ANLY 590: Neural Networks and Deep Learning

Bitcoin Price Prediction

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Introduction

Our project used web-scraping to obtain Bitcoin historical data, NASDAQ index historical data, volatility data. Then obtained feature engineering by adding 12 technical indicators. Then we explored different kinds of methods to do the price prediction including traditional trading strategies, time series machine learning models and LSTM deep learning models. Compared with traditional financial instruments, cryptocurrency is very difficult to predict due to the lack of indicator data. On the other hand, the fact that cryptocurrencies do not heavily depend on news, the market, crude oil, metals and other factors makes cryptocurrencies more suitable for prediction using deep learning than stocks.

Data Description

Our primary dataset is obtained by using CoinBase API to scrape historical data containing date, open price, close price, highest and lowest price, market cap and volume. Other supporting stock market datasets are obtained from Yahoo Finance. The datasets are merged on date. There are empty rows in stock market datasets due to the fact that the stock market does not operate on weekends and holidays whereas the Bitcoin market never closes. The NA values are filled by the mean of the previous open day and the open day afterwards.

	date	open	high	low	close	volume	amount
0	2020-12-06	19154.180593	19390.499895	18897.894072	19345.120959	2.529378e+10	3.591235e+11
1	2020-12-05	18698.385279	19160.449265	18590.193675	19154.231131	2.724246e+10	3.555639e+11
2	2020-12-04	19446.966422	19511.404714	18697.192914	18699.765613	3.387239e+10	3.471114e+11
3	2020-12-03	19205.925404	19566.191884	18925.784434	19445.398480	3.193032e+10	3.609339e+11
4	2020-12-02	18801.743593	19308.330663	18347.717838	19201.091157	3.738770e+10	3.563810e+11

Methodology

VWAP: We used one of the most important indicators in trading, VWAP, to mimic the trend of Bitcoin price. The volume weighted average price (VWAP) is a trading benchmark that gives the average price a security has traded at throughout the day, based on both volume and price.

Time Series models: We used time series models on the Bitcoin prices as baseline models. We implemented both ARIMA and Prophet time series models and the resulting graphs are shown in the Results section. Prophet is an automatic time series forecasting model developed by Facebook.

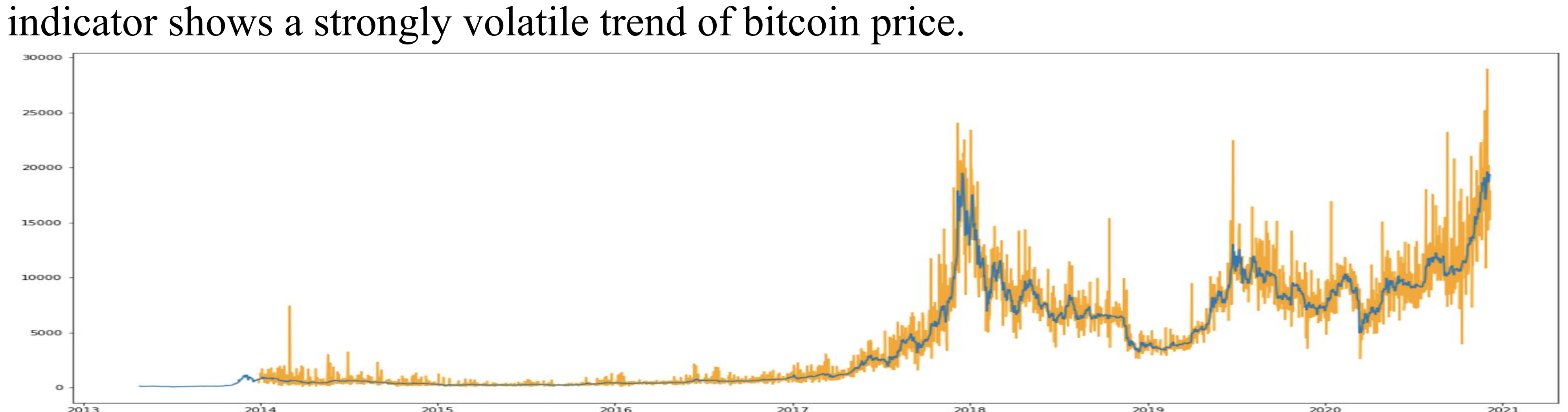
GAN architecture: The GAN architecture used a two-layer dense network (GRU and CuDNNLSTM) and one dense output layer with relu activation.

Methodology (Cont.)

LSTM: We built an LSTM recurrent neural network with a window method to predict the last value of a sequence of values. We prepared the data into windows with a length of sixty days. The model takes in the previous sixty days of Bitcoin price to predict the price of the next day, which means there will be input units in the input layer. This method only predicts the value of the next day. So, in order to predict the future price, we applied the Seq2seq method to this model which uses predicted value as input in the next step.

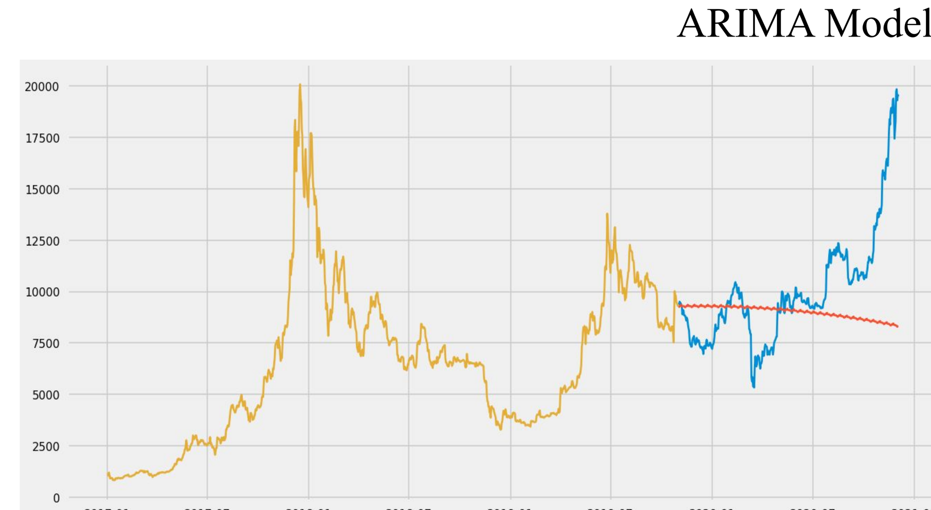
Results

VWAP: Due to the extreme instability of the volume of the bitcoin market, the VWAP indicator shows a strongly volatile trend of bitcoin price.

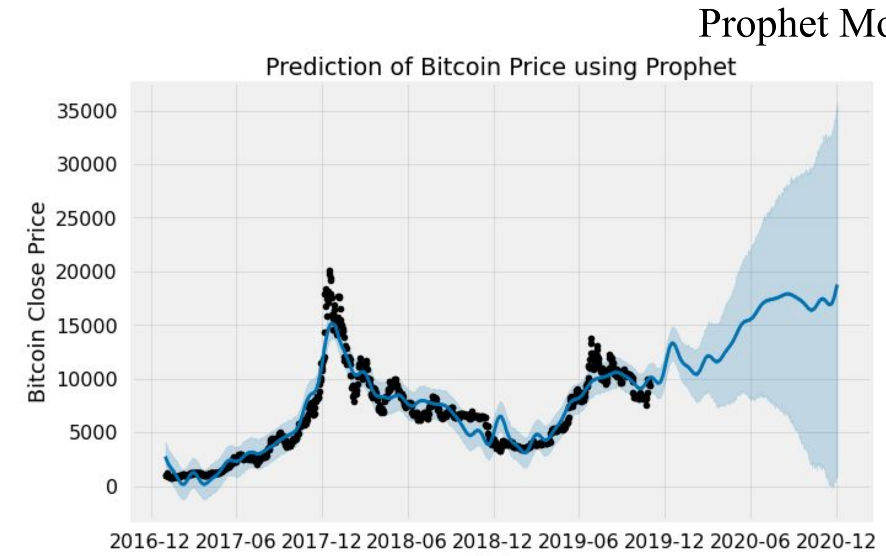


Time Series: The basic time series models: ARIMA and Prophet, did not fit well with test data and the root mean square errors and mean absolute errors were all really large. Although the Prophet model had higher errors than the ARIMA model, it successfully predicted the increasing trend in testing data and also predicted the highest price in December. Due to the lack of seasonality and trend in Bitcoin prices, we realized that predicting the prices simply based on the prices was not ideal. We then tried to use other models and implement more indicators.

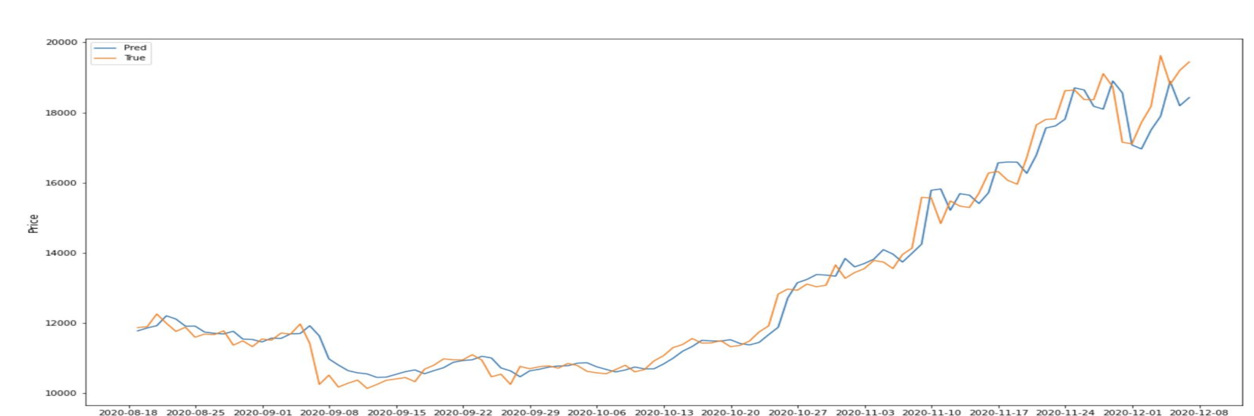
ARIMA Model, RMSE: 3175, MAE: 2132



Prophet Model, RMSE: 5078, MAE: 4569

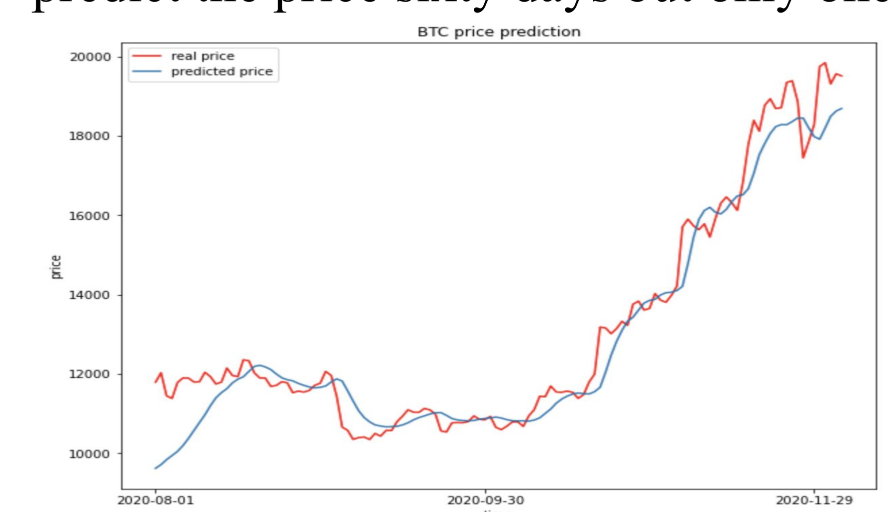


GRU: The loss of GRU cannot go lower than 0.18 on the validation set with look back equals 1.

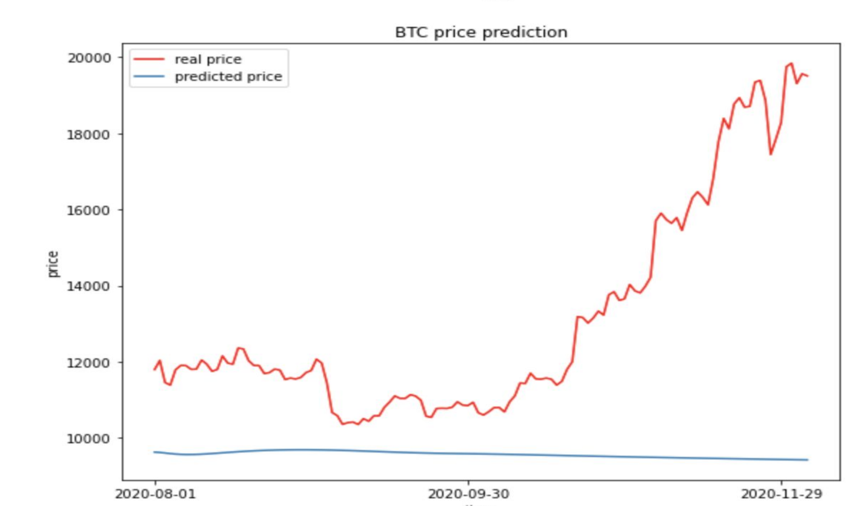


Results (Cont.)

LSTM: The result of this approach looks pretty similar to the actual price since neural networks can fit even the most wiggly lines really well after enough epochs. In the seq2seq method, we take the output of the current step as the input for the next input. However, the result is very inaccurate. The predicted price is always around the average price of the training set. The downside of this method is that it can't predict the price sixty days but only one day ahead.



Training with sixty days window



Training with seq2seq

Conclusion

Although our models could not perfectly predict the Bitcoin's price, they still picked up some useful knowledge of forecasting. To be specific, the GRU and LSTM model which uses the training data within a sixty days window managed to obtain persistence that is a term in price forecasting when a model uses today's price to predict that of tomorrow. And it is often served as the baseline predicting strategy in any forecasting task. In the ARIMA and LSTM model which was adapted into seq2seq, the model once again managed to make the best prediction on future price, which results in the lowest loss, by guessing the average of maximum and minimum price that occurred in the training set. Moving forward, we recommend not to solely use previous price, because essentially tomorrow's price will never be completely or even predominantly determined by today's price

Reference

1. K. Zhang, G. Zhong, J. Dong, S. Wang, and Y. Wang, "Stock Market Prediction Based on Generative Adversarial Network," Procedia Computer Science, vol. 147, pp. 400–406, 2019.
2. S. Siami-Namini and A. S. Namin, "Forecasting Economics and Financial Time Series: ARIMA vs. LSTM," pp. 1–19, 2018.

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