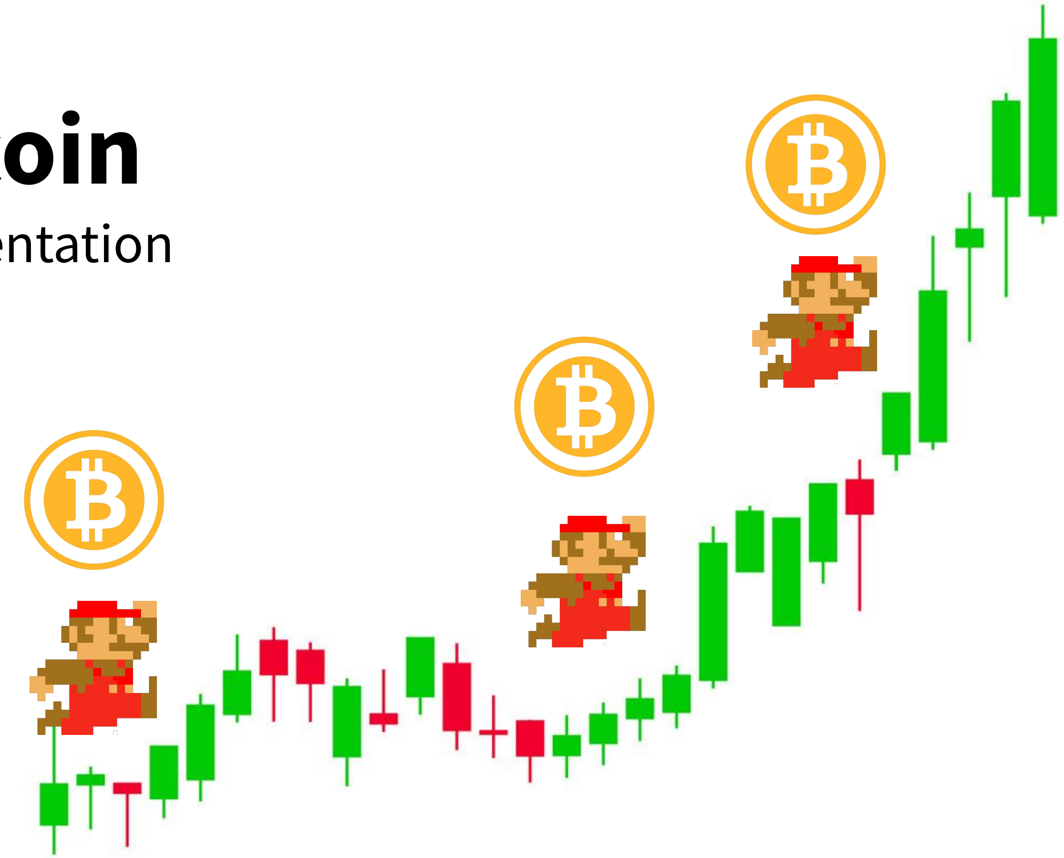
Forecasting Bitcoin

Time Series Final Project Presentation



By Manaswi, Jainam, Andrew & Michael

Agenda

- Problem statement
- Assumptions
- Data properties and transformation
- Proposed Approaches (Models)
- Proposed Solution (Model Selection)
- Results (Accuracy)
- Future Work

Problem statement

What is Bitcoin?

- Digital currency created in January 2009
- Offers the promise of lower transaction fees than traditional online payment mechanisms
- Operated by a decentralized authority, unlike government-issued currencies

The Opportunity

- Bitcoin and other cryptocurrencies may be a risky, but highly lucrative alternative in times of current uncertainty
- However, prices have been subject to major volatility since inception
- We plan to decipher this volatility by using basic as well as advanced time series forecasting tools

Assumptions

- Did not take into account internal factors (security Breach, new blockchain) or specific external factors (speculation markets, exchange closure/opening) of Bitcoin into the model.
- Did not consider that Bitcoin resembles gold mining, where there is a decrease in the supply, making it deflationary towards currency value
- Assume data can be made stationarity, upon which all modeling is done.
- Assumed that there was no significant information prior to 2016
- Uncorrelated random error: We assume that the error term is randomly distributed and the mean and variance are constant over a time period.

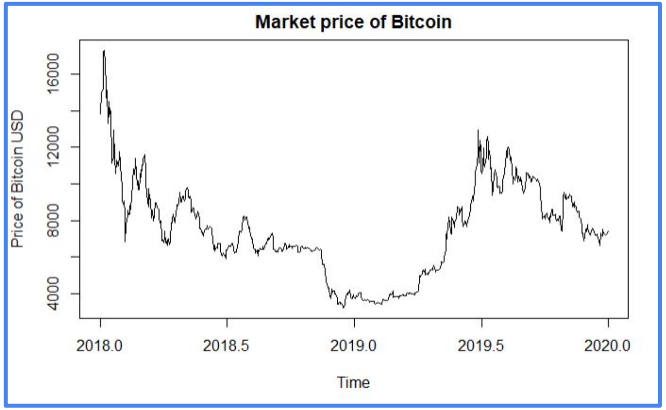
Data Exploration

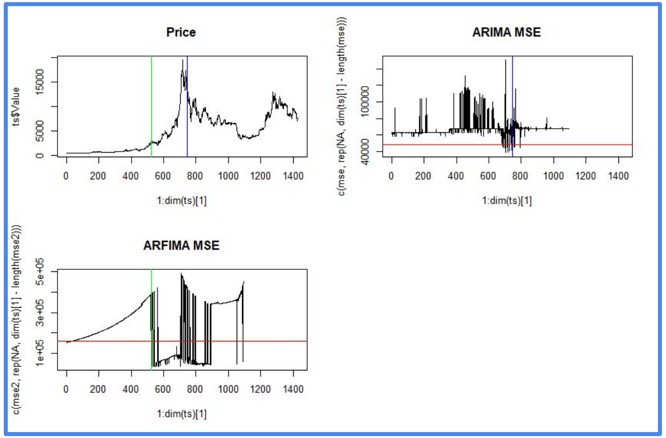
Data Source: Bitcoin market price in USD updated daily (Jan 2009- Jun 2020) was pulled from Quandl, which is a website that publishes data related to finance.

The data provides variables associated with bitcoin such as the number of users, market price, exchange trade volume, avg. block size etc.

Training window was selected from 01 Jan 2018 to 31 Dec 2019 by cross-validation using ARIMA and ARFIMA.

Test window is 01 Jan 2020 to 30 Jan 2020.



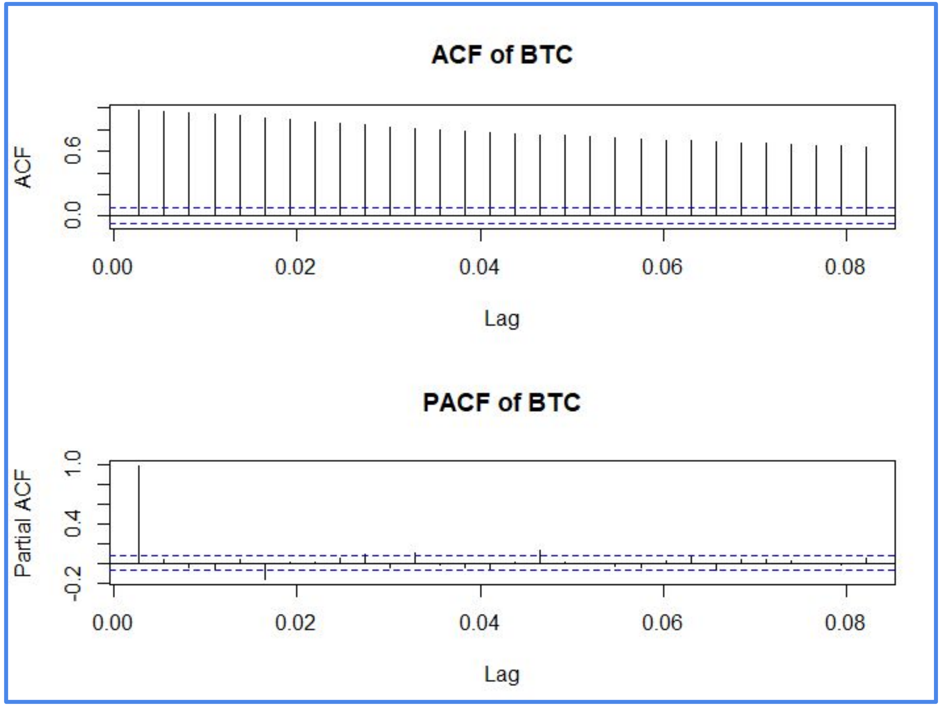


Data Transformations

ADF Test and KPSS tests showed that the data was non-stationary

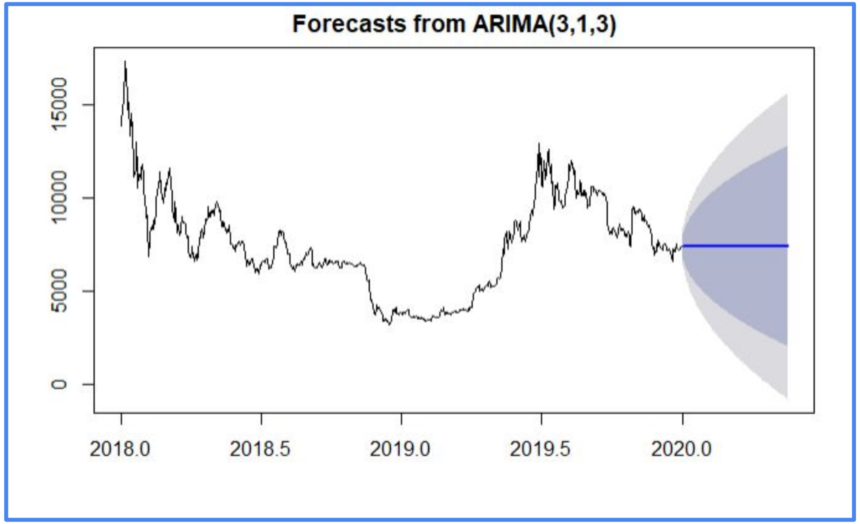
1st differences were taken to make the series stationary

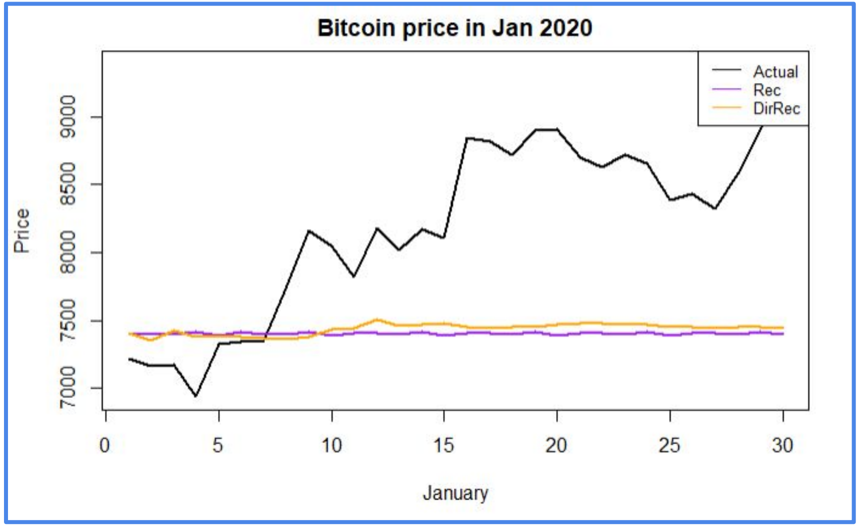
Optimal Box-Cox coefficient was near zero, so data was log-transformed



ARIMA (Rec & DirRec)

- Auto.arima, which suggested an ARIMA(3,1,3), however forecasts quickly revert to the mean
- Recursive and DirRec methods provide slightly better forecasts, but still have large autocorrelation within the residuals

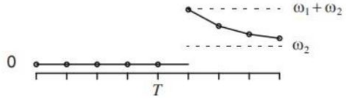




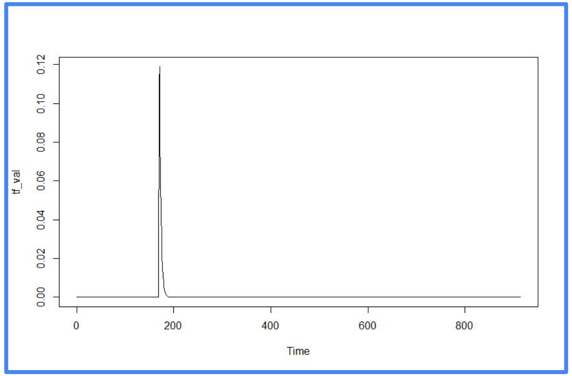
Intervention Analysis

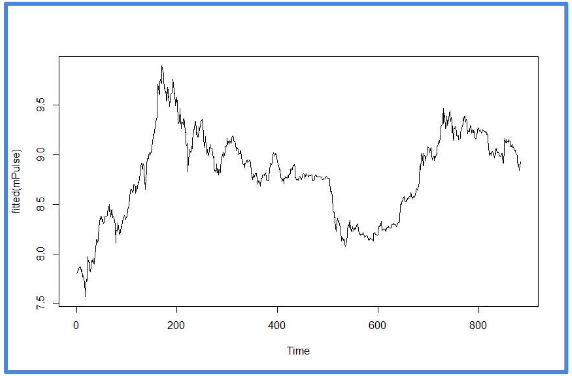
- Intervention analysis was performed to determine the impact of the 2017 Bitcoin craze
- Effect was optimized to step function centered as crash on December 8, 2017

(b) $\left[\frac{\omega_1 B}{1-\delta B} + \frac{\omega_2 B}{1-B}\right] P_t^{(T)}$



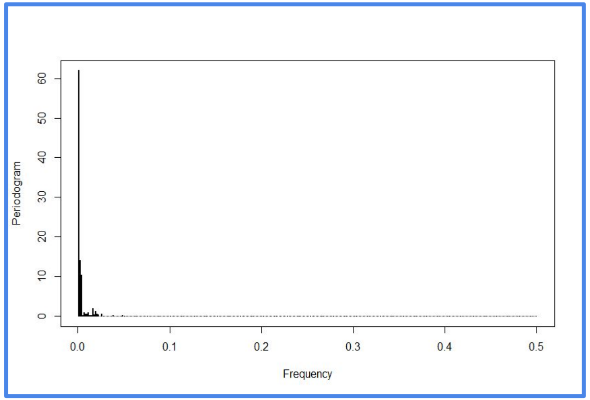
- Top plot shows estimated transfer function, which decays to 0, making this model meaningless for prediction
- Critically, it shows an estimated 12% impact on the price of Bitcoin, as the data is log-transformed
- Bottom shows ARIMA with intervention

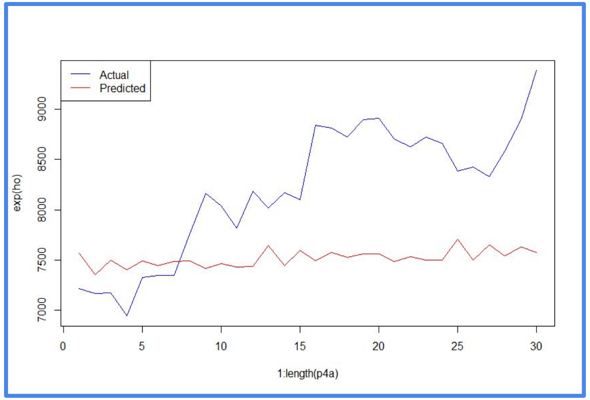




ARFIMA + Holt-Winters Ensemble

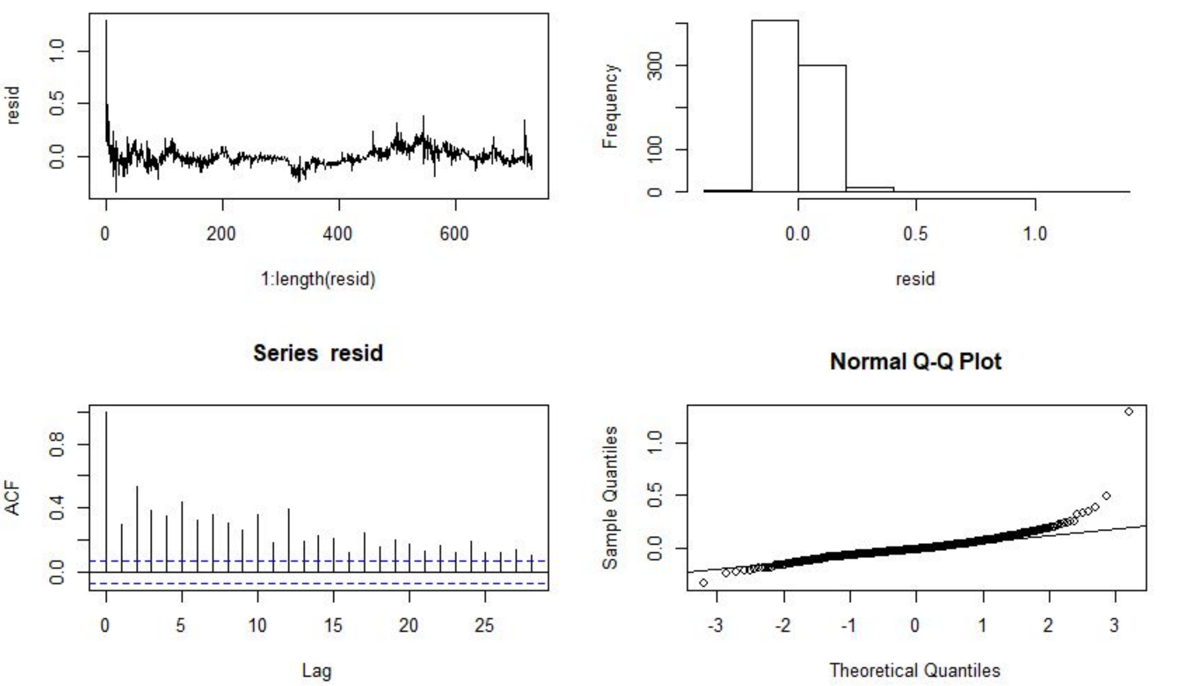
- To encapsulate both the fractional differencing useful in financials, and the seasonal component of the data, we combined an ARFIMA and Holt-Winters model
- The ARFIMA model was built on the original data, and Holt-Winters built on the residuals
- The AR and MA component are predicted as zero, resulting in a rather flat prediction
- Holt-Winters seasonality (12 days) was chosen based on the best fit from the top values specified by the periodogram





ARFIMA + Holt-Winters Ensemble

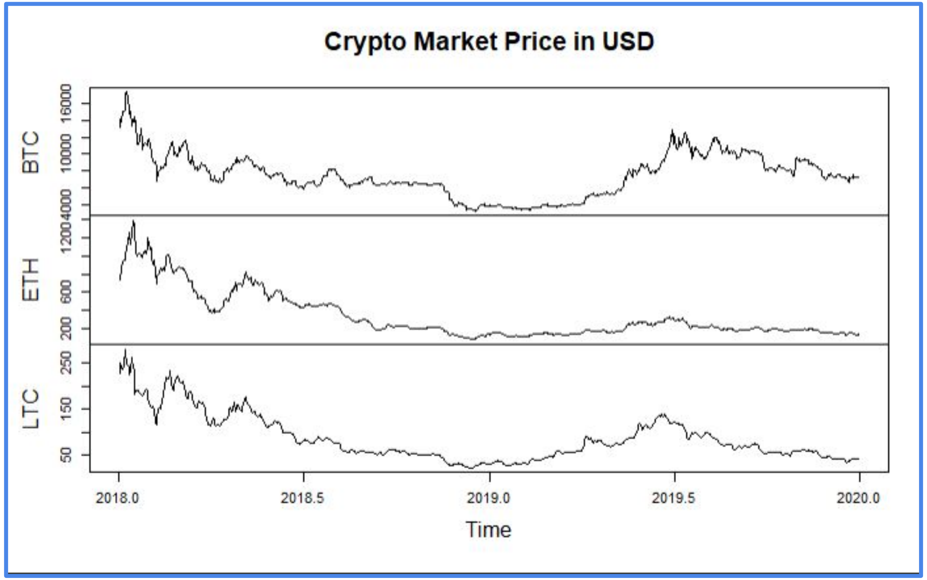
Residual Analysis



VARMA

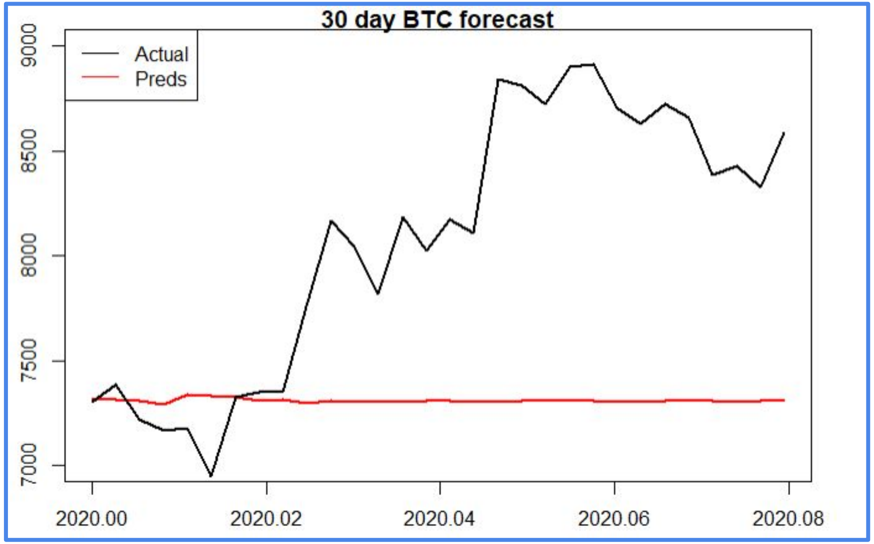
- Multivariate analysis of BTC, ETH and LTC
- First difference was taken to make the series stationary
- Granger Causality tests showed that BTC caused ETH and LTC, but also also that ETH and LTC caused BTC

	BTC	ETH	LTC
BTC	1.00	0.59	0.70
ETH	0.59	1.00	0.89
LTC	0.70	0.89	1.00



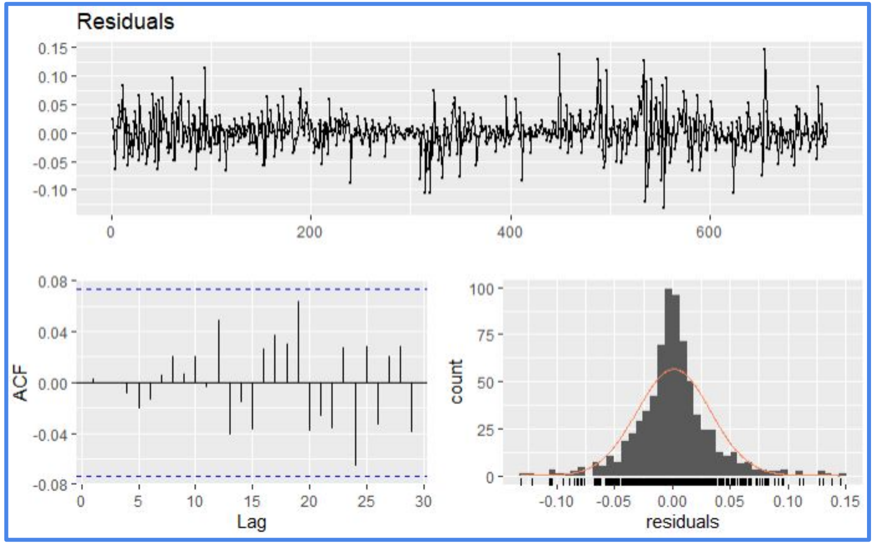
VARMA

30-day forecasts with VARMA



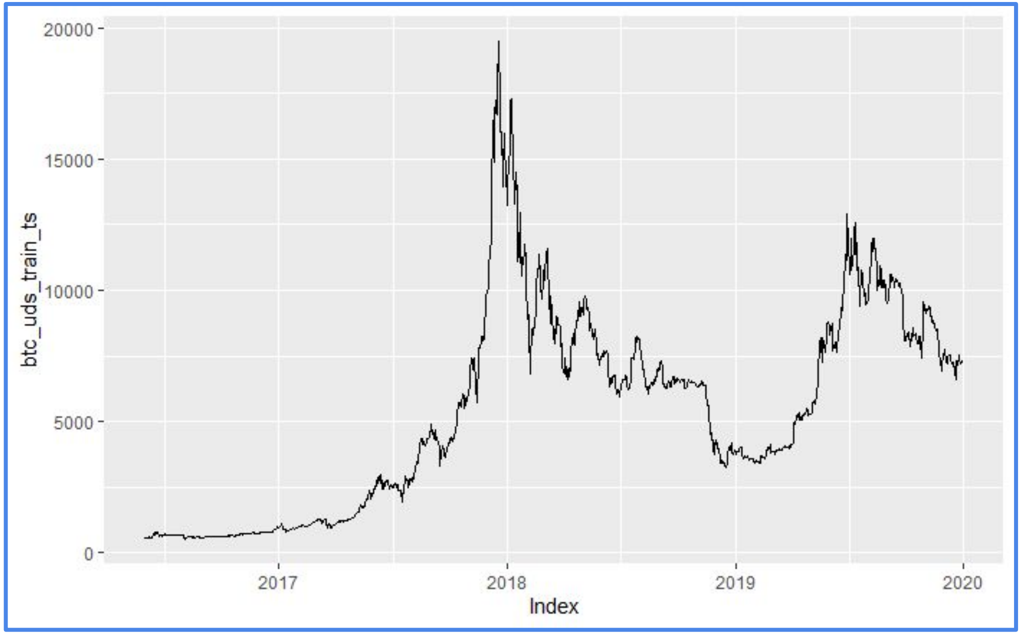
MAE: $814

Residual Analysis



Facebook-Prophet

- Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well
- Features:
  - Accurate and fast
  - Tunable forecasts



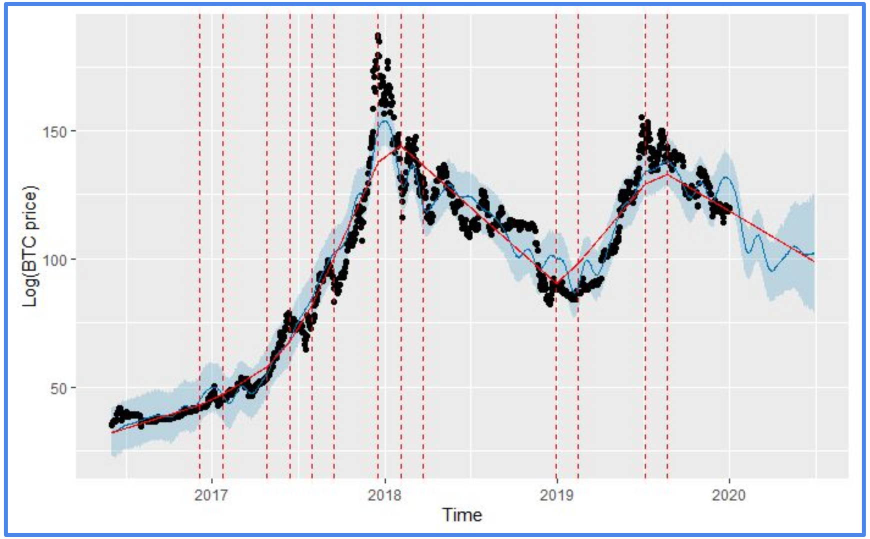
Models Model Selection Results Future Work

Facebook-Prophet

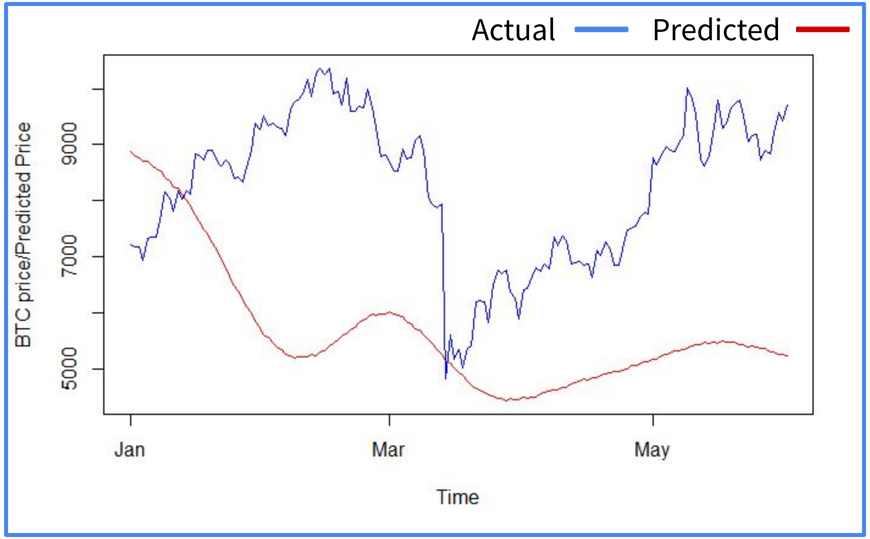
- Switch in approach and try to visualise what might be present in the data
- Assumption- Usually such TS tend to normalise after cycles of volatility
- Identification of a damped multiplicative cycle
- Prophet allows fine tuning of parameters
  - Changepoint
  - Seasonality
  - Changepoint range

Facebook-Prophet

Model Output:

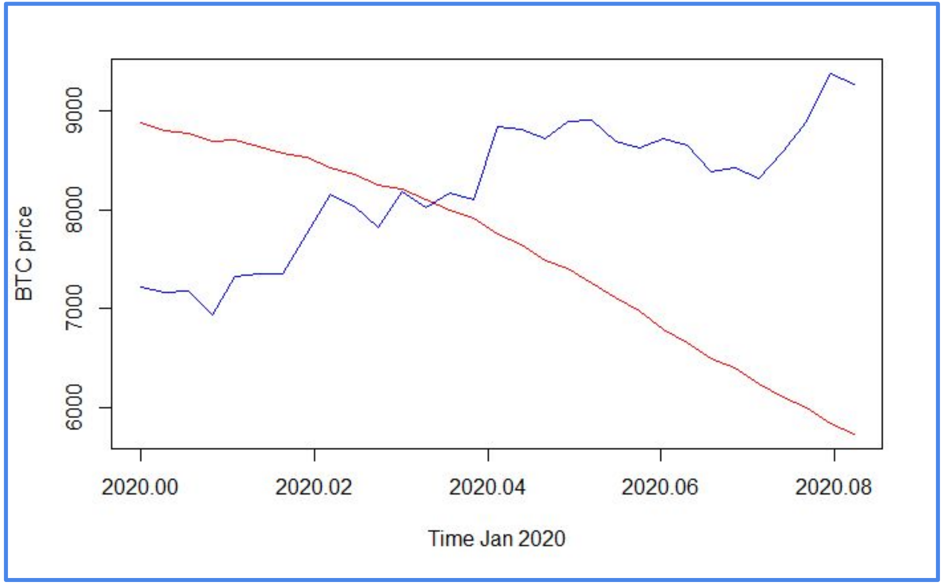


6 months forecast:

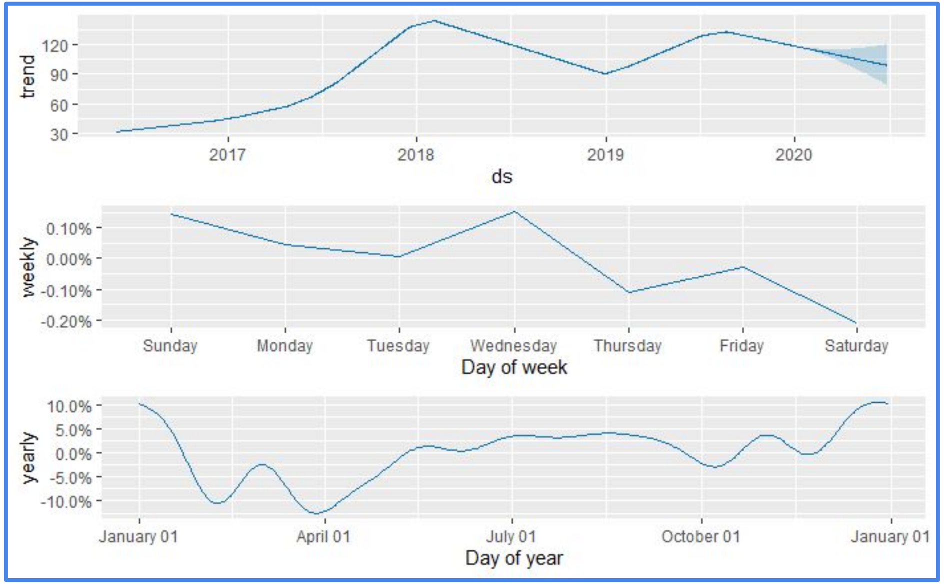


Facebook-Prophet

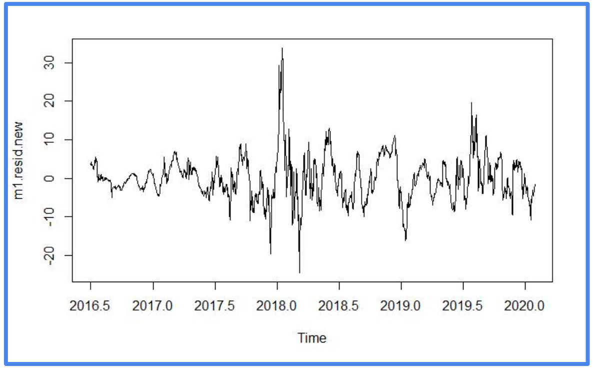
Output:

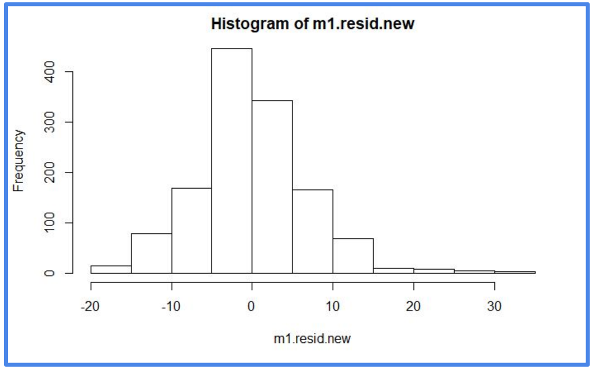


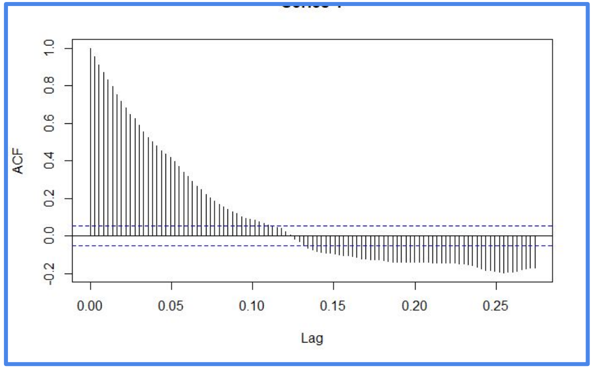
Prophet Components:

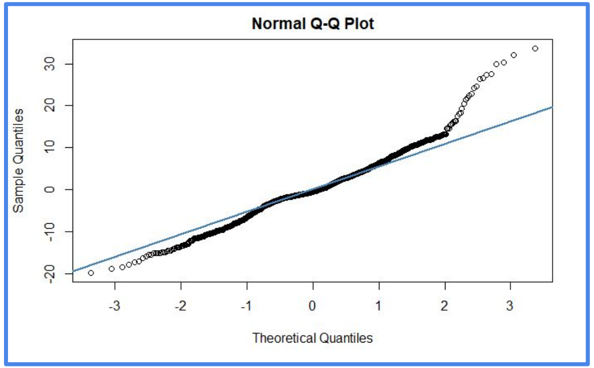


Prophet (Residuals Analysis)



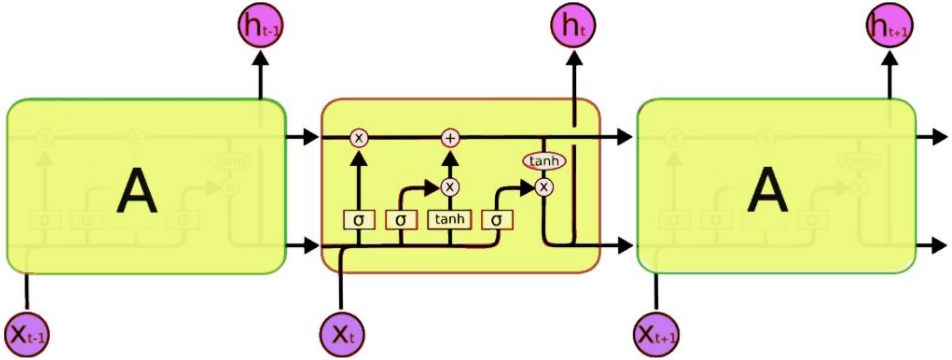






Neural Network-LSTM

- RNN is a family of neural networks with loops that allow the modeling of temporal or spatial sequences.
- RNN is a composition of identical feedforward neural networks, one for each moment, or step in time referred to as “RNN cells”
- LSTM- Special kind of RNN capable of learning long term dependencies
- Holds internal state (c t) across time steps
- Updates cell state information by using adaptive gates (soft switches)
- Neuron replaced with a Memory cell having an input gate, an output gate and an internal state



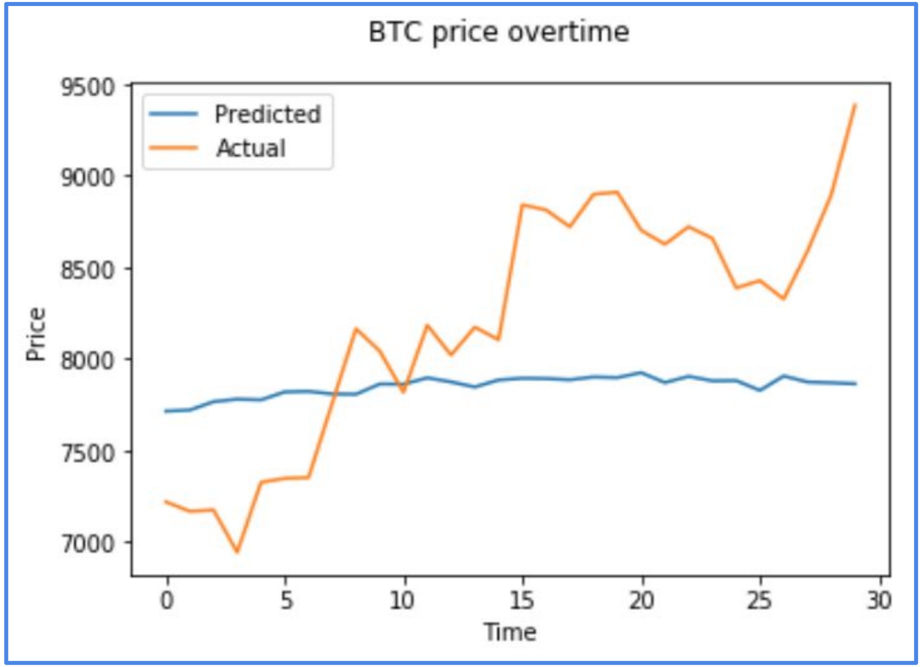
Neural Network-LSTM (BPTT)

- Used Backpropagation through time
- Converted time series data to a supervised data for 30 days windows to predict the next 30 days BTC price
- Model Parameters:
  - Loss-MSE
  - Optimizer-ADAM
  - Metric-MAE
  - Callback-3 episodes
  - Run for 50 epochs

```
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_7 (LSTM)                (None, 400)               643200
_________________________________________________________________
dense_10 (Dense)             (None, 100)               40100
_________________________________________________________________
dense_11 (Dense)             (None, 30)                3030
=================================================================
Total params: 686,330
Trainable params: 686,330
Non-trainable params: 0
_________________________________________________________________
```

Neural Network-LSTM

- Performance (early stopped at epoch 17):
    - 30-day MAE: 917.03
    - Forecasted MAE 603.79
    - sMAPE 7.45%
- Best model for LSTM compared to S-LSTM and Bidirectional LSTM
- LSTM are difficult to train because they require memory-bandwidth-bound computation



Model Selection & Results

Model selection was done based on a comparison of MAE and sMAPE scores.
The model with lowest sMAPE score was selected.

	MAE (US$)	sMAPE
ARFIMA	840.91	10.52%
ARFIMA + HW	787.45	9.81%
VAR Model	814.48	10.33%
Prophet	1386.31	18.78%
LSTM	**603.79**	**7.44%**

Average Prediction error: US$ 603.79

Future Work

Future
Work

- Identification and use of external variables such as:
  - Bitcoin sentiments over the internet
  - Miner revenues across
  - Number of daily transactions
  - Performance of alternative coins
- Develop LSTM for further improvement
- Investigate frequency domains to see whether Bitcoin price can be represented and predicted as such

Thank you!

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Appendix

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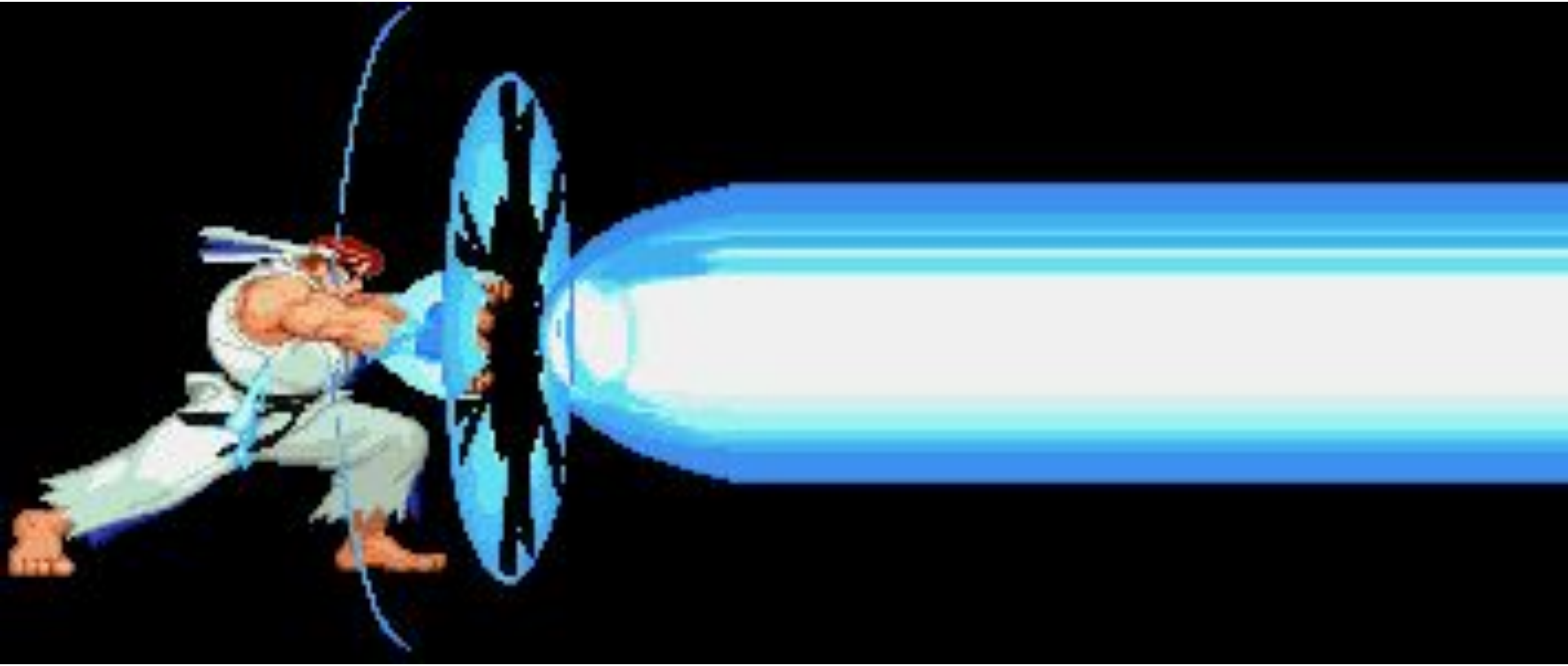
ARIMA(0,1,0) forecasting



“We predict a price of $1 million by 2021, with 40% certainty”