Featherstone, Jack Bartholomew

**A Final Year Research Project On: Predicting Price Fluctuations of Cryptocurrencies Using a Temporal Convolutional Network**

**Project Student:**

***Jack Featherstone***

**Project Supervisor: Dr. *Andrea Visentin***

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**Abstract**

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Cryptocurrency fluctuation prediction is a conversation that can be shared among various disciplines, including Computer Science, Mathematics, Data Science and Economics.

Despite the various factors that contribute to cryptocurrencies volatile behaviour, many machine learning and deep learning networks have been used to predict cryptocurrency prices with great accuracy.

It is no secret then, why price forecasting for cryptocurrency has become a trending research topic globally.

In this project a Temporal Convolutional Network (TCN) algorithm was used to predict the prices of three types of cryptocurrencies, namely, Bitcoin (BTC), Ethereum (ETH) and Ripple (XRP).

The time-series data that was used was of hourly duration, from 17/08/2017 up until 01/01/2022.

* Results

The main goal behind this algorithm was to achieve a reliable dependable model that investors can rely on, based on past cryptocurrency prices.

**Introduction**

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**WHERE MY INTEREST STEMMED FROM**

I was introduced to cryptocurrency from my colleagues and friends raving about this get rich quick scheme, so I decided to invest. When I didn’t become a multi-millionaire in one day, I panicked and sold back, I didn’t fully understand the process and technology.

After this escapade I was relatively captured on how people did this for a living and how they decided at what time to invest and what time to sell.

**CRYPTO’S RAISE TO FAME**

Since April 2011, when Bitcoin first surpassed one dollar, the term crypto has become progressively recognized as something that is here to stay, rather than some convoluted pyramid-scheme.

At the time of writing this 10/03/2022, the global crypto market capitalization is 1.83 trillion dollars with 18,000 crypto currencies available. – from Investopedia

Binance is one of the largest crypto exchanges in the world, figure 1 shows the increasing rate of users per year.

Lark Davis presented the figure below which depicts the whole concept of crypto having the highest adoption rate of any technology in human history. It is being compared with the initial growth of the internet, and we all know how that story ended.

Table

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**Figure 1.** Binance users per year

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**Figure 2.** Adoption rate of the term ‘crypto’

**CRYPTO VS STOCKS**

Crypto is a piece of data that is used as a medium of exchange without the need of a third-party intervening (bank). Its goal is to be as commonly accepted as cash or credit.

There is this common misnomer that crypto is just like a stock, this is just not the case. When we buy a stock offered by a particular company, we own a percentage in that company (assets / profit).

When we buy crypto, we are given a certain amount of that digital currency in which we can do as we please. We only own the rights of a particular amount of a digital currency.

Although Stocks and Crypto are fundamentally different, the way in which they are treated are quite typically the same. As of 2022 most day-day companies still do not accept crypto as an acceptable form of credit. As a result, the primary role crypto plays are a store of value in which you can hold onto or sell. This is the same ideology as stock market operates on only rather than store of value, you own a store of ownership.

It is no secret that Stock markets are rather unpredictable and are affected by many factors causing the high volatility in the market. The exact same can be said about cryptocurrency if not more factors that contribute to the volatile behaviour, one rather comical example of this would be the ‘Musk Effect’ a term coined from when Elon Musk’s tweets had a direct and substantial effect on the price of certain crypto’s. With factors such as media hype lending itself as a cause to why crypto produces unstable behaviour, as well as many other factors, predicting something in this unstable market will be extremely difficult.

**IMPORTANCE**

Before crypto, Investors were always on the search for tools and techniques that would increase profit and reduce risk within the stock market. Buying a certain stock involves risk,

the aim of the investor is to keep this risk as low as possible while maximizing profits. So naturally, any instrument that could minimise the risk would be valued highly.

Since the virtual explosion of crypto as outlined above, the exact same can now be said about cryptocurrency price prediction. Cryptocurrency price prediction has become a trending research topic globally and it has created a big opportunity for research.

The importance of being able to predict these high valued currencies, cannot be understated.

Students from various majors are constantly working on ways to more accurately predict the upswing or downswing of a particular currency to know when to invest and when not to.

I believe as technology is advancing, this is the opportunity to find the most informative indicators to make better predictions.

**MODEL I USED**

I used a machine learning model for time series forecasting to accurately predict fluctuations of crypto prices.

A time series is a sequence of data points that are listed in order of time. Time-series forecasting is a common technique used in many real-world applications such as weather forecasting and financial market prediction. It uses the continuous data for a particular period, to predict the result for the next period (e.g., using the past 3 years of daily temperature in a particular area, to predict next week’s temperature in the same area).

The stock market and now crypto market is a typical area that presents time-series data and many researchers have proposed various models using this data, for various aims.

Many time-series forecasting algorithms have shown their effectiveness in practice. The most common algorithms are now based on Long-Short Term Memory Networks which are based off Recurrent Neural Networks. One model that was been showing promising results in the Financial Time Series is the Temporal Convolutional Network (TCN).

In this project, I applied a TCN to predict the upswing or downswing of a particular crypto based off its closing price (The price this crypto was during a specific time of the day).

**Background**

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In the past, statistical time series models have been used to predict the price of stock prices.

The most popular statistical forecasting method for finance is the ARIMA method.

The ARIMA model stands for Auto Regressive Integrated Moving Average model. It includes both an Auto-Regressive component and a Moving Average component with differencing.

The main benefit of using the ARIMA model is that its transforms a non-stationary timeseries into a timeseries without seasonality or trend by predicting the differences of the timesteps from one timestep to the next, giving a constant mean over time, Figure 3.

The ARIMA model does require statistical assumptions about the data. Hence why it would be used in situations where the timeseries is stationary or stationary except for a moving mean.

Some previous work has been done on a model for forecasting Bitcoins’ Exchange Rate Bakar N.B. et al. [1]. Although this method produced a reliable forecasting model, highly volatile environments such as cryptocurrency price prediction creates larger error.

More recent techniques in deep learning have come out such as Recurrent Neural Networks (RNN). Two examples of RNN’s are Long Short-Term Memory (LSTM) and Grated Recurrent Unit (GRU) algorithms. These networks behave in the same way, that is, the output of the previous timestep is fed back into the current timestamp, to help in memorize previously seen inputs, Figure 4.

Hamayel M.J. et al. [2]. The deep learning models considered for this study involves learning algorithms such as LSTM, bidirectional LSTM and GRU to predict the prices of three different cryptocurrency prices -Ethereum (ETH) , Bitcoin (BTC) and Litecoin (LTC).

The GRU algorithm outperformed the other algorithms. It was shown to be reliable and acceptable for cryptocurrency prediction, Figure 5. However, all algorithms were noted as having excellent predictive results.

The influence the news and social networking cites have on cryptocurrency prices has also been a topic of great research. Kraaijeveld O. et al. [3]. It was found that Twitter sentiment analysis has predictive power for the returns of BTC , Bitcoin Cash (BHS) and LTC. It was also noted that favourable sentiment is less likely than unfavourable sentiment with BTC.

Shumin Deng et al.[4] discovered that TCNs significantly outperformed baseline models like ARIMA and LSTM when forecasting stock trend with abrupt changes. It achieves much better performance than either traditional ML models, or deep neural networks (such as LSTM and CNN), suggesting that TCN has a more obvious edge in sequence modelling and classification problems. Hence the reason why a Temporal Convolutional Network (TCN) will be implemented in this paper.

**Graphical user interface, text, application, email

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Google, (2017) , [Stationary and non-stationary data]. Retrieved Wednesday 23 , 2022 from <https://www.quora.com/What-are-stationary-and-non-stationary-series>

**Figure 3.** Transformation from non-stationary data to stationary, having a constant mean over time.

Diagram

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**Figure 4.** An intuition on how the internal memory works, X2 relying on the output of X1 .

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**Figure 5.** Here we have the predictive results from M.J. Hamayel et al. [2].

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**TCN Model**

In the past, Recurrent Neural Networks (RNNs) such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) have been the architecture of choice for sequence modelling. There has been results put forward, to prove that convolutional networks should be considered in the conversation as the primary model for predicting sequential data (S.Bai , 2018).

These results showed that convolutional networks outperformed the forementioned RNNs in many tasks, while simultaneously avoiding the vanishing gradient problem, a problem that plagues RNN’s. As the backpropagation gradient flow is not dependent over time, this brings additional benefits such as the ability to train in parallel for much faster training using GPU optimization.

Temporal Convolutional Networks (TCNs) are a class of time-series models that capture long-range patterns using the order of temporal convolutional filters.

A TCN is a variation of a CNN with 2 main features. Firstly, each hidden layer is the same length as the input layer. This is achieved using zero padding.

Secondly, the network only uses information from past time steps. This is implemented by using casual convolutions, both features can be seen in Figure 6.

The last thing to consider for TCN models is the receptive field. The receptive field is the outputs dependencies from the original input. The larger the receptive field the greater the chance of capturing long range dependencies. With casual convolutions it is not feasible to capture long range dependencies without your network growing too large from adding too many layers. It is not recommended to use larger kernel sizes either as this adds weights in order to describe the kernel, this is not parameter efficient as most of the time we have multiple filters per layer, this could quite quickly lead to overfitting.

The solution is to use dilation casual convolutions, we stretch the kernel position out by a dilation factor so as a result, the receptive field is also extended by a dilation factor. We stack these dilated casual convolutional layers, so we use all inputs as a receptive field as seen in Figure 7.

( The network I used had a ….. )

The formula’s below are to calculate the number of layers in the network and the padding for each dilated layer.

A picture containing text, clock

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Figure to calculate the number of layers needed in the network, l = input\_size, b = dilation\_base, k = kernel\_size. Roundup the result.

Text

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Figure to calculate padding for each layer, b = dilation\_base, I = number of layers beneath , k = kernel\_size

Timeline

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Figure 6. Here we can see 24 timesteps, padded at each convolutional layer to keep input same length as output. The output of timestep 1 is only ever dependent on timesteps that come on and before timestep 1.

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Figure 7. Here we can see that less layers are needed using dilated convolutional layers.

**Dataset**

The data used in this research project was collected from Binance.com, an open-access website. Binance is one the largest cryptocurrency exchanges where users can trade cryptocurrencies.

The data consisted of three different csv files, the first sheet for BTC (**Figure 8)**, the second for ETH and the least sheet for XRP. The recorded prices in this dataset were collected on an hourly basis, for BTC and ETH the data was collected from 17 August 2017 to 11 February 2022 with 39221 records and for XRP the data was collected from 04 May 2018 to 11 February 2022 with 33017 records.

The data collected had five features, which are as follows.

- **Open**: Opening price of the cryptocurrency for the day.

- **Close**: Closing price of the cryptocurrency for the day.

- H**igh**: Highest price of the cryptocurrency for the day.

- **Low**: Lowest price of the cryptocurrency for the day.

- **Volume**: Volume of the cryptocurrency traded in the day.

Data Pre-Processing

In the pre-processing step the data was normalized using the minmax normalization to convert the values in the range of 0-1.

After normalization, the data is then arranged into multiple input-output pairs (rolling window format) in preparation to be fed into the model. **Figure 9.** Shows an example of data in the rolling window format.

The model then predicts the next hourly closing price. This predicted price can then be fed back into the model to forecast the subsequent timestep. This process will proceed until the number of predictions made equals the number of timesteps you want to predict in the future. **Figure 10.** Illustrates predicting 3 timesteps into the future.

The Models were trained with 70% of the input-output pairs. The validation data used 20% of the input-output pairs and the Testing dataset was left with 10% of the input-output pairs.

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**Figure 8.** Screenshot showing a sample of the data from the BTC dataset.

Text

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**Figure 9.** A simplified view of how rolling window splits the data for input to a model

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**Figure 10** A simplified view of predicant 3 timestamps into the future using window size of 16.

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**Baseline Model**

A baseline was picked so the results found using the TCN model described in this paper could be compared against the findings of the baseline model.

After an appropriate amount of reading and enquiring on numerous articles, the baseline that was decided on was Patel M.M. et al. [5].

The reasons why this particular model was picked as a baseline, was that it was recently published - 04/06/2020, it had been moderately cited and its subject matter suited our project description.

The model proposed in the Baseline is a hybrid model, consisting of two Long Term Short-Term Memory Networks (LSTM) networks and a single Gated Recurrent Unit (GRU) network.

**Figure 11.**

LSTM’s and GRU’s serve relatively the same function (attempting to capture long term temporal patterns). Although GRU’s use two gates inside its cell, rather than three, like in a LSTM cell. This modification makes the GRU less computationally expensive as it does not have to carry an additional vector of numbers.

The baseline model was trained and tweaked using the BTC dataset, then the same model was adopted for the XRP and ETH datasets. **Figure 12** shows the results gathered from the baseline model on the forementioned datasets.

Diagram

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**Figure 11** The LSTM and GRU based hybrid model used as the baseline.

**Figure 12** Recorded results from the LSTM and GRU hybrid model.

**Google Cloud**

Training sophisticated deep learning models can take a significant amount of compute. Google Cloud enables users to run an instance in the cloud to handle all the heavy computation.

The models presented in this report were not extremely complex. Despite this, the models training process would have taken significantly more time if ran on a local machine with average specifications, than with Google Cloud.

The specifications of the machine used in this project:

**GPU**: NVIDIA Tesla T4.

**CPU**: 8vCPU, 30GB memory.

**Pre – Packaged with**: TensorFlow2.8/Keras. CUDA11.3.

**Boot Disk Image:**  Debian GNU/Linux 10 (buster) with 200GB (standard persistent disk).

TheNVIDIA Tesla T4 was picked because it was specifically designed for high performance computing and deep learning training. This GPU was the least powerful GPU on offer.

The option was there to upgrade the hardware including the GPU in the instance, although it was not necessary as these models were not in need of anymore computation power.

This instance enabled immediate learning, with all the pre-packaged frameworks, libraries, and drivers pre-installed.

Save for personal reflection

“

A benefit of analysing these articles was that accepted standards for data preparation with time series data were monitored. For example, a common occurrence across every article was the way the data got manipulated before inputting into the various models. (Rolling window/ normalizing the data).

I was able to appreciate that even though my reference came from a published article there could still be some flaws in sinit, for example, they did not seem to notice that they left some leakage in their model.

“

, although saying this, at first, I was not getting the results I had hoped. Rather than getting nine minutes per epoch, I was now getting twelve minutes per epoch!

After a large amount of research and a great deal of help from some of Andrea’s students, the problem was not with Google Cloud, sadly it was a testament to my code.

My training runs were not making the most out of the GPU supplied by the virtual machine.

Increasing the batch size, and also getting rid of the data generators increased the usage of the Graphics Processing Unit (GPU). By calculating the batches in parallel in the GPU memory, this reduced the communication overhead in the CPU. However, it was about finding the balance because I didn’t want the batch sizes too big so that the model could not converge to the best of its ability. The batch size which I ended up deciding on was 512.

**References**

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