University of Waterloo

Winter 2018 – ECE457B Computational Intelligence
ECE Dept, University of Waterloo
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Catastrophes in Volatile Financial Markets – Predicting Cryptocurrencies

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Abstract and Overview:

The aim of this project is to compare different methods for forecasting the future behavior of a cryptocurrency. Two methods involving neural networks are investigated – Feedforward and LSTM to identify which method gives the most accurate cryptocurrency price prediction. Both neural networks were trained and tested on search history data from Google Trends and historical price data from Bitcoin and Ethereum blockchain explorers. The FeedForward and LSTM methods predicted the future price of a cryptocurrency with ??% and ??% accuracy respectively, thus making LSTM the better forecaster of cryptocurrency behavior.

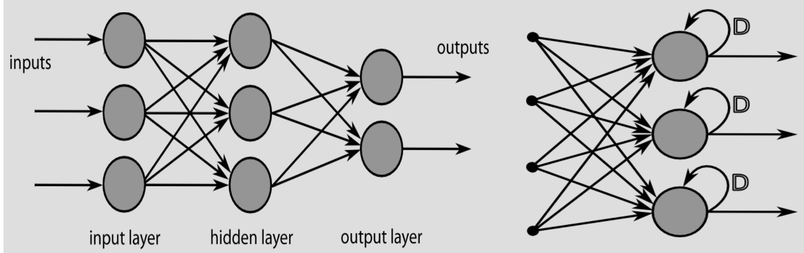
Problem Formulation:

Volatile markets, such as those of cryptocurrency, experience major price fluctuations driven by a handful of power-traders who hold a majority of the total crypto-asset. As a result, quantitative trading algorithms fail to make accurate forecasts of future cryptocurrency prices.

Proposed Solution:

We aim to first implement price prediction for both Bitcoin and Ethereum using the standard FeedForward neural network. Once the network is implemented, we will attempt to implement different solutions in an effort to compare their individual accuracies.

Tools, Algorithms:



Feedforward Neural Network *Recurrent Neural Network*

•Python • Tensorflow • Keras • ScikitLearn • MatPlotLib • Pandas • Google Trends

We created a solution using both **FeedForward** Neural Networks (using Tensorflow) and Recurrent Neural Networks, specifically **LSTM** (using Keras) to be able to compare and contrast between multiple solutions and their accuracy.

Each solution used the same dataset for two popular cryptocurrencies, **Bitcoin** and **Ethereum**. Using data from the past, we trained our models to predict the next day's price.

After building a model and obtaining a decent prediction, we used data from **Google Trends** on each specific cryptocurrencies to be able to elicit correlations between the popularity and the rise and fall of the corresponding cryptocurrency markets.

Experiments, Analysis:

Experiment Setup

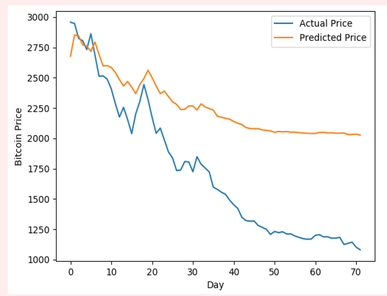
For both neural networks the same number of neurons, the same number of epochs and the same number of data batches were used so that each network's behavior could be studied under similar configurations.80% of data was used to train the network, and 20% was used to test it in both cases.

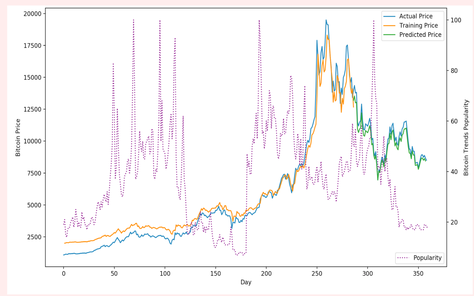
Evaluation Metrics

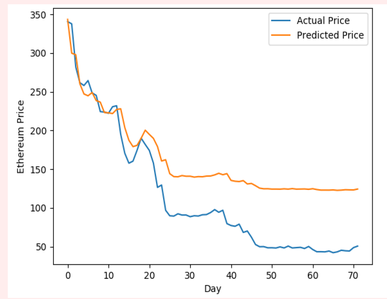
- Accuracy of Cryptocurrency price prediction for a range of days (1 -5 days)
- Assessing the fit of the prediction graph with the graph of actual prices

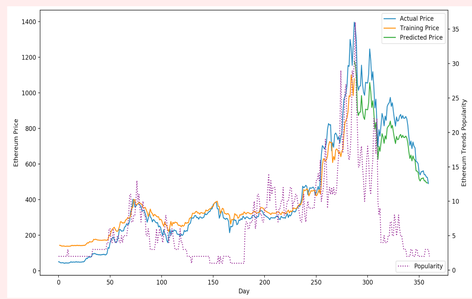
Graphs

FeedForward(20% dataset) **LSTM** (full dataset)









Conclusion:

From this experiment, we implemented both **FeedForward** Neural Network and **LSTM**. We found the difference between the two to be quite substantial. In **LSTM** the problem of vanishing gradient is not present. This means the network can remember prices from the past which allow the LSTM neural network to identify long-term dependencies and predict more accurate prices based on them. Additionally, it was observed that there is a positive correlation between the search frequency of a cryptocurrency - obtained from Google Trends data - and its price. Further research will determine the extent of this correlation.