Application of AI/ML Techniques for Economic Forecasting Problems

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***Abstract*— The popularity of cryptocurrencies skyrocketed in 2017 due to several consecutive months of exponential growth of their market capitalization. Bitcoin (BTC) had the highest market capitalization of $1.28 trillion on November 9, 2021. Although machine learning has been successful in predicting stock market prices through a host of different time series models, its application in predicting cryptocurrency prices has been quite restrictive. The reason behind this is obvious as prices of cryptocurrencies depend on a lot of factors like technological progress, internal competition, pressure on the markets to deliver, economic problems, security issues, political factor etc. Their high volatility leads to the great potential of high profit if intelligent inventing strategies are taken. Unfortunately, due to their lack of indexes, cryptocurrencies are relatively unpredictable compared to traditional financial predictions like stock market prediction. To tackle this problem we use two different models RNNs and GRUs to predict and compare their results. You can find our code base here.**

I. INTRODUCTION

Cryptocurrencies are a new form of a financial asset which are based on a decentralized ledger. One of the few downsides to cryptocurrencies is that they do not have any resources backing their value, other than the energy expended while mining it. Also, since there is no sovereign backing to its value, the price of almost all cryptocurrencies have extremely volatile prices. Bitcoin, in particular, has the largest market cap of all cryptocurrencies.

Long short-term memory (LSTM) is a form of Recurrent Neural Networks that ingests data and cycles information utilizing a slope based learning algorithm. Providing more data improves the accuracy of the algorithm. So according to us for predicting cryptocurrency prices, LSTMs would be most effective as they can analyze pre-existing historical price data dating back many years. These predictions will help in convincing venture capitalists to invest in cryptocurrency products with potentially high returns.

II. PROBLEM STATEMENT

The rapid development of digital currencies during the last decade is one of the most controversial and ambiguous innovations in the modern global economy. Significant fluctuations in the exchange rate of cryptocurrencies and their high volatility, as well as the lack of legal regulation of their transactions in most countries resulted in significant risks associated with investment into crypto assets. Therefore, the issue of developing appropriate methods and models for predicting prices for cryptographic products is relevant both for the scientific community and for financial analysts, investors and traders. Methodological approaches to forecasting prices for financial assets depend on an analyst's understanding of the causal relationships in the pricing process. For example, the forecasting model can be specified as a price formation model:

- Based on the interaction of market players (demand-supply models) that make economic decisions based on some indicators or regularities, taking into account objective economic laws or laws of behavioral finance (econometric and balance models);
- Given the past dynamics (time series models and autoregressive models),
- Taking into account production-technological possibilities of creating the corresponding asset (in particular, for commodity markets, fundamental valuation of shares, technological opportunities for mining cryptocurrency, etc.);
- Based on the consideration of random factors and events, for example, external shocks, which complicate the formal description of cause and effect relationships (stochastic models).

It should be noted that forecasting cryptocurrencies' prices is fundamentally different from forecasting other financial assets, in particular, ordinary (fiat) currencies, which have a large number of theoretical and empirical studies focused on studying their dynamics model.

A number of recent cryptocurrency market studies show that, unlike other financial assets, cryptocurrency prices are influenced by a number of specific factors that shape their demand, such as the number of Google trends searches, the number of posts in social networks and other mass media. These studies substantiated the feasibility of using non-typical factors as predictors. All of these factors complicate the development of casual econometric models of cryptocurrency price dynamics. Recently, non-parametric methods based on Machine Learning and Deep Learning have gained popularity for the analysis and forecasting of financial and economic time series.

III. APPROACH

A. Dataset

Our dataset comes from Yahoo! Finance and covers all available data on Bitcoin-USD price. We have a total of 3201 data points representing Bitcoin-USD price for 3201 days (9 years). We're interested in predicting the closing price for future dates.

There is a total of 9 years worth of data in the dataset. It is broken up into sequences of 99 days each. The data is hence a timeseries, as it is sorted by time and recorded at equal intervals, which is 1 day in this case.

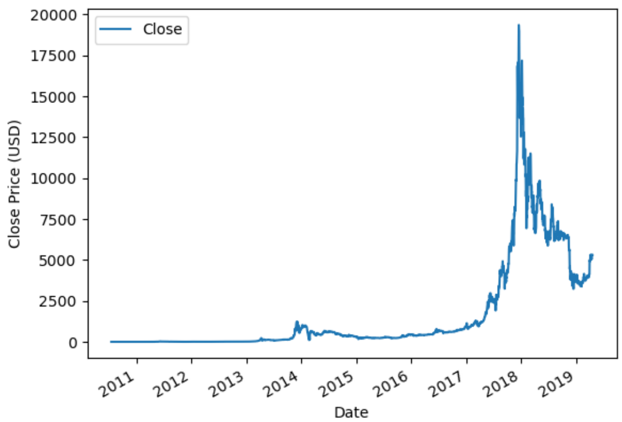

Fig. 1. Closing Prices

B. Time Series

As mentioned above, a time series is a sequence of data points which are arranged in increasing order of time and with an equal interval of time between two successive points. Common examples include stock market daily closing prices, number of sunspots at a given time and the height of tides.

Time series forecasting is therefore a very fruitful topic of research. A model which can predict the stock markets perfectly can theoretically generate infinite money for its creator. Even a time series analysis on a person's heart rate can reveal how he is feeling.

Autocorrelation is one of the major factors involved in time series forecasting. A majority of non-random variables have some extent of autocorrelation. Few other factors include cyclicity, stationarity etc.

Various methods of time series forecasting exist. We use a Neural Network model in this project to predict the new price of Bitcoin.

C. Data Preprocessing

We first scale the targets (Closing prices in this case) between 0-1. We can do this by using MinMaxScaler from scikit-learn. The NNs expect data in the following dimensions [batch_size, sequence_length, n_features]. We keep aside 5% of the data which will be used later for testing.

```
def to_sequences(data, seq_len):
    d = []

    for index in range(len(data) - seq_len):
        d.append(data[index: index + seq_len])

    return np.array(d)

def preprocess(data_raw, seq_len, train_split):

    data = to_sequences(data_raw, seq_len)

    num_train = int(train_split * data.shape[0])

    X_train = data[:num_train, :-1, :]
    y_train = data[:num_train, -1, :]

    X_test = data[num_train:, :-1, :]
    y_test = data[num_train:, -1, :]

    return X_train, y_train, X_test, y_test


X_train, y_train, X_test, y_test =
 preprocess(scaled_close, SEQ_LEN, train_split =
    0.95)
```

D. Model

To use time series as the dataset for a Neural Network, we have to use a modified network. This type of network is called a Recurrent Neural Network or RNN in short. This is a special type of network where the output of the network is used as a new input.

One of the major problems with RNN is that of diminishing and exploding gradients. In simple terms, this means that a RNN cannot infer long term causality, and if it tries to do so, then it exaggerates it. For this reason we use special Gated Recurrent Units (GRU in short) or Long Short-Term Memory (LSTM in short). These models have special modifiers (three for LSTM, two for GRU) which help us differentiate between long term effects and short term effects.

We demonstrate the same prediction problem with Simple RNN and GRU. Clearly, one can notice that GRU gives better predictions, at the cost of some computational complexity. The model itself has 3 layers of RNN cells/ GRUs respectively. We also add Dropout which randomly exclude some weights to prevent overfitting.

```
DROPOUT = 0.2
WINDOW_SIZE = SEQ_LEN - 1
model = keras.Sequential()
```

We use linear activation function, which means our output: y = m • x We are also using Mean Squared Error (MSE) and Adam optimizer.

```
model.add(Bidirectional(
  GRU(WINDOW_SIZE, return_sequences=True),
  input_shape=(WINDOW_SIZE, X_train.shape[-1])
))
model.add(Dropout(rate=DROPOUT))
model.add(Bidirectional(
  GRU((WINDOW_SIZE * 2), return_sequences=True)
))
model.add(Dropout(rate=DROPOUT))
model.add(Bidirectional(
  GRU(WINDOW_SIZE, return_sequences=False)
))
model.add(Dense(units=1))
model.add(Activation('linear'))
```

We can now make predictions using our model and then scale them back using the scaler.

IV. RESULTS AND OBSERVATIONS

After compiling our model and training it for aronud 30 epochs on both the RNN and GRU model we can make predictions using our model and then scale them back using the scaler. Our loss functions for the RNN and GRU models are as shown below.

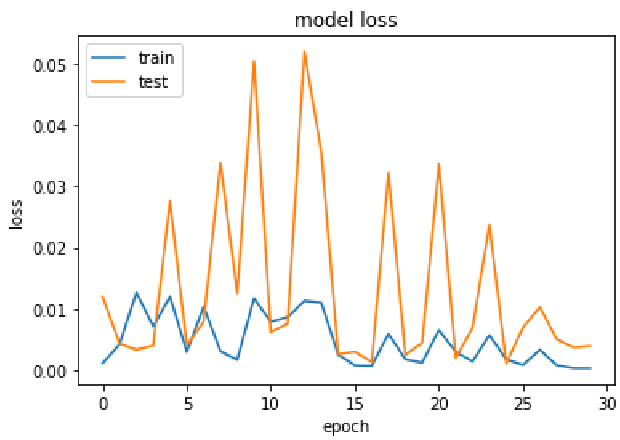

Fig. 2. RNN Loss

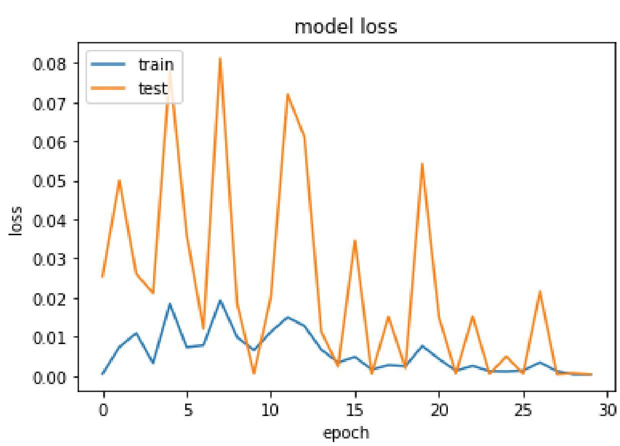

Fig. 3. GRU Loss

The predicted values of our models show that the GRU model predicts the direction of Bitcoin prices with much more accuracy than the RNN model.

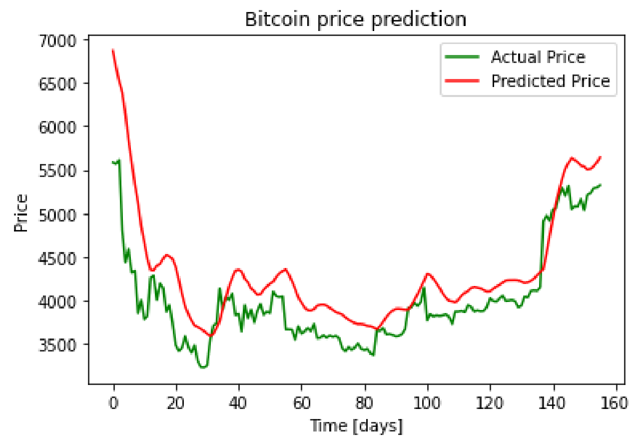

Fig. 4. RNN Predicted

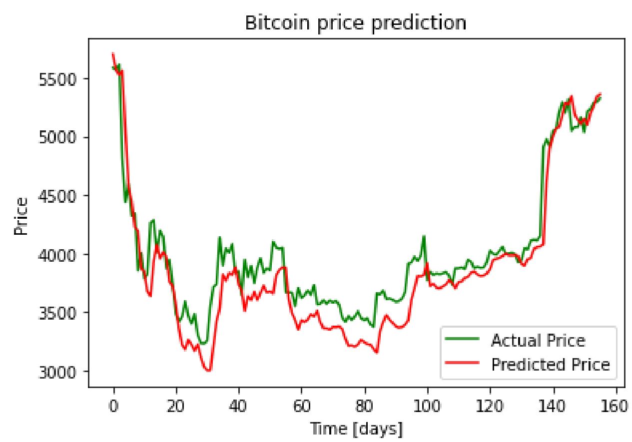

Fig. 5. GRU Predicted

V. FUTURE WORK

Until now, we were focussing on the autocorrelation of the price of Bitcoin. But there can be cross-correlation of the price of Bitcoin and other Cryptocurrencies as well. Also, there must be some correlation between the price of Bitcoin and even the stock market indices. One more source of information about the future price can be the people's emotions regarding Cryptocurrencies, as it is new and widely misunderstood technology. This information can be gathered and processed using natural language processing on various news outlets and social media platforms.

VI. CODE AND TEAM MEMBERS

Our final code can be found here.

Our team consisted of:

- Aryan Jha - 20MA20012
- Chaitanya Gaur - 20MA20017
- Karan Ralhan - 20MA20025
- Piyush Kumar -20MA20041
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