Bitcoin Price Change Prediction Model Using Pricing History, Google Search History, and Twitter Sentiment Analysis

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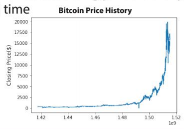
Introduction

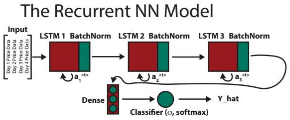
In this work our goal is to use artificial neural networks (aNNs) as a tool to predict the fluctuations in Bitcoin price in order to buy and sell cryptocurrency for profit. Because of the volatility of the cryptocurrency market [1], large fluctuations can lead to large profits if transactions are timed accordingly. Additionally, there are many sources of data updated in real time that give information about the confidence in Bitcoin [2] (which is directly related to price), such as Tweets and Google search history. Here, we use a Bitcoin price dataset (shown on right) from December 2014 to January 2018 (obtained with Kaggle) for our training and test sets.

Bitcoin Price History



RNN Model using Pricing Data

The Recurrent NN Model



RNN Model Settings

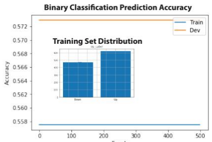
Layer (type)	Output Shape	Param #
batch_normalization_53 (Batc	(32, 4, 6)	24
lstm_40 (LSTM)	(32, 4, 64)	18176
batch_normalization_54 (Batc	(32, 4, 64)	256
lstm_41 (LSTM)	(32, 4, 64)	33024
batch_normalization_55 (Batc	(32, 4, 64)	256
lstm_42 (LSTM)	(32, 64)	33024
batch_normalization_56 (Batc	(32, 64)	256
dense_14 (Dense)	(32, (1 or 7))	455

Total params: 85,471
Trainable params: 85,075
Non-trainable params: 396

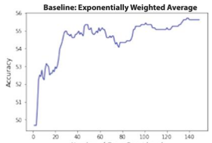
In this work, we chose to use a simple RNN which utilizes a hidden state and uses the previous 4 days of price data as an input. The model allows us to iterate quickly but is still complex enough to fit the training set.

Binary classification of price change (Up or Down)

Binary Classification Prediction Accuracy

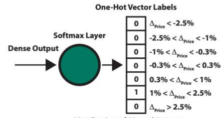


Baseline: Exponentially Weighted Average



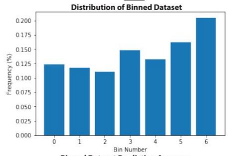
Initially, we attempted to frame the problem as a binary classification problem where the NN predicts whether or not the price of Bitcoin will increase. However, the RNN was unsucessful at fitting the data due to the randomness of the price changes. The inset shows that the accuracy is tied to the distribution of the data, i. e. the model will always guess "up" to achieve maximum accuracy.

Binning the NN Output

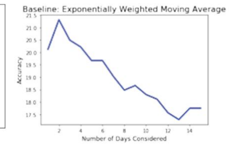


Next, we binned the dataset into six categories corresponding to the magnitude of the Bitcoin price change for each day. This allows the user to buy and sell at a threshold price change rather than in response to minimal price increases.

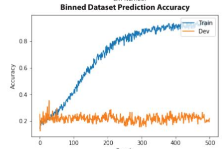
Distribution of Binned Dataset



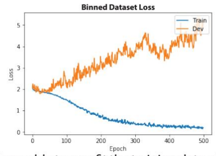
Baseline: Exponentially Weighted Moving Average



Binned Dataset Prediction Accuracy



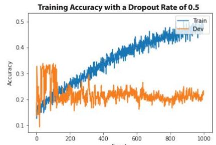
Binned Dataset Loss



As seen in the above graphs, the model was able to overfit the training data with enough training time, but failed to generalize to the development set. Next, we tried regularization to see if the model could generalize better.

Regularization

Training Accuracy with a Dropout Rate of 0.5

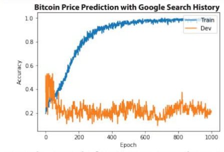


Training Accuracy with L2 Regularization

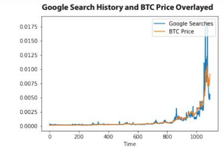
We tried to use regularization techniques to eliminate the variance we found in our model. Neither droput nor L2 regularization were effective.

Input Google Search Data

Bitcoin Price Prediction with Google Search History



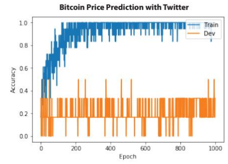
Google Search History and BTC Price Overlayed



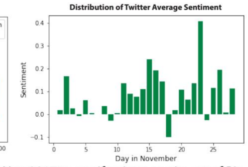
Google search frequency correlates with Bitcoin price changes, so using the search frequency should help our model to more accurately predict price changes. However, we still overfit the model.

Twitter Sentiment Analysis

Bitcoin Price Prediction with Twitter



Distribution of Twitter Average Sentiment



We performed a small case study on Nov 2017 to see if twitter sentiment of Bitcoin can better help our model. We used the VADER sentiment model [3] to get the sentiment value on a small random distribution of tweets. However, due to the small amount of data, we were not able to improve the validation accuracy.

Conclusion

At this time, we were unable to utilize available data to create a generalized model that can fit Bitcoin price changes. Some of the issues we experienced were: too little data on Bitcoin price history (only 1000 days), very little correlation between past and present price change, and not enough Twitter data to utilize sentiment analysis. Additionally, using data such as Google search history was not effective because the Bitcoin price and search history and price overlap, preventing us from using one as a predictive tool for the other.

References:
[1] Estrada, J., Analyzing Bitcoin Price Volatility. University of Berkeley Doctoral Thesis. (2017)
[2] Bollen, J., Mao, H., Zeng, X., Twitter mood predicts the stock market. Journal of Computational Science. 2, 1, (2011)
[3] Hutto, C.J. & Gilbert, E.E. (2014). VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text. Eighth International Conference on Weblogs and Social Media (ICWSM-14). Ann Arbor, MI, June 2014.