COMS4507 The University of Queensland

Project Title :

Cryptocurrency Transaction Monitoring, Analysis, Prediction

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Project Definition

The rapid growth of cryptocurrencies has created unprecedented opportunities for investors around the world. Bitcoin, being the one of most widely traded cryptocurrencies, has attracted significant interests and attention from both individual and institutional investors. As the market dynamic evolves, there exists a need for advanced tools that can assist investors in making informed decisions and capitalize on the fluctuating prices of Bitcoin.

The goal of this project is to develop a trading bot capable of predicting future price movements of Bitcoin and notifying users on buy/sell signals, enabling them to optimize their trading strategies. This aims to help solve the evolving needs of cryptocurrency investors. The trading bot predicts prices using ML models that analyze a vast amount of historical price data. The predictions made by the bot are then used to generate trading signals that are displayed to users textually and graphically. The bot will then use these trading signals to perform buy and sell orders, following a set of trading strategies.

This project is implemented by utilizing fake money for demonstration and it is neglecting gas prices, transaction fees and other operational fees which must be considered if operated in real-life situations.

Background

In addition to being a lucrative passive investment tool. Cryptocurrency trade bots have become increasingly important in the Cryptocurrency world. They have a significant role in maintaining the stability of a coin, which is crucial for the overall health of the cryptocurrency market. Additionally, trade bots can also help increase the popularity of specific coins, as they can execute trades automatically, potentially leading to an increase in demand and price. Another important type of trade bot is the arbitrage bot, which plays a crucial role in unifying the prices of cryptocurrencies across different exchange platforms. By identifying price discrepancies between different exchanges and executing trades accordingly, arbitrage bots help ensure that prices remain consistent across the market. In this project, we focused on trading with a pair of Bitcoin and USD, which is a common trading pair in the cryptocurrency market. Since Bitcoin is the most famous cryptocurrency and many trading bots are designed for it, it may not always be the best choice for trading. This is because Bitcoin is not as volatile as other cryptocurrencies, which can limit potential profits. However, given its popularity and widespread adoption, Bitcoin remains an important player in the cryptocurrency market. We used Coin Market Cap API as the reference API. This API provides prices and market capitalization of any pair of Currencies, which is essential for making informed trading decisions. We also made 2 ML models that are going head-to-head with algorithms. The ML models are trained on historical data from Yahoo Finance. In this report we found a lot of challenges.

Methodology Approach

Execution

The code was implemented after considering 5 important constants. These constants are :

- Initial Balance: The amount of money that is going to be given to the crypto bot to trade with, i.e (1,000,000 USD).
- Interval time: for trading which can vary upon preference, i.e 60 seconds or 86400 for a day.
- Minimum Growth: The minimum price the bot can buy and sell by, i.e 0.02.
- Stop Loss Percentage: The cap of loss you would accept from the bot, i.e 0.05 for 5%.
- Goal: The acceptable net profit goal for the bot, i,e 1,200,000 for 20% profit.

The code starts with getting the price of bitcoin from Coin Market Cap. The API is going to provide the real-time price of Bitcoin.

Some information is going to be passed to the function for taking buying and selling orders. These information are the following:

- Current Price
- Predicted Future Price
- Balance

The function for taking the decisions is going to provide predictions for the price depending on the ML model or the Algorithm it uses. From these predictions it will also generate buy or sell orders.

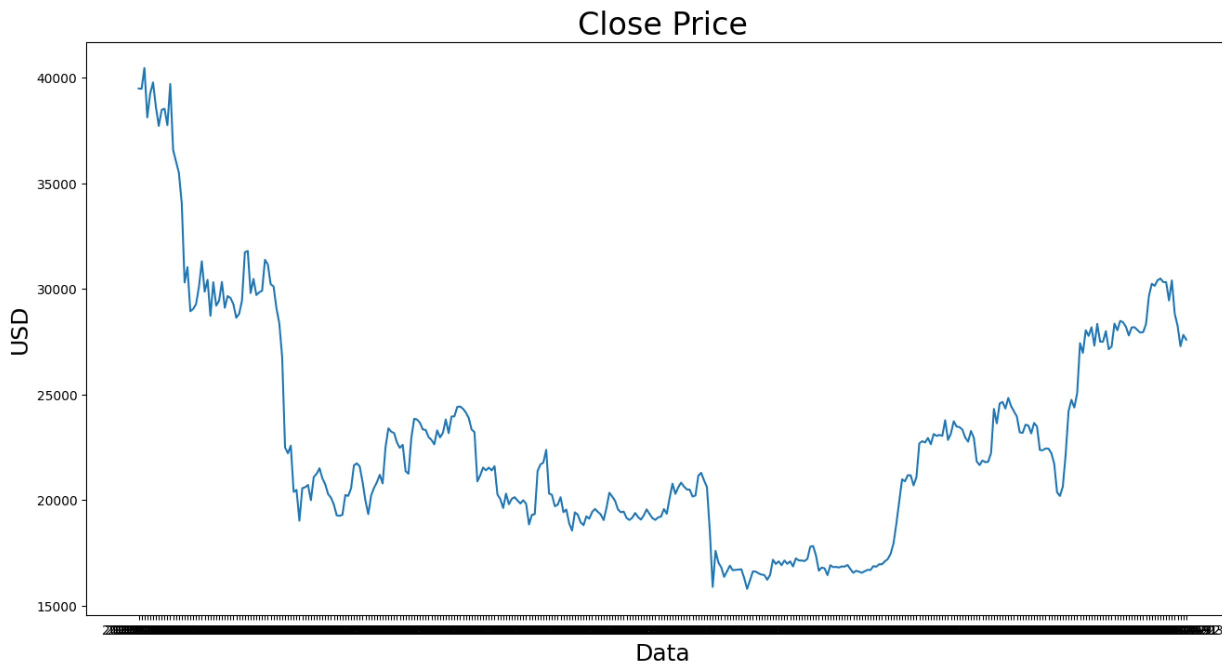
The bot is going to pass decisions to the model until a loss or goal is reached.

Data Acquisition

To train and test the ML price prediction models, historical daily Bitcoin price data from the past 365 days will be retrieved from Yahoo Finance. The dataset will contain the following features:

- Date
- Open price (USD)
- High price (USD)
- Low price (USD)
- Close price (USD)
- Volume

Real-time live prices are needed by the trading bot to make trading decisions. The live prices are retrieved through an API call to CoinMarketCap. Although this API is free to use, the limitation is that it only allows 30 API calls per minute for its free tier. The live Bitcoin prices in USD are retrieved.



Bitcoin Price Historical Data retrieved from Yahoo FInance

Data Pre-processing

The historical Bitcoin price data from Yahoo Finance is contained in a csv file. The Panda python library is used to extract features and remove redundant features.

Firstly as we are training on daily prices, it is impractical to use live prices, else we will wait weeks or months to view the results. So we will remove the last 120 days of the csv file and use this as the 'live' data to feed into the query prediction on the model, which is trained on the remaining of the csv data.

The bitcoin price data (less the last 120 days) will be split into training and testing sets. The allocation is 85% training and 15% testing.

ML Models

Approach for the ML Model:
The ML model is divided into two parts, train and query.

Train Model

The train portion is performed on the historical daily bitcoin prices and associated daily metrics (Open, High, Low, Close, Volume). Note that bitcoin trading is available 24 hours, unlike share trading that only operates during local business hours. However the terminology such as Open and Close are used for the UTC 24 hour period. Similarly High, Low and Volume are based on this period.

Query Model

Note here we use the last 120 days of the csv data, that was kept aside to use as ‘live’ data. This data was not used in training, validation or testing and so completely independent.

In a real live version, the query portion is performed after the daily metrics are released, which are fed in as inputs. This generates a prediction on the next day value of bitcoin.

Also at this point the current actual bitcoin price and tomorrow's predicted bitcoin price are graphed. Note this graph will always show the actual line trailing the predicted line.

Analyze Prediction & Plan Action

Following the prediction query the Analysis Prediction and Plan Action algorithms are processed, which analyzes the prediction prices against purchased value and suggests a buy or sell action accordingly. This is expanded in detail in the below Trading Strategies section.

LSTM (Long short-term memory)

The Long Short Term Memory (LSTM) ML model is based on an improvement to the Recurrent Neural Networks (RNN) ML model. The RNN model is a neural network that feeds its outputs back to its inputs, that has an effect of a very short term memory as the data cascades through the layers, to increase the duration of this memory additional modules are added to hold and adjust the data for a longer period. The RNN model also has a disadvantage of vanishing and exploding gradients, due to this feedback loop, that is resolved in LSTM.

LSTM (and indeed RNN) models are best suited for time series data and extrapolation.

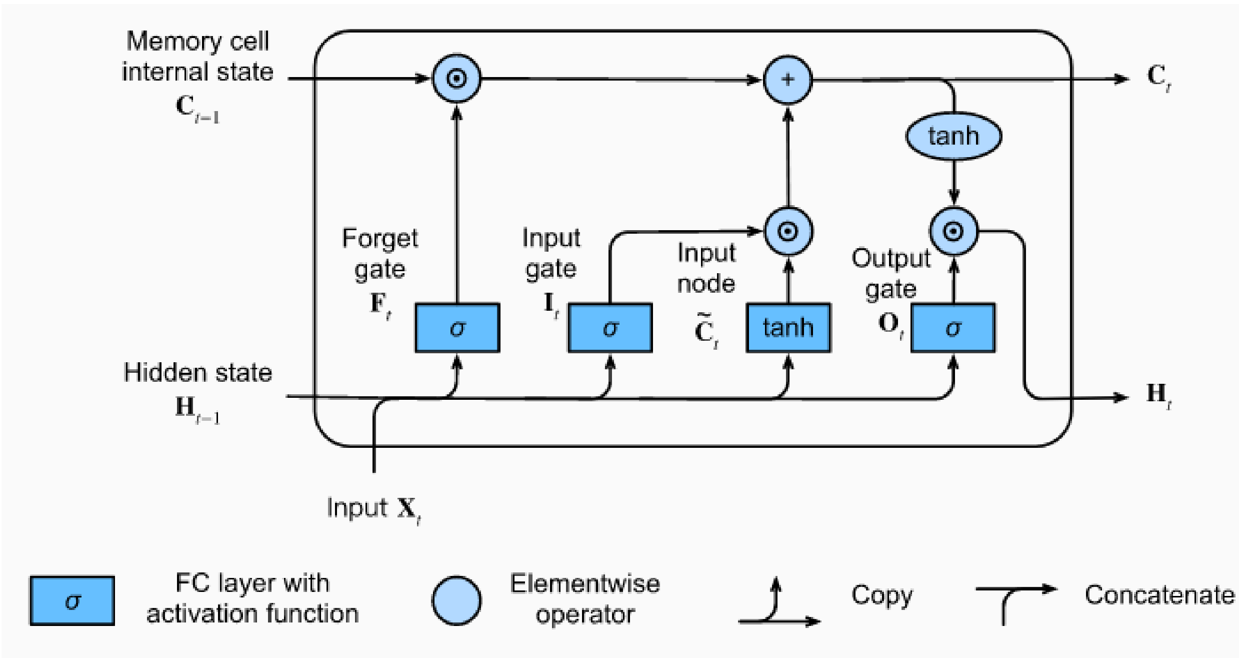


Figure 1. LSTM module example

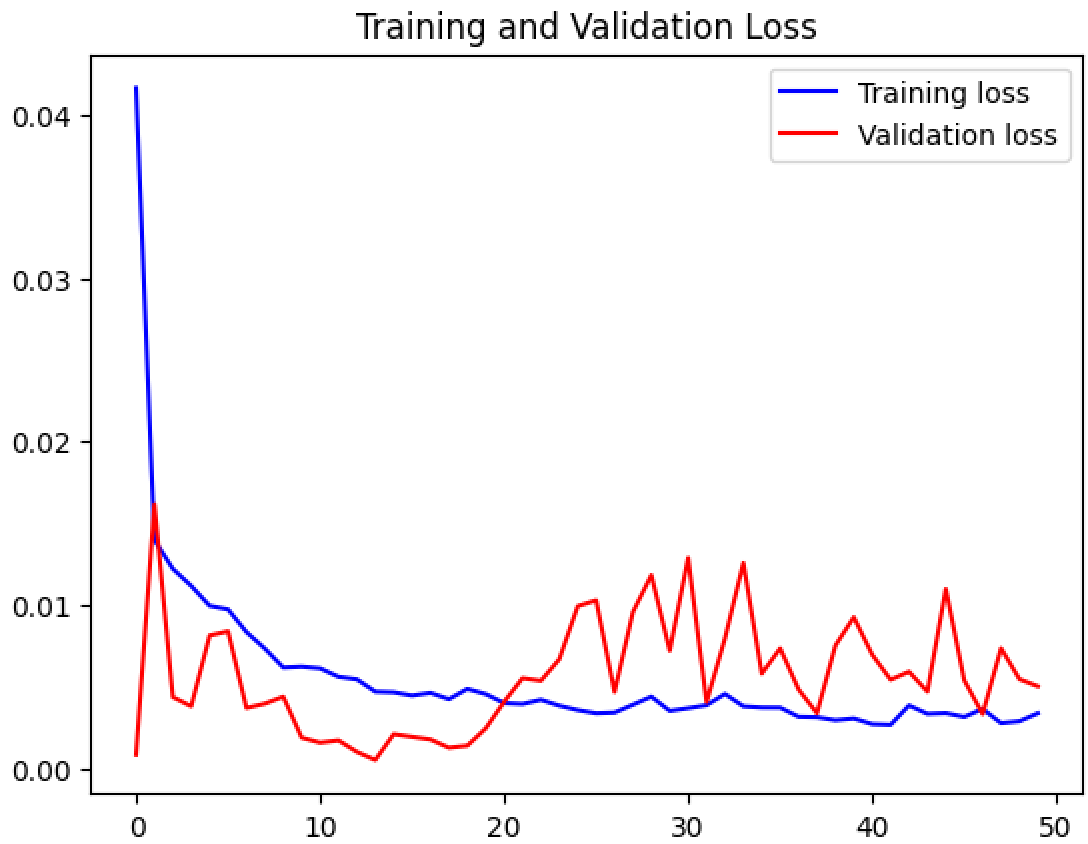
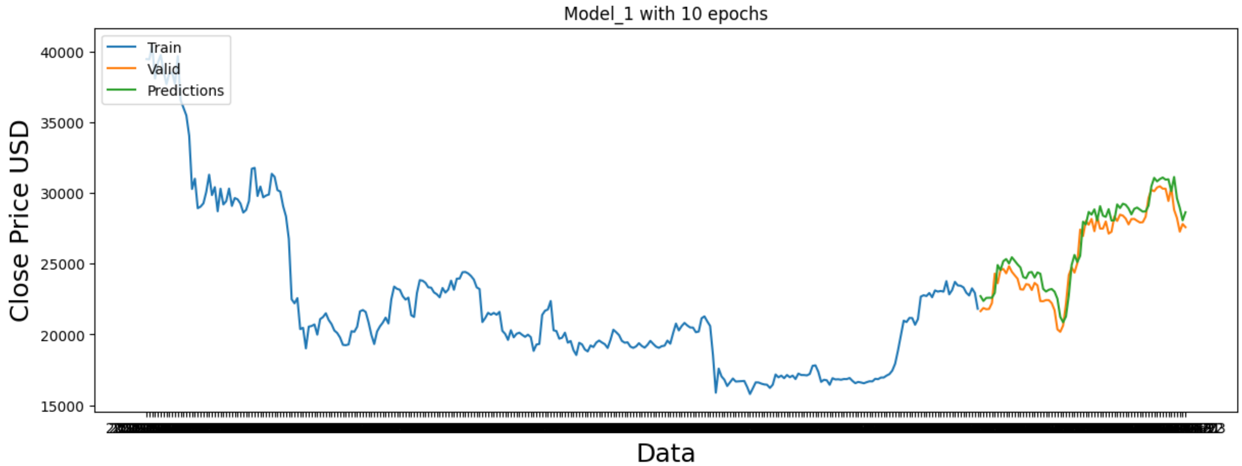
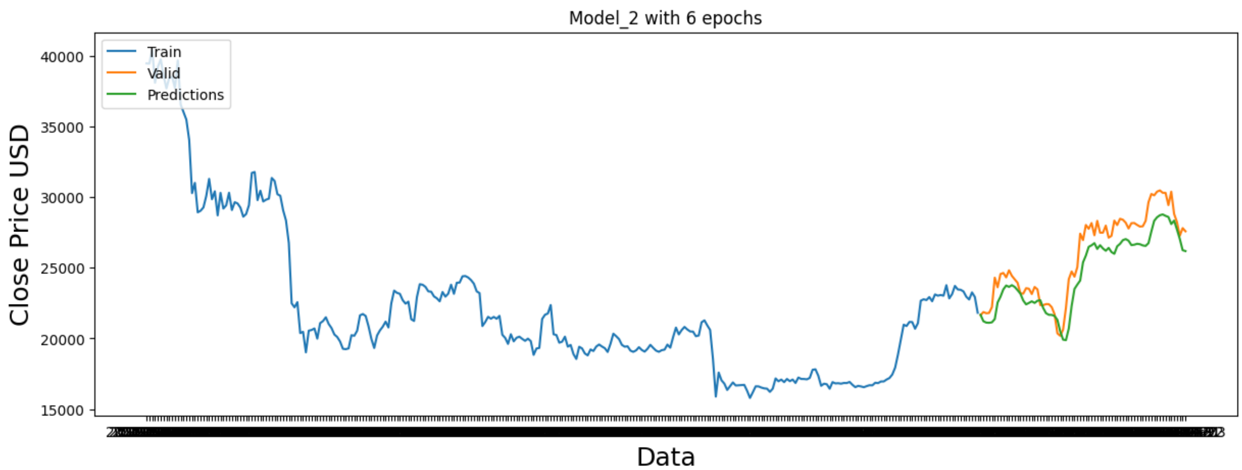


Figure 2. LSTM training and validation loss over 50 epochs

Prophet

Time Series data is not always stationary i.e. have constant mean and variance throughout its duration. Previous use cases reveal that Facebook's prophet works really well with non-stationary data. Thus, making a well fit for volatile data like cryptocurrencies. This algorithm not only estimates the predicted value but also predicts an upper limit and lower limit. Thus providing a broader idea about the price. The Prophet algorithm is also very easy to implement thus, making it suitable for this use case.





Trading Strategies

After attaining the predicted future Bitcoin price from the ML models, the trading bot will follow a set of trading strategy rules to determine whether to place a buy/sell order, or simply sit out and wait.

For placing buy orders, the bot will check if the predicted future price is greater than the current price plus a minimum growth percentage. This is to ensure that prices are expected to rise high enough to compensate for any brokerage fees and actually make a profit. The bot will always check for sufficient funds before placing buy orders.

Given a previous buy order had already been placed and the investor holds some amount of Bitcoin, the trade bot will perform a sell order (in the same amount of Bitcoins as the previous buy order) if any of the following conditions have been triggered.

1. The current price of Bitcoin has fallen below a pre-specified stop-loss percentage of the original buying price. This is to minimize the loss to the investor.
2. The total assets value (remaining cash balance + value of held Bitcoin) exceeds the investment goal amount. This is to stop taking further risk.
3. The predicted future price falls below the current price minus the stop-loss percentage. This means that prices are expected to decline greatly. Hence, it is logical to sell now and prevent future losses.

Besides the use of ML price prediction models, our trading bot mainly implements the stop-loss trading strategy (Kramer). This strategy is widely used by traders and investors to limit the potential losses on a security, which is particularly important in a volatile market such as Bitcoin. It works by setting a predetermined percentage for which the security will be automatically sold if its price falls beyond that percentage. The purpose is to prevent further losses if the security's price continues to fall. However, a drawback of the stop-loss strategy is that it can potentially limit gains if the stop-loss percentage is not set correctly. The stop-loss percentage should not be set too low, otherwise it would be too sensitive for the volatility of Bitcoin. On the other hand, it should not be set too high such that it allows for large losses.

Textual Display

After each run, the trading bot will display the current price and the predicted future price for the next day. Depending on the trading decision, the bot will display the action performed along with the transaction details if a transaction has been carried out. For example, if a sell order has been placed, the trading bot might display the following transaction details:

("New sell order placed: Transaction ID: 8f531883-744d-4b18-9dd8-0529b9661bbc, Transaction Type: TransactionTypes.SELL, Price: 30132, Amount: 1294195.598056259 BTC, Volume: 42.950869442992804, Profit/Loss: 132718.18657884776, Transaction Trigger: Investment goal reached").

```
~/w/U/A/COMS4507  on  main ↓1  python3 bot.py
Current price of BTC: $ 26875.723401969604
New buy order placed: {'amount': 37.20830077923463, 'price': 26875.723401969604}
Current price of BTC: $ 26885.2364924922
Waiting for price to reach sell threshold
Current price of BTC: $ 26890.64101687493
Waiting for price to reach sell threshold
Current price of BTC: $ 26892.8971499738
Waiting for price to reach sell threshold
Current price of BTC: $ 26891.692438537026
Waiting for price to reach sell threshold
Current price of BTC: $ 26891.776061980385
Waiting for price to reach sell threshold
Current price of BTC: $ 26879.541728791166
Waiting for price to reach sell threshold
Current price of BTC: $ 26879.541728791166
Waiting for price to reach sell threshold
Current price of BTC: $ 26878.726862933214
Waiting for price to reach sell threshold
Current price of BTC: $ 26879.309669812515
Waiting for price to reach sell threshold
```

Example of Textual DIsplay of Trading Bot

The bot will also display the reason for carrying out each transaction, based on the mentioned trading strategies. Finally, the remaining balance will be displayed after each transaction.

When the trading bot stops trading, either due to insufficient balance or investment goal reached, a record of transactions and the profit/loss of all sell transactions will be displayed textually.

Graphical Display

The graph of actual and predicted values is generated as a sliding graph, so after 120 measurements the oldest drops off and the graph slides left. The actual and predicted line graphs are differentiated by colour, as defined in the legend.

The graph is generated by the Javascript library “chart.js” and is loaded via the browser through the Content Delivery Network `cdn.jsdelivr.net`. Hence no direct plugins require to be loaded for it to run on Jupyter notebooks or Google Colab, other than IPython which handles the browser/Python interface.

The LSTM model generates a graph of normalized BTC USD dollars values between 0 and 1, some effort is required to de-normalise the values back to actual USD dollars. However the delta between actual and predicted is indicative of any profit or loss margin.

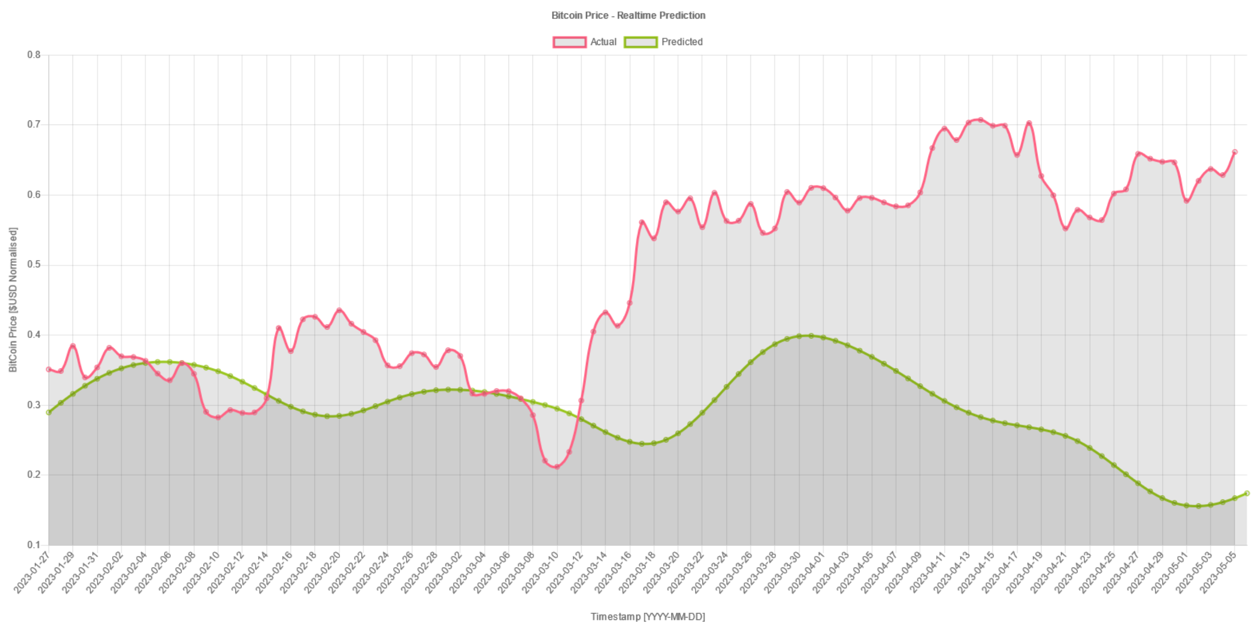


Figure 2: LSTM Prediction and Actual over last 120 days

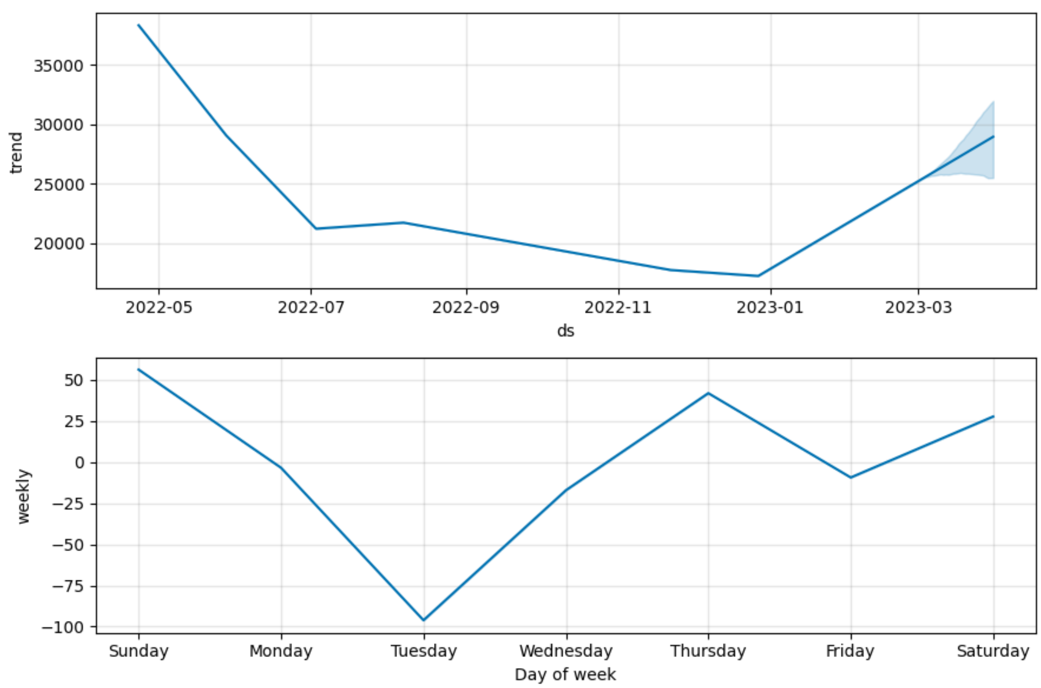


Figure 3:The graph showing the trend of predictions versus time as well as the trend of predicted price for each day of the week.

The graph depicts the prophet model utilizing the trend in the price of bitcoin from may 2022 to 27 march 2023 to forecast the bitcoin prices for the next 5 days.The shaded region at the end of the first graph shows the range of the predicted prices. The second graph visualizes the trend in the predicted prices for bitcoin for each day of the week. The highest price is predicted on Sundays.

Implementation, Results and Discussion

It was not feasible for us to train LSTM models on historical data for minute or hour intervals because it would require information requiring paid subscriptions and a lot of computational power. So LSTM models were trained for historical data on daily intervals.

The LSTM and Prophet models were both trained on a ML model to learn the regression association of the bitcoin price over time only on the five inputs of the market trading metrics. Namely, *Open*, *High*, *Low*, *Close* and *Volume*, as these were readily available and supplied from the same source. Had more time been available we could have extended the metrics outside of bitcoin and into the general consumer sentiment. This may have included consumer price index, inflation and even social media [6].

Additionally both ML models predicted bitcoin prices only one day into the future. This has risks and benefits.
The benefit is the simplicity. For example, if the price is predicted to go up then we buy early and sell late the next day. So at the end of next day, if it is predicted to rise again we repeat, else dont buy. Another benefit is that any error in the model will compound over each additional day, so planning to sell further into the future adds additional and increasing risk.
The risk is the unknown time when the bitcoin will peak on that day. As it is assumed that if we regularly buy and sell at a constant time these higher profits and losses will even out over time, otherwise we will need to revisit this strategy.

The LSTM model attempted after its prediction to add the end of day actual metrics as a training iteration to update the model to the most recent data, however this was unsuccessful, and would be resolved if more time was available to investigate.

There are also newer time series ML models than LSTM, such as Transformer networks, which were briefly investigated but we decided that our group’s experience with LSTM and Prophet ML models would allow quicker implementation and introduce less risk than learning a new ML model from scratch.

We discovered that bitcoin might not be the best choice since it is a relatively stable coin with not much movement. The Cryptocurrency bots are usually used for volatile currencies to have a higher impact.

It was also discovered that the API token registered from CoinMarketCap not only had frequency limits but also credit limits. Once exceeded the 10000 monthly credit limit, the token can no longer retrieve price data from the API. This was rather inconvenient as a new API token had to be registered regularly using different email addresses. In the future, we will seek other Bitcoin market data providers.

Conclusion

For models working on Intervals less than a day, it is very difficult for AI models working on the history of the currency to work well. Algorithms are more suitable in this case since they are depending on indicators that are not related to the history like volume of trade. The prophet model utilizes the training data till 26 March to forecast the bitcoin prices for the next 5 days from 27 March 2023 to 31 March 2023. The model also predicts a lower limit and upper limit for each prediction. This range gives the user a more clear idea about their action. If the purchase value is more than the lower limit the user will incur losses if he sells the bitcoin and vice versa.If the purchase value is less than the lower limit, it is profitable for the user to sell their bitcoins.

We managed to test all these models against each other, and we saw that (Prophet Model) is slightly more accurate. But LSTM is more promising but needs way more training. The inputs into our ML models, of whatever flavor, should be expanded to include other economic and social metrics, as the 5 current inputs are not sufficient to solely produce a regression model.

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