Predictive Analysis of Cryptocurrency Price

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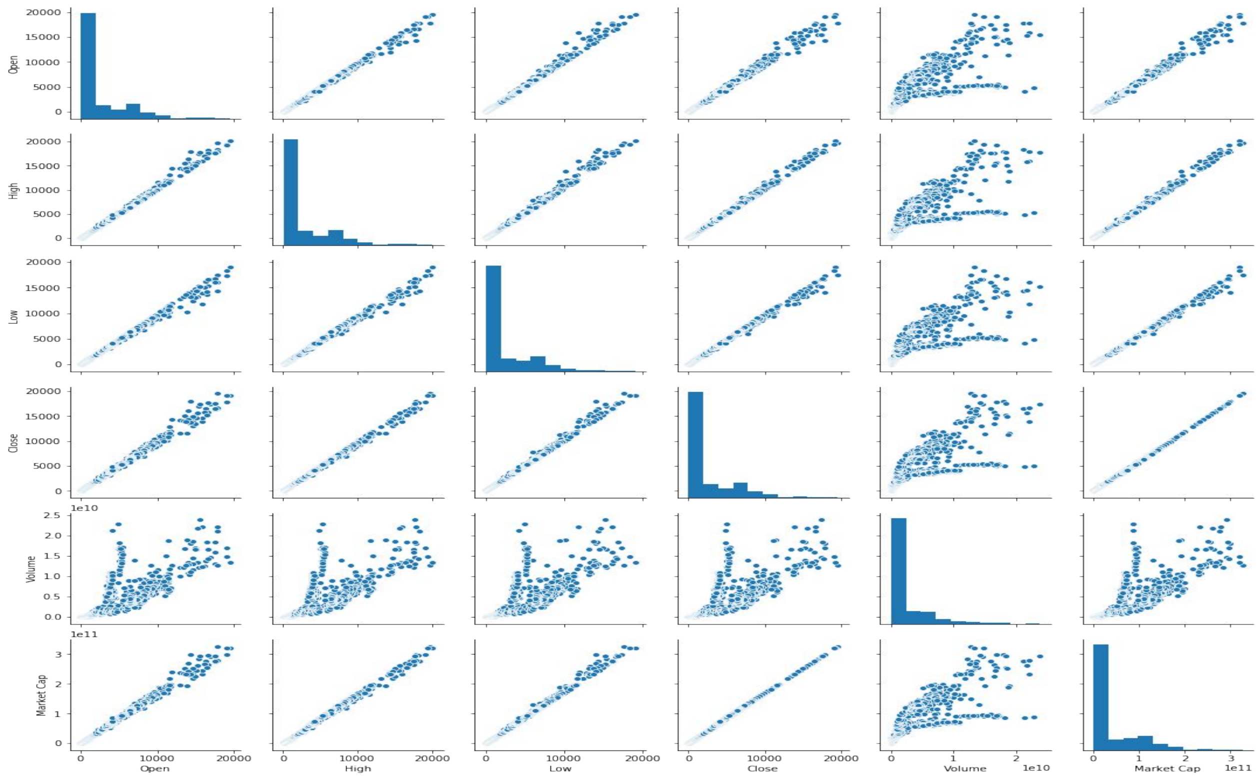
- Introduction
- Data Analysis
- Neural Network for Bitcoin price prediction
- Twitter sentiment analysis for Bitcoin price prediction
- Observations
- Conclusion

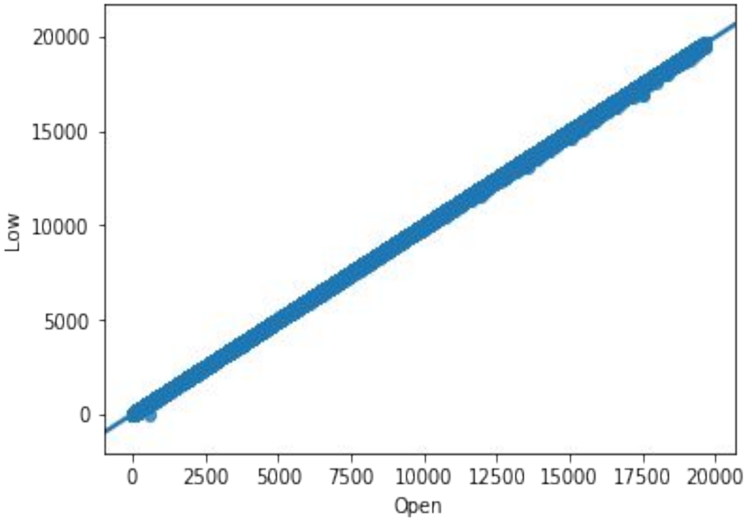
Data Analysis

Pairplot of All Fields

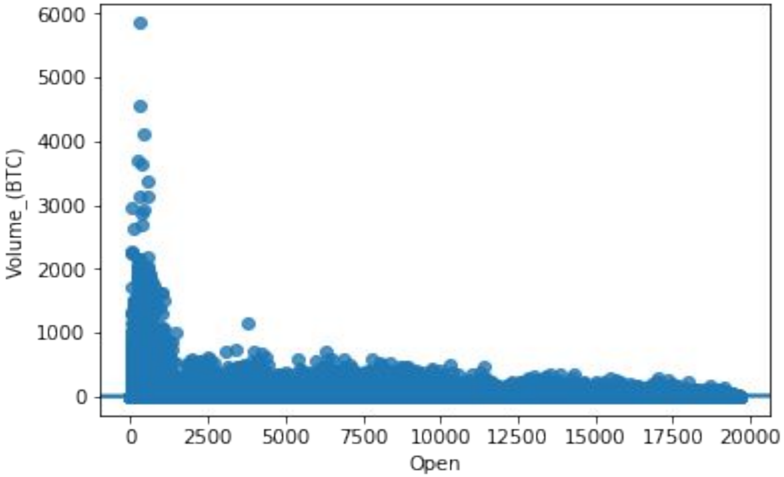


Correlation between features:

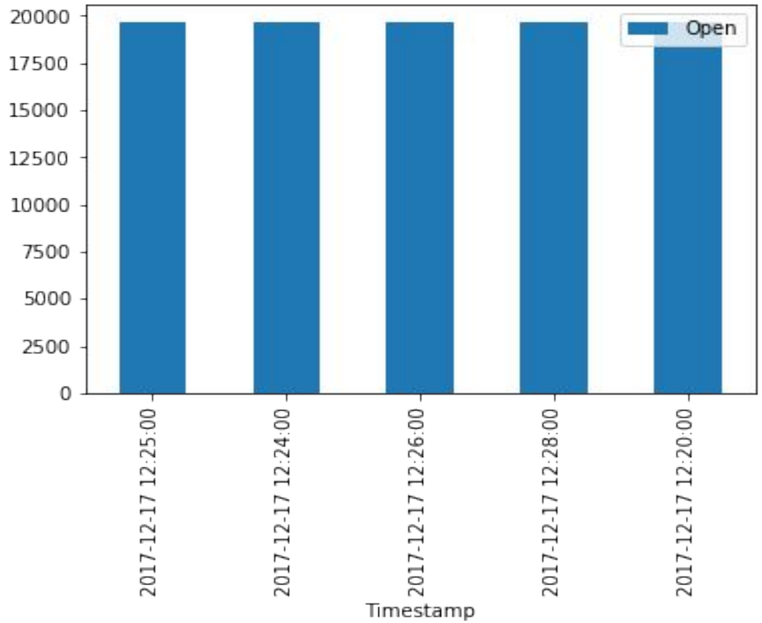
Open and Low Price



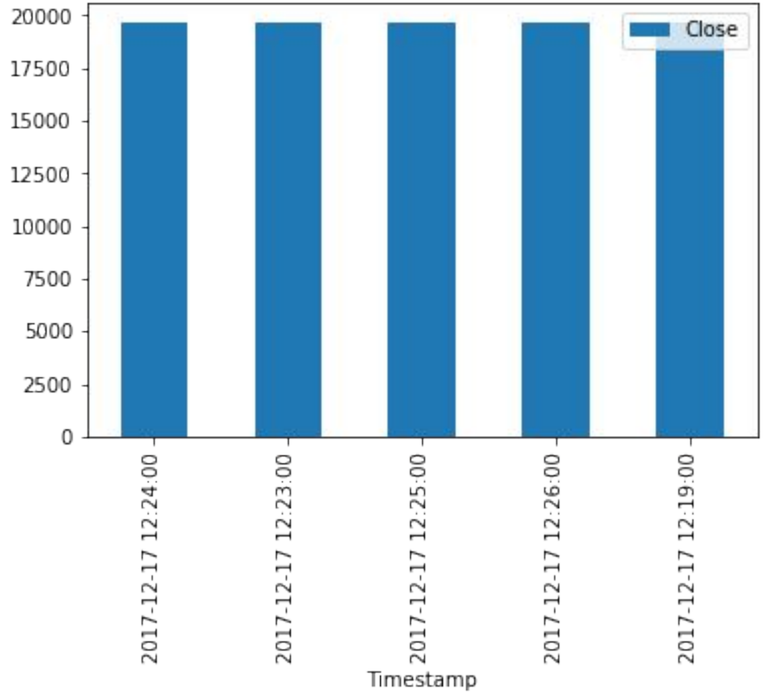
Open and Volume



Top 5 opening prices

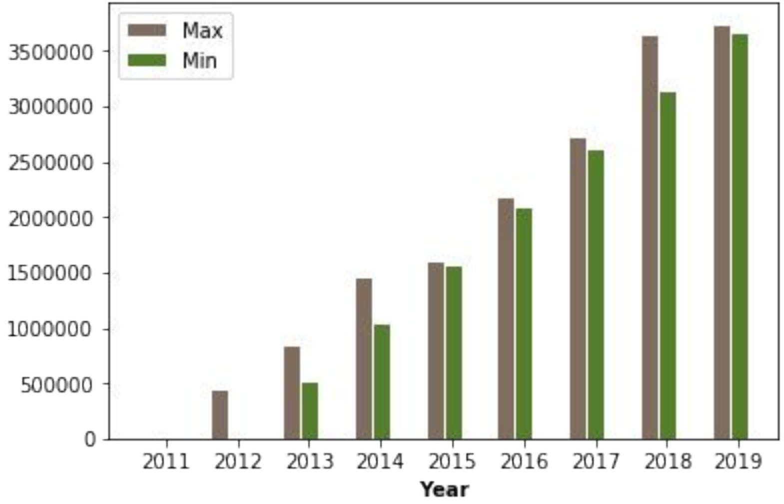


Top 5 closing prices



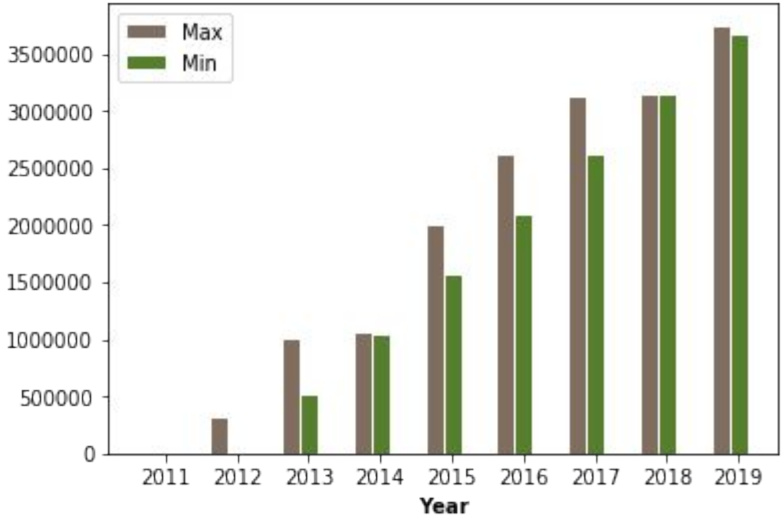
Year wise Analysis

Volume



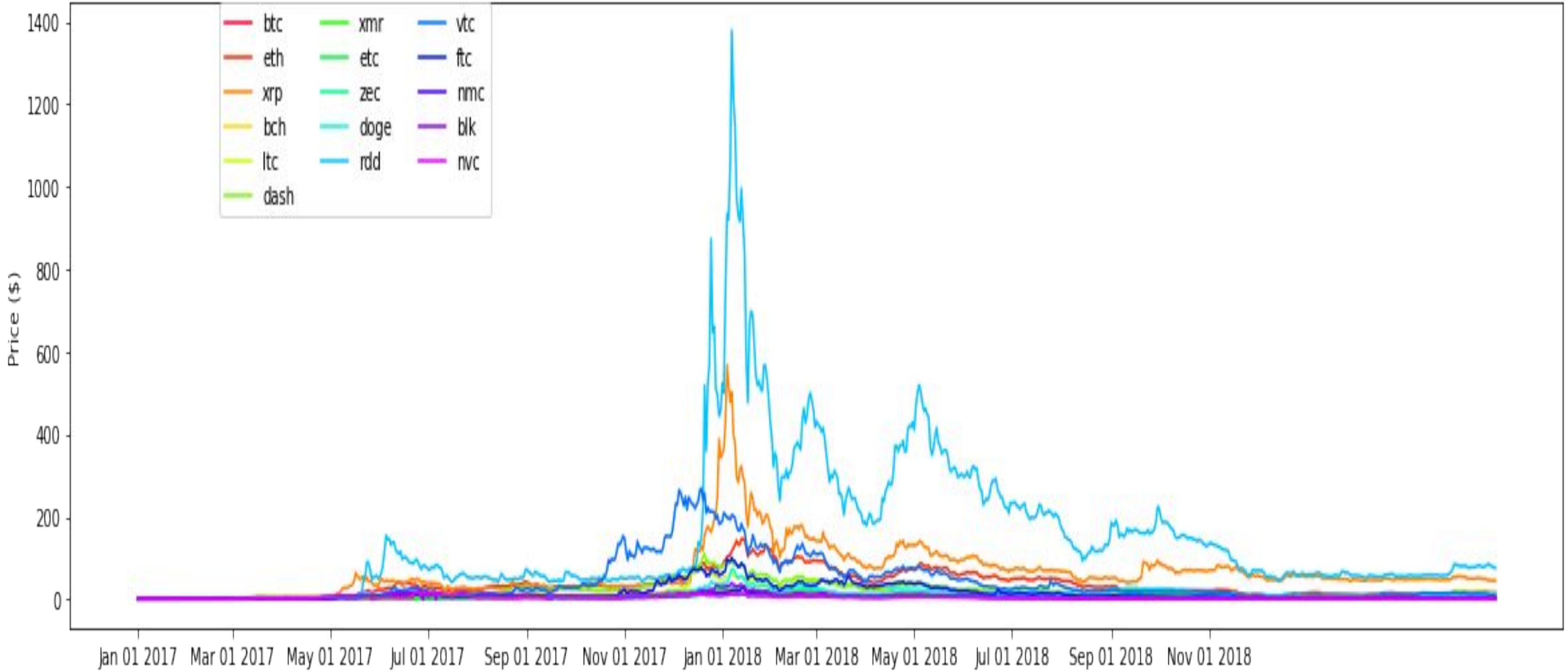
Highest Variation 2018

Price



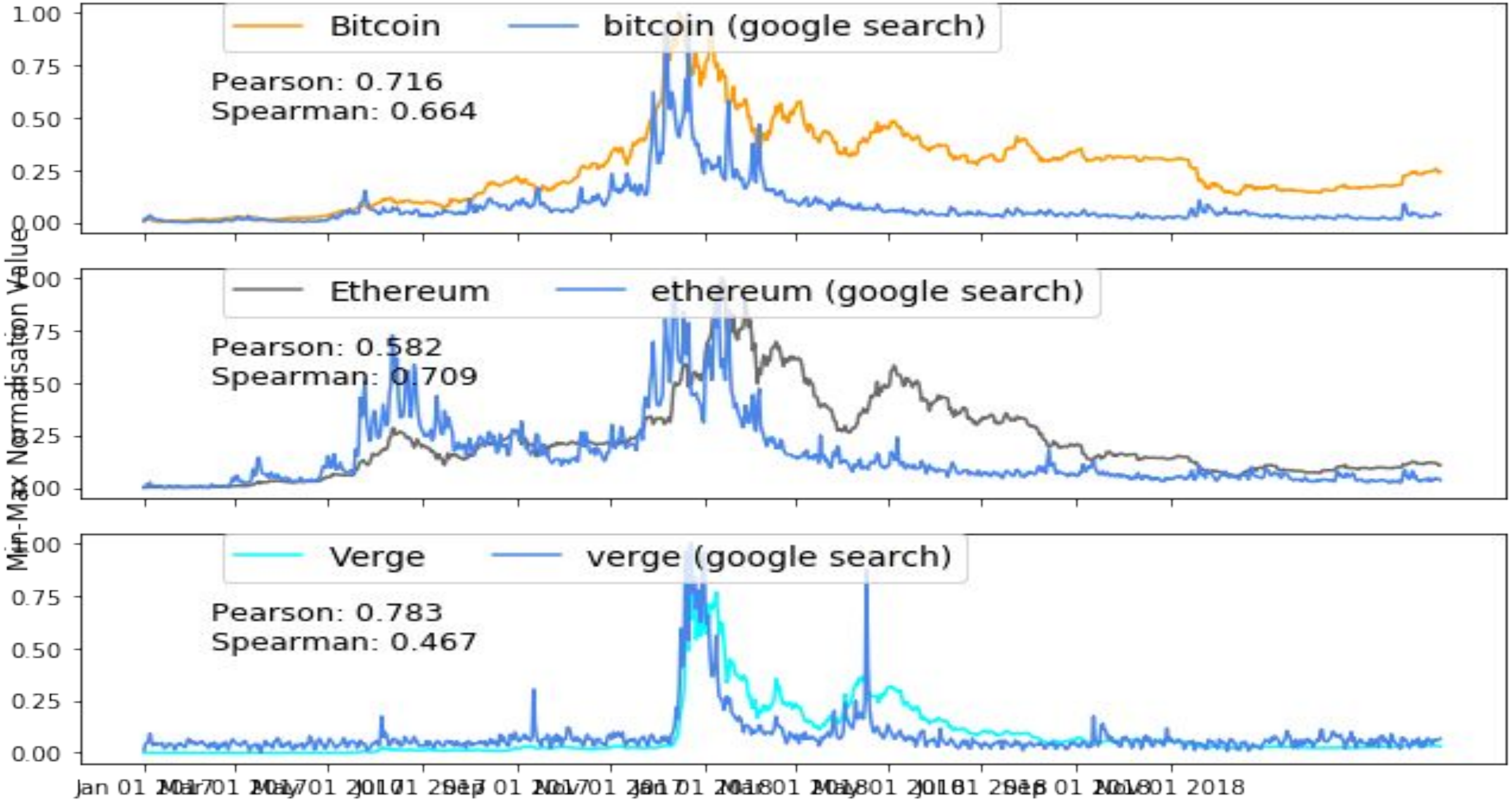
Highest Variation 2018

Data Analysis: Social Media Perspective

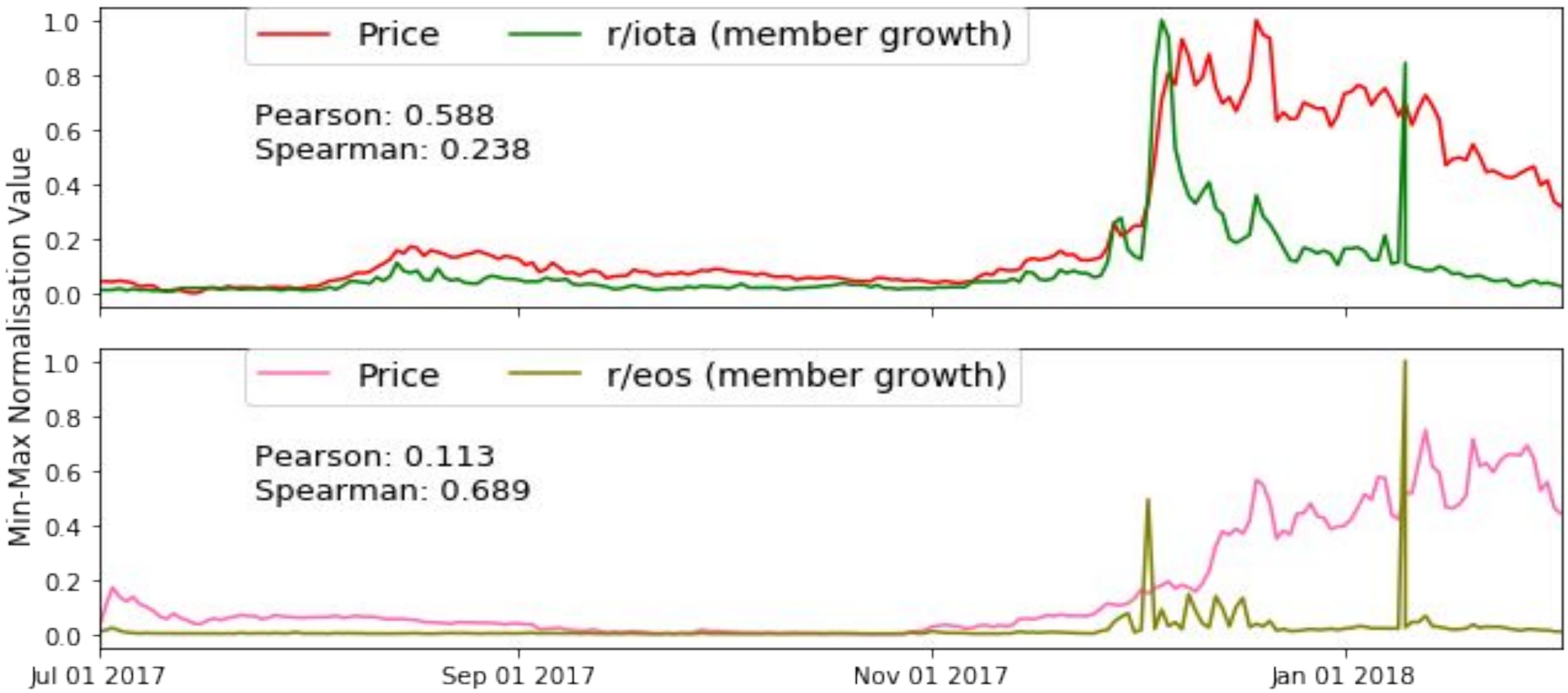


Fluctuation of various cryptocurrency price from Nov 2017 to Nov 2018

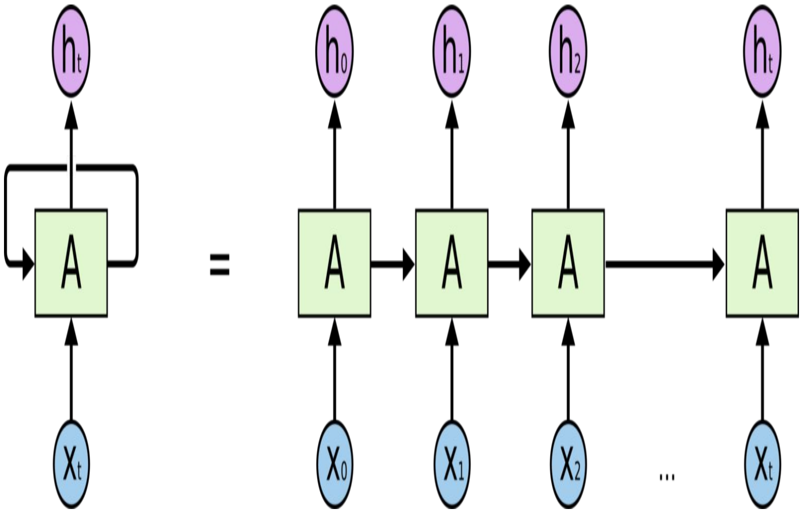
Data Analysis : Google Trends



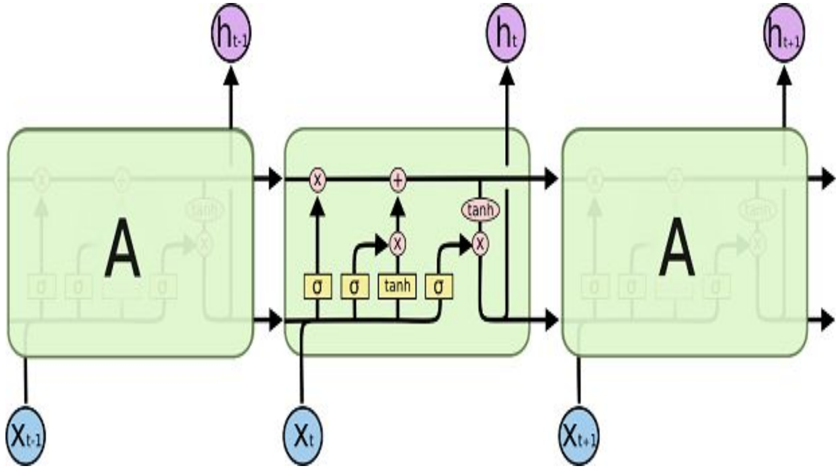
Data Analysis :Reddit Subscriber's Growth



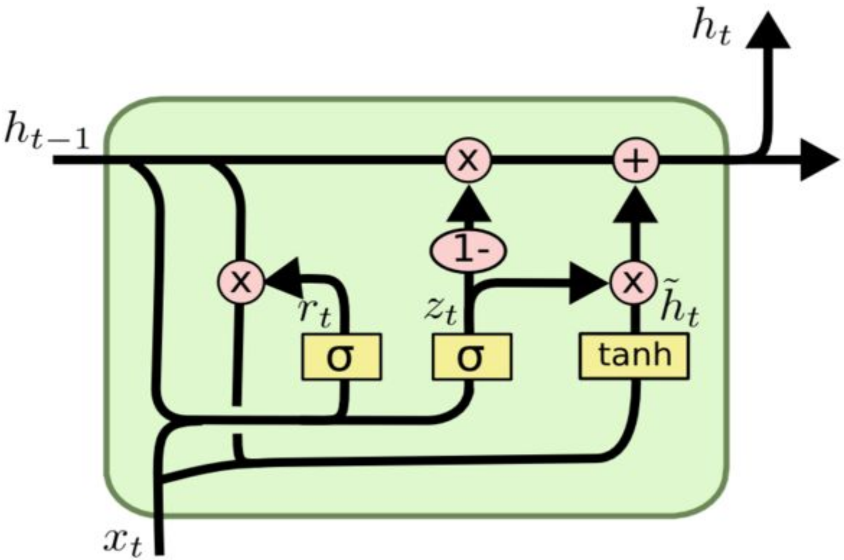
Neural Network for Bitcoin price prediction



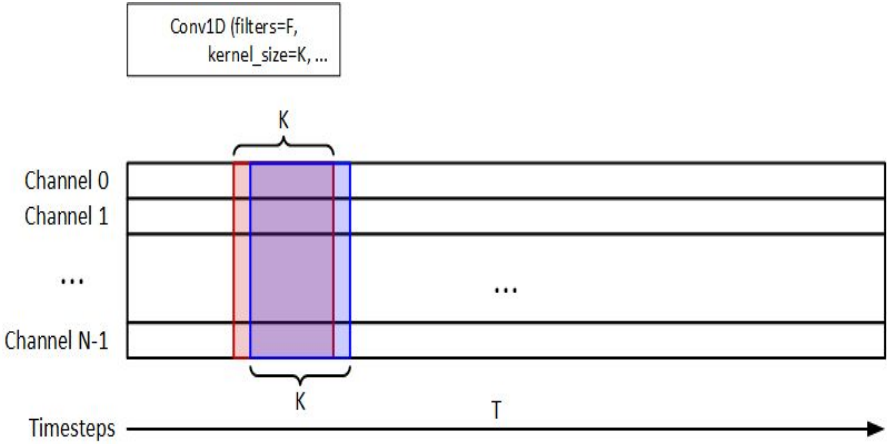
RNN



LSTM


h_t
h_{t-1}
r_t
z_t
1-
$\tilde{h}_t$
σ
σ
tanh
x_t

GRU


Conv1D (filters=F,
kernel_size=K, ...
K
Channel 0
Channel 1
...
...
Channel N-1
K
T
Timesteps

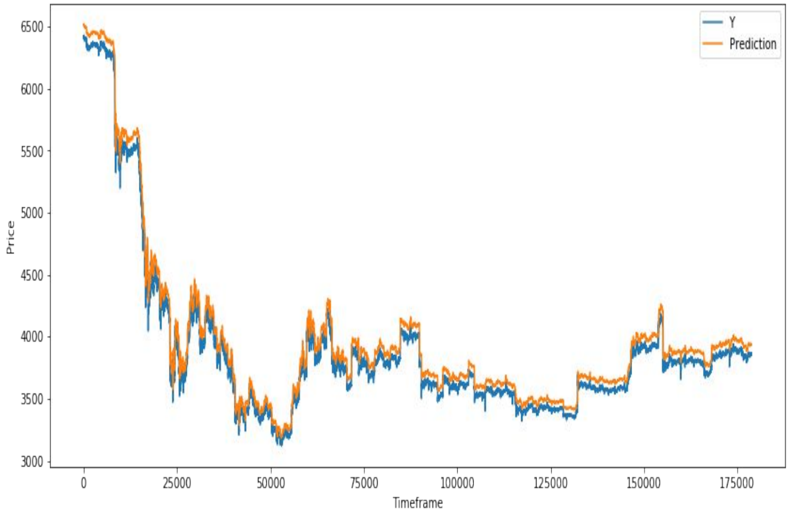
CONV1D

Architecture

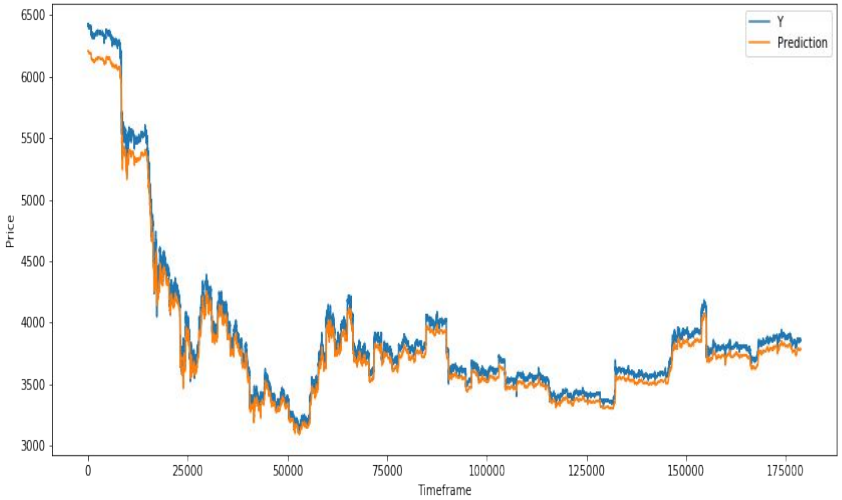
LSTM	GRU	CONV1D
LSTM - 32 units	GRU - 32 units	CONV1D - (64, 3)
Dropout - 0.2	Dropout - 0.2	MAXPOOL - 2
LSTM - 64 units	GRU - 64 units	LSTM - 100
Dropout - 0.2	Dropout - 0.2	Dropout - 0.2
LSTM - 128	GRU - 128	CONV1D - (32, 3)
Dropout - 0.5	Dropout - 0.5	MAXPOOL - 2
LSTM - 256	GRU - 256	Dropout - 0.2
Dropout - 0.5	Dropout - 0.5	Flatten
Dense	Dense	Dense

Performance

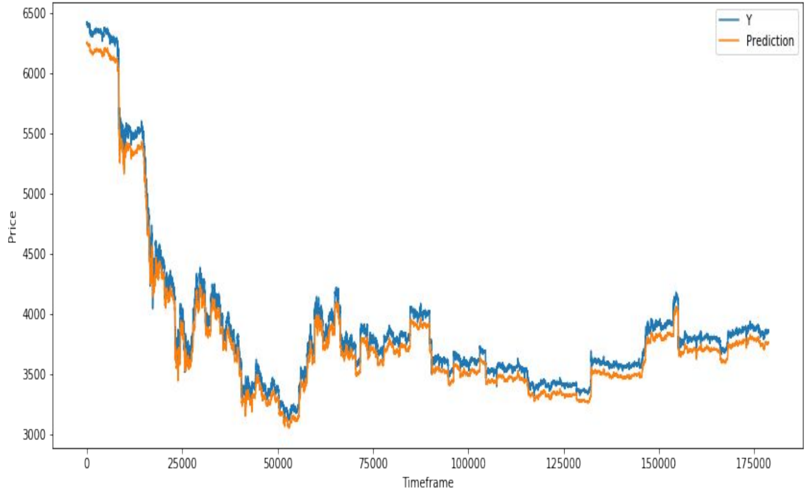
Prediction vs Actual



LSTM



GRU



CONV1D

ERROR COMPARISON USING VARIOUS NN ARCHITECTURE

Architecture	MSE	MASE	SMAPE	MAE
LSTM (32, 64, 128, 256)	1.64761e-05	0.00019	1.94857	0.00392
GRU (32, 64, 128, 256)	1.96731e-05	0.00019	1.95842	0.00400
CONV1D ((64,3), (32, 3))	2.61811e-05	0.00024	2.52501	0.00497

Errors on various cryptocurrencies

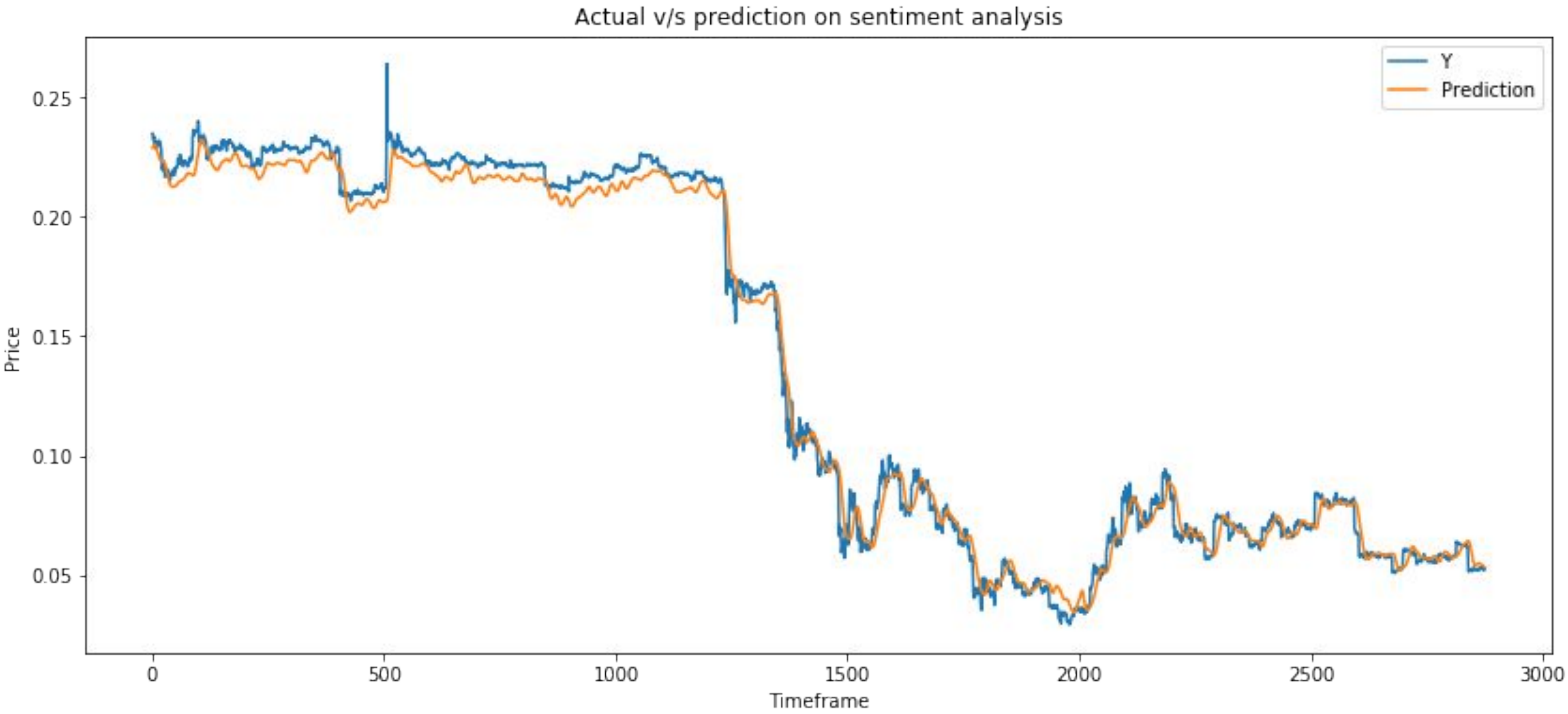
Cryptocurrency	MAE	SMAPE	MAPE
Bitcoin	0.01987	7.33737	0.01064
Litecoin	0.09476	8.39628	0.00730
Bitcoin Cash	0.00671	11.91254	0.26043
Ethereum	0.00671	11.91254	0.26043
Ripple	0.01552	14.75899	0.013525
Stellar	0.01680	10.26539	0.01185
Cardona	0.00362	6.70209	0.14048
EOS	0.01659	7.98707	0.06755
Tether	0.014260	2.17750	0.01348
Binance	0.09476	11.97607	0.12174

Using Tweets to improve prediction

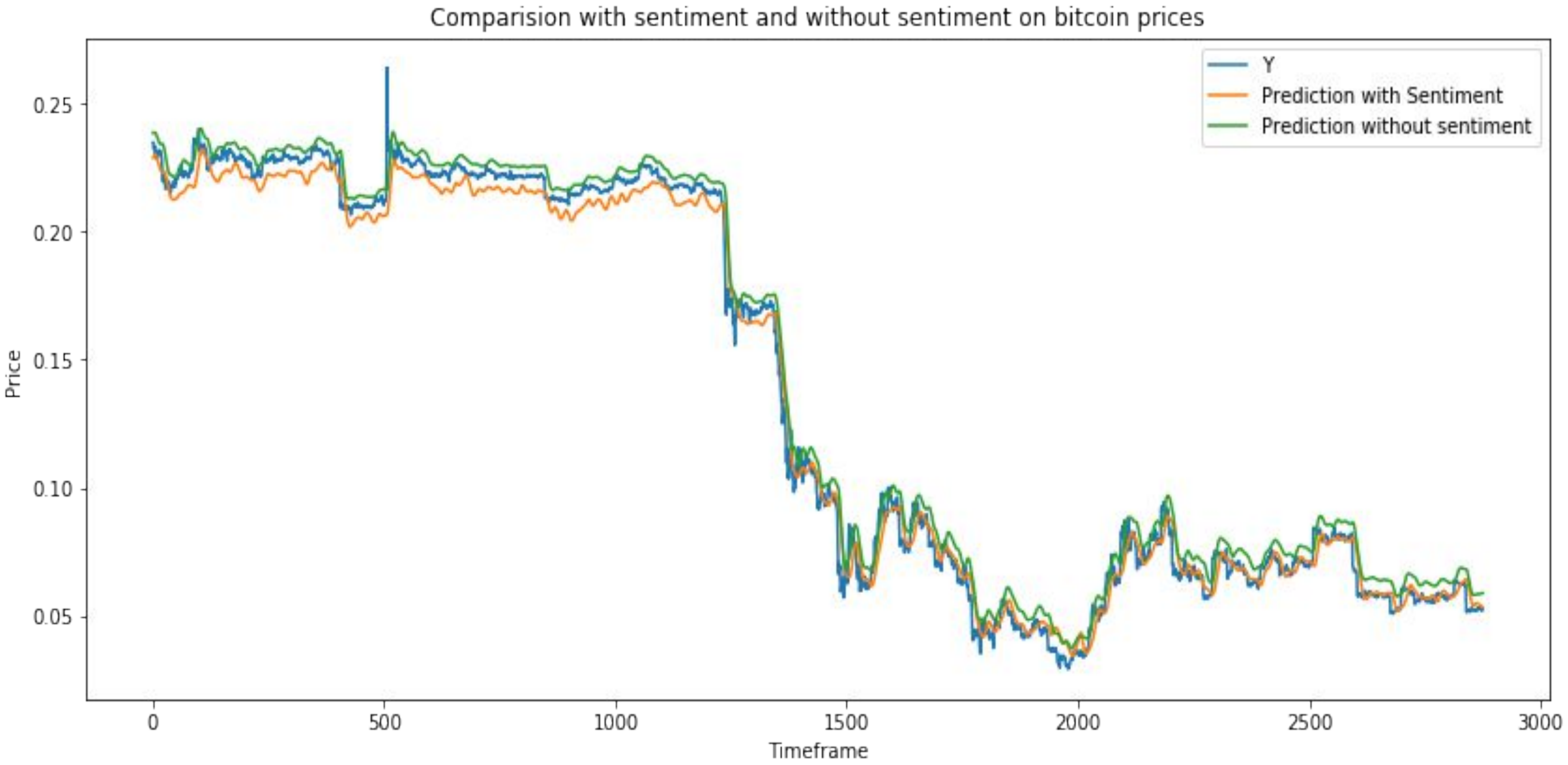
- Tweets of people help to get insight on the general trend following in market.
- We use positive and negative sentiments on tweets in addition to Bitcoin price.
- We used the sentiment of around 17.7 million tweets (in compressed form).
- Features used:
  - Number of tweets
  - Positive sentiment tweets
  - Negative sentiment tweets
  - Closing price of stock

Architecture used is same as before.

Prediction on training



Comparison of Bitcoin Price with and without sentiment data



Other experiments

- Giving weights to the prices with decreasing order of time (largest weight being the current) to make timeseries data for LSTM
    - This didn’t perform as expected.
    - The prediction were very poor. Reason for this was the change in price from the original price in past which resulted in inaccurate data to the model.
    - Model performs best when given data without any modification.
- Training price prediction model solely on twitter sentiment data.
    - Training data solely on sentiment data didn’t work very well. The predictions were very poor.
    - It seemed necessary to include bitcoin prices to predict well.

Conclusion

- We have applied GRU, LSTM, CONV1D to predict bitcoin price and the results were promising.
- We have also incorporated sentiment analysis of twitter data to predict bitcoin price using LSTM neural network.
- Future research should extend the proposed approach by considering additional parameters such as the political environment, human relations, and regulations, which vary across countries.