility.
3. Portfolio Diversification: Bitcoin forecasts can help portfolio managers plan diversification strategies. Professionals can optimize portfolio allocation, lowering exposure to market risks and improving overall performance by analyzing the association between Bitcoin and traditional assets such as stocks or bonds.
4. Analysis of the Cryptocurrency Market: Bitcoin's influence extends beyond its own market. Forecasts that are accurate can help inform larger cryptocurrency market analysis. Analysts use these estimates to obtain insights into market sentiment, trade volumes, and overall cryptocurrency adoption, which helps them make strategic decisions.
5. Regulatory Compliance: Bitcoin time series forecasting can help regulators and compliance officers monitor and enforce market restrictions. Predictive models aid in the detection of anomalous trading patterns, potential market manipulation, and compliance violations, all of which contribute to the integrity and security of cryptocurrency markets.

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