Time Series Forecasting of Bitcoin (BTC) Price

In this paper, we will test three different models on crypto-currency prices to check their forecasting ability. In the first place, we will have a look at the challenges of times series forecasting. Then, we will see how we extracted and analysed the data used in our analysis. Finally, the ARIMA model, the Prophet procedure, and the LSTM model, as well as all their results will be detailed.

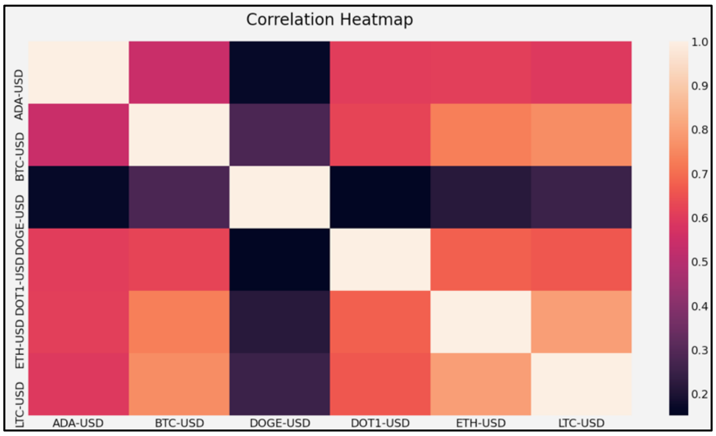
I- Challenges of time series forecasting

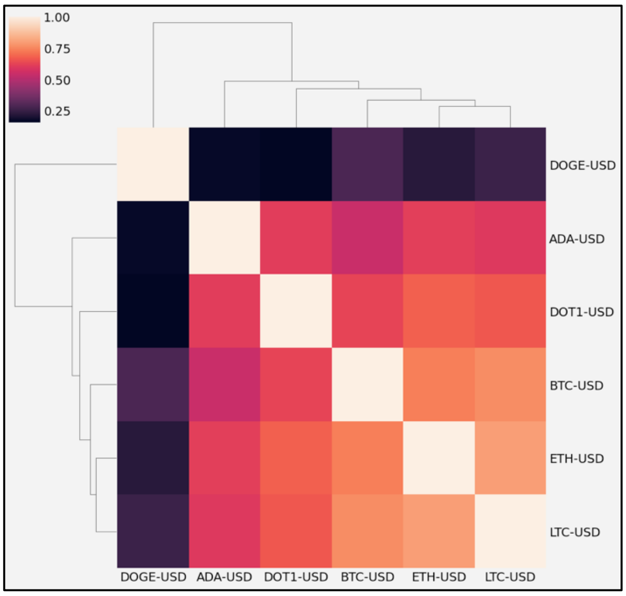
Time-series data is collected sequentially, with one axis monotonically increasing, which is measurable with time or other metrics. And structure of time-series data is characterized across data points of seasonality and cycle, autocorrelation (if data is noisy), trends, etc. Besides, time series data have a stochastic behaviour even as to behaviour regime: stochastic shift to a different regime and change point identification.

Time-series analysis can serve various purposes. We can understand the temporal behaviour of the data seasonality through stationarity tests. Seasonal data could be weather or business boom-and-bust cycles, for instance. Also, we can identify underlying distributions and the nature of temporal process producing data (hypothesis about fundamental factors). Times series analysis also allows us to estimate past, present and future values. When necessary, it can also be about filtering. To be specific, we can tell medical sensor measurement error and true value using time series analysis. We may also classify normal and abnormal time series in our analysis and understanding of data and detect anomaly such as outlier or problematic points within a time series.

II- Data fetching and analysis

We used the yfinance package to fetch our data. This package allows to extract data from Yahoo Finance for any asset and for any time period. In order to have a better and deeper idea of the data, we conducted some basic statistic calculations for various cryptocurrencies: annualized returns, annualized volatility, correlation between cryptos, maximum drawdown, Calmar ratio ($Annualized\ returns/Maximum\ drawdown$), annualized Sharpe ratio ($(Portfolio\ return - risk\ free\ rate)/\sigma$). We deepened the correlation analysis with heatmaps (see left below) and clustermaps (see right below) built with the seaborn package.





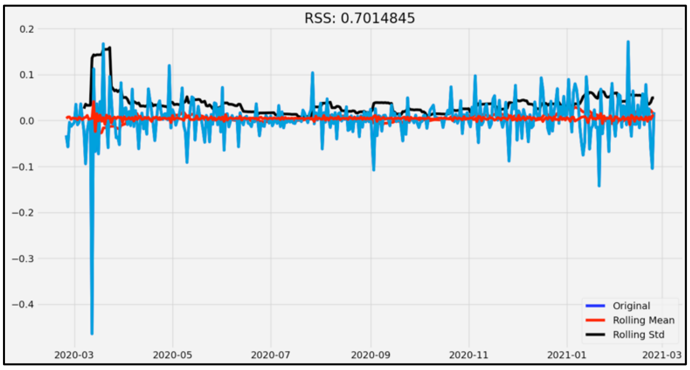
We also analysed the results of the Simple Moving Average and the Exponential Moving Average trading strategies applied to BTC:

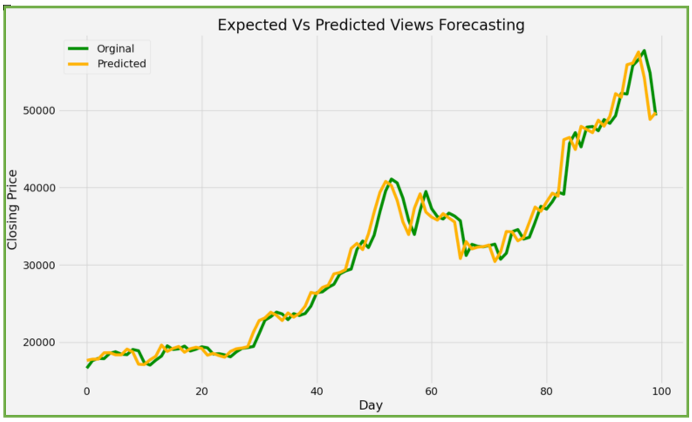
III- Models and results

1. ARIMA

The first model we tested is the Autoregressive Integrated Moving Average model, which is quite broadly used in econometrics. It is a "stochastic" modelling approach and a mix of the auto regressive model and the moving average model. Before starting, some stationarity tests are needed. To avoid biases in our results, we need to chase non-stationarity. We need the Null Hypothesis (H0) of the unit root test (e.g. Dickey Fuller test) to be accepted. Non-stationarity is verified when p-values are below 0.05 so that H0 is rejected. If the series is stationary, we can log-transform it and use differencing to finally remove all signs of trend and seasonality.

For the Bitcoin, we needed to go up to the differencing step to fully un-skew the time series. Please find the time series on the left-hand side below and the forecast on the right-hand side below.



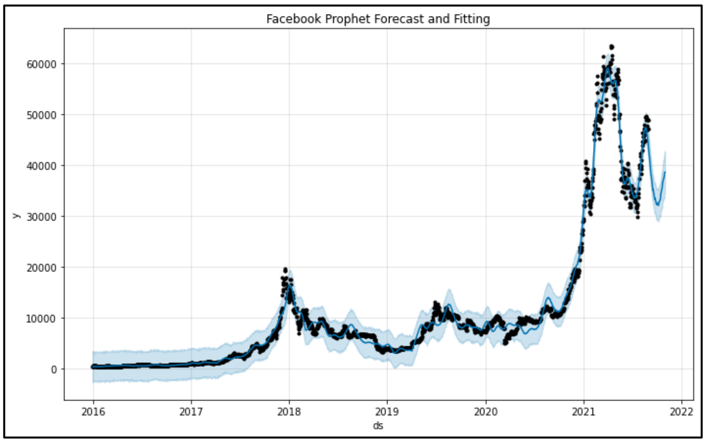


We can clearly observe that the yellow line of predictions is constantly ahead of the green line representing the actual prices. The forecasting power of the ARIMA model is great in the case of Bitcoin for the March 2020 to March 2021 period.

Mean Absolute Error: 761.7104

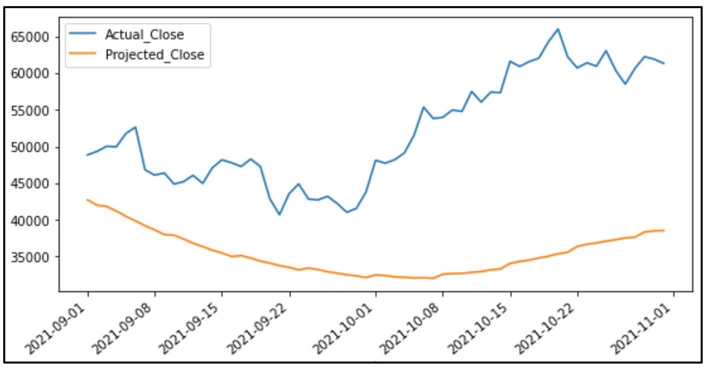
2. Prophet

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. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well. We used prophet for predicting a highly volatile cryptocurrency which lack seasonality and we were not able to receive satisfactory results. Model was trained on the data from '2016 01-01' to '2021-08-31'. Predictions were made for '2021-09-01' to '2021-11-01'.



Legend
Blue line = Forecasted values
Black dots = Observed (actual) values
Blue region = Uncertainty intervals

Predictions (see graph below)
It is the delta description between the predicted value and the actual values of the Prophet Model

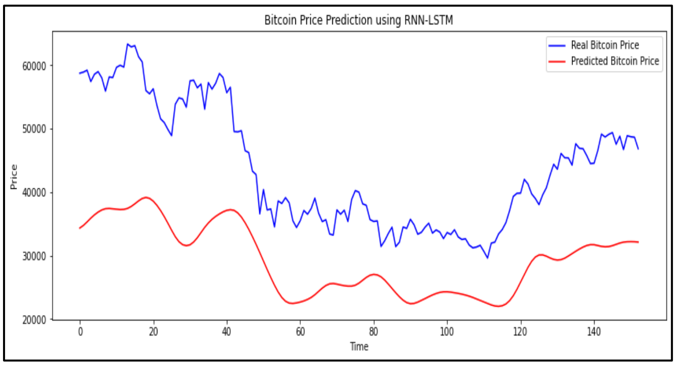


COUNT	61.0000
MEAN	16,581.2514
STD	7,463.7900
MIN	6,121.1073
25%	9,390.7277
50%	15,292.4230
75%	23,373.4981
MAX	30,606.4214

Mean Absolute Error: 16581.25

3. LSTM

Long Short-Term Memory networks are an extension of recurrent neural networks, which basically extend the memory. Our model was trained on the data from 2015 to March 2021 and predictions were made for the April 2021 to August 2021 period.



LSTM however requires a lot of data, and it is complex to implement since it has a lot of parameters to be tuned. Efficient hyperparameter tuning needs a lot of experience. LSTM models are also very expensive computationally.

Mean Absolute Error: 13210.96

Conclusion

We can easily conclude that the ARIMA model is, from far, the best model. It's probably due to the rolling basis logic, to calculate the forecasted upcoming value, which is similar to the "recency" heuristic method. Prophet did not produce good results out of the box for highly volatile Bitcoin prices. LSTM produced more convincing results and it could predict the trend much better than prophet. Predictions via prophet were stagnant and it could not recognize the trend in the prices. Prophet will perform better with trends that have some sort of seasonality, for example in cases where we have to predict website hits on an e-commerce website.

LSTM produced an MAE of upwards of 13000 in just 25 epochs, it can improve with more layers in the model and more epochs. Prophet produced an MAE of almost 17000 and since there is not much seasonality when we consider a highly volatile value of interest like the price of Bitcoin, there's not a lot of parameters that can be tuned for the model. However, certain spike events can be added to slightly improve the model, but that is not a practical approach.

References

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