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Prediction of Cryptocurrency Price Rates and Price Bubble Detection

Pranjal Vaidya, Dr. Meenakshi Thalor, Tejas Khairnar, Aniket Raut, Joe Joseph
Department of Computer Engineering, Savitribai Phule Pune University, Pune
Email: crazybeamer6@gmail.com

Abstract- Cryptocurrency trade is now a prominent type of investment. Cryptocurrency market has been treated analogous to stock markets. But because of its volatility there remains a necessity of a prediction tool for finance decisions. Artificial Neural Networks based tools are commonly used in stock exchange predictions. The ANN methods will be used to develop the model to anticipate the close value of bitcoin in the succeeding day. It makes use of ANN methods namely Backpropagation Neural Network (BPNN) and Hidden Markov Model (HMM). Financial price bubbles have formerly been linked with epidemic like roll out of an investment idea; such bubbles are seen in cryptocurrency prices. It focuses to forecast such bubbles for a number of cryptocurrencies using a Hidden Markov Model. To validate this methodology, a trading strategy is built and tested on historical data. This trading stratagem outdoes a buy and hold strategy. The work reveals both the broader utility of epidemic sensing Hidden Markov Models in the identification of bubble-like behavior in time series, and that social media can deliver valued predictive data relating to cryptocurrency price movements.

Index Terms- Cryptocurrency; Bitcoin; Prediction; Artificial Neural Network (ANN); Cryptocurrency Price Bubbles; Social Media Data Mining; Hidden Markov Model; Trading Strategy; Epidemic Detection.

1. INTRODUCTION

Cryptocurrency market has been treated akin to stock markets. But because of its volatility there is a demand of a prediction tool for investment decisions. Artificial Neural Networks based tools are frequently used in stock exchange predictions. The ANN methods will be used to develop the model to predict the close value of bitcoin in the next day. Because of its volatile nature the undesirable features could be the result of bubbles that have been observed in cryptocurrency prices, which makes the early detection of such bubbles an important topic of research. It is our hypothesis that it is possible to detect patterns in social media usage to detect the earlier stages of a cryptocurrency price bubble.

The remainder of this paper is structured as follows. Section II details the data and sources of data which we are going to use for price prediction and bubble detection. Section III reviews about system architecture. Section IV reviews references.

2. DATA AND SOURCES OF DATA

For this study secondary data has been collected from the website **cryptocompare.com**. The cryptocurrency prices are obtained for last five years for the purpose of price prediction and live tweets are extracted from tweeter for sentiment analysis to find the burst.

3. PROPOSED SYSTEM ARCHITECTURE

A system architecture illustration is used to show the association between different components. Usually they are made for systems which comprise hardware and software and these are characterized in the illustration to show the interaction between them. Following figure(1) shows the system architecture:

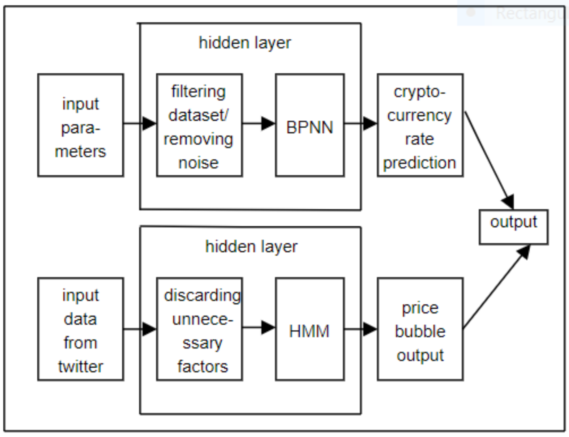

Fig.1. System Architecture

3.1 Hidden Markov Model

Hidden Markov Model is a statistical Markov model in which the system being modelled is assumed to be a Markov process with unobserved states. The hidden Markov model can be characterized as the simplest dynamic Bayesian network.

An HMM has a number of underlying hidden states, which are transitioned between. Each state has associated possible observations. Given an observed series of data an HMM can be used to identify the most likely hidden state the model is in at each data point. The model has also previously been applied to Twitter data to categorise 'trending' vs 'non-trending' topics.

The model uses two hidden states, epidemic and nonepidemic, which are unobserved. The hidden states have associated emission probabilities. Emission probabilities give the likelihood of seeing particular output values, and can be sampled from different distributions depending on which state the system is in. Differenced time series data (for example, for one of the social media indicators) is observed.

3.2 Back Propagation Neural Network

Backpropagation Neural Network is a technique used in artificial neural networks to compute a gradient that is needed in the calculation of the weights to be utilized in the network. Backpropagation is shorthand for "the backward propagation of errors," hitherto an error is computed at the output and distributed backwards throughout the network's layers. It is commonly used to train deep neural networks, a phrase representing neural networks with more than a single hidden layer.

3.2.1 Forward Pass

This is the first phase in the backpropagation neural networks.
The following formula is used to calculate forward pass: -

To calculate net input for h1:

$$net_{h1} = w_1 * i_1 + w_2 * i_2 + b_1 * 1$$

Then squash it using the logistic function to get the output of h1, which is also denoted as sigmoid function or activation function:

$$out_{h1} = \frac{1}{1 + e^{-net_{h1}}}$$

3.2.2 Total Error:

Now we can calculate error for each output neuron using the squared error function and sum them to get the total error, given by E(total):

$$\textbf{E(total)} = \sum \frac{1}{2}(\boldsymbol{target} - \boldsymbol{output})^2$$

3.2.3 Backward Pass

This is the next phase in the backpropagation neural networks. By applying the chain rule:

$$\frac{\partial E_{total}}{\partial W_5} = \frac{\partial E_{total}}{\partial_{out_{o1}}} * \frac{\partial_{out_{o1}}}{\partial_{net_{01}}} * \frac{\partial_{net_{o1}}}{\partial_{w_5}}$$

Some sources extract the negative sign from so it would be denoted as:

$$\frac{\partial E_{total}}{\partial_{W_5}} = -\delta_{o1} out_{h1}$$

4. CONCLUSION

This study opens several possibilities for future study related to bitcoin prediction. Future study focused on other machine learning methods such as fuzzy logic based machine learning methods and or support vector machines will enrich the analysis of best prediction method for bitcoin.
Regarding with the prediction target, this study only focuses on one day prediction. In real practice, one day prediction may not be enough for investors. The more days can be predicted, the more benefit investor can obtain by making long time investment decision. This work has demonstrated a strong relationship between twitter usage and cryptocurrency prices; as a result, the work has highlighted twitter as a valuable source of information.
It is hoped that this work will motivate further research into the role of twitter within cryptocurrency markets and also encourage further exploration of twitter within other area in the field of social media data mining.

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