Bitcoin Response to Twitter Sentiments

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Abstract. The paper investigates the Bitcoin exchange rate response to the daily Twitter data. Sentiment score is computed for the number of obtained tweets. The prediction accuracy for the Bitcoin exchange rate employing the sentiment score reveals the influence of the Twitter social network on the news diffusion and target exchange rate volatility. We used the historical data on the Bitcoin exchange rate and the daily sentiment score of the pertinent tweets to forecast the direction of change for the Bitcoin. The results show better performance of the developed forecasting method with both historical data on the exchange rate and the sentiment score than using only the exchange rate data as an input.

1 Introduction

Prediction of the exchange rates has been the topic of hot debates since decades if not centuries. In the economic literature, different opinions exist on whether it is ever possible to forecast exchange rates. Recently, the crypto currencies were introduced as the possible substitute to the money issued by the central banks. The volatility together with abnormal interest of the economic agents to the crypto money has spurred the discussion among the economists and researchers about the underlying reasons of the decision-making for crypto trading and its forecasting.

The deep learning methods (subset of the artificial intelligence repertoire) have been employed for the exchange rate prediction. Our previous finding prove that the convolutional deep neural networks provide relatively accurate results on the out-of-sample data for the directional prediction of the selected reserve currencies k-days ahead [1]. However, the one-day directional forecasting for the crypto currencies remains surprisingly challenging. Moreover, the changes in crypto currencies' regulation may cause the market volatility which is difficult to forecast even with methods of machine learning.

In the study, we test our hypothesis that the exchange rate of crypto currencies (in particular the Bitcoin rate) depends on behavioral signals rather than any fundamental conditions and thus the forecasting technics must consider the "crowd" sentiments. This statement conforms to the ideas of the behavioral economic mainstream. The behavioral economics insists that the emotions may lead the market participants more significantly than the fundamental factors. The traders' sentiments may cause the market corrections or shocks which cannot be explained by the efficient market hypothesis neither by the fundamental or technical analysis. The number of crypto cur-

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rencies has been created since 2009 but the Bitcoin is one of the most popular. It motivates us to focus on the Bitcoin exchange rate in the study.

Recently the social networks have been introduced (i.e., Facebook, Twitter, etc). Now a lion share of communication is made through the social networks and the speed of the news diffusion increased vastly with respect to the end of 80s. Moreover, recently Twitter became of the most conventional tools of the communication among the politicians, country leaders, main economists and market-makers with the society. Thus, we cannot ignore the role of the social networks, in particular Twitter, in the evaluation of the crypto currencies market sentiments.

Our research agenda foresees integrating the sentiment analysis of Twitter data together with the historical data on the exchange rates for the prediction of the direction for the exchange rates of Bitcoin to US Dollar. The rest of the paper is organized as follows: Section 2 discusses the related literature, Section 3 gives the analysis of the crypto currencies market, Section 4 reports the data, Section 5 focuses on methodology and methods employed, section 6 presents the results, Section 7 concludes with some further research agenda outline.

2 Related Works

One of the most prominent economic mainstreams with regard to the exchange rate prediction is the efficient market hypothesis (EMH). The random walk model has been seen as a proof of the EMH. However, the market traders together with the academics disclose the number of cases where statistical and machine learning methods could beat the random walk. Most of these methods, though, show only slightly better performance at different time horizons (see [2]). Behavioral economics poses the main challenge to the EMH. The traders decisions are not always rational and behavioral factors are important for the market reaction. The use of crypto currencies anticipates the participants' irrationality as these assets are not recognized as the money in most of the countries.

The recent opinion article of R. Shiller in New York Times (October 19, 2017) [3] on the traders behavior during the financial crash in 1987 reveals the importance of the market sentiments. In 1987 people did not use Internet for social networking so R. Shiller sent around 3500 surveys to the investors with the questions underlining the traders reasoning during October 19, 1987. The survey revealed no fundamental factors caused the panic among investors. Even the news in the leading economic reviews before the very day has not contributed much. However, in the morning of October 19 the World Street Journal published the article comparing the situation before the crises of 1929 and the market circumstances in 1987. The information and the graph coincided to the extent that it "raised the thought that *today, yes, this very day* could be the beginning of the end for the stock market" [3]. The author also adds 'Given the state of communications then, it is amazing how quickly the panic spread" [3]. We believe, now the social networks help diffuse the news much faster. Twitter is one of the main instruments for the communication. It spurs our interest in exploiting Twitter data for our study.

The economic literature still adjusts to the new instruments of interests such as Twitter data. Despite some papers discuss the "wisdom of crowds" [4,5], we consider the findings of [6] as the most pertinent to our study. The researchers use the Twitter data to compute the market sentiments of FOMC meetings. The authors empirically prove the correlation between the stock market fluctuations and the sentiment score of the target tweets. The study [8] uses the sentiment score and the exchange rate of the reserve currencies in their forex prediction with different methods including neural networks. Our study is focused on the Bitcoin market and contrary to the authors we use the convolutional neural networks. They prove their classification accuracy for the number of implications in finance [1].

The paucity of papers is still observed in the realm of the Bitcoin prediction. Among the recently published papers the one of [9] discusses the relationship between the Bitcoin rate and the flow of its transactions. [10] employ VAR methods in the point forecasting of the Bitcoin rate. In our paper we focus on the directional prediction. The paper [11] discusses the trend prediction for the Bitcoin with the shallow neural networks. Authors praise the acceptable performance of the developed method. They point out that the additional data on the volume of transactions improve the results only marginally. We go further in our study using the convolutional neural network as the deep learning technic to predict the target rate change.

3 Analysis of the market for crypto currencies

Anonymous character of the turnover of the crypto currency with open crypto graphic code and available for all interested transactional storage (blockchain) makes it possible to avoid both bureaucratic procedures when making calculation, and legislative acts on tax control. The crypto currency became rather attractive speculative investment center for stock exchanges traders and for those who want to get quick returns, reminding financial pyramid. However, using the blockchain technology for transactions and specific form of money mining, the assumptions about financial pyramids are questionable. At least 1076 of the crypto currencies are involved in the stock exchanges trades and are owned by millions of people. The opportunity to pay for goods and attendance without intermediaries and for a minimum commission fee have led to the increasing of the crypto currency market capitalization in 2017 up to 1250% (700 billion dollars), where Bitcoin accounts for 40% of the total share. Such rapid growth of capitalization is nothing else, but the expansion of cryptocurrency into the global financial system, which can have both negative and positive effects on financial system of the world countries. Fig.1. Describes the Bitcoin exchange rate over 2017.

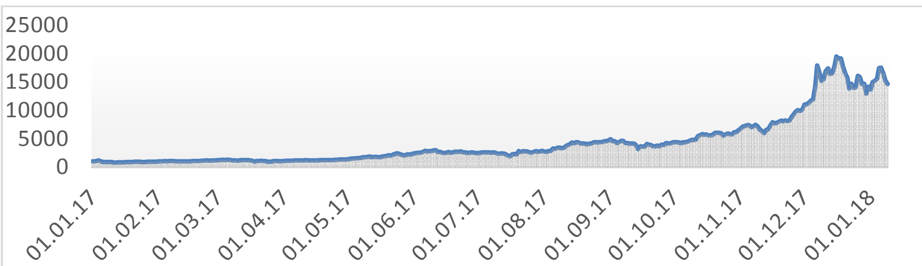

Fig. 1. Bitcoin exchange rate.

700 billion US Dollars of the cryptocurrency capitalization in the scale of the world financial markets is not a large sum and is equal to the capitalization of the largest companies in S&P500 rating such as Microsoft Corp. ($ 671 billion), Amazon.com ($ 605 billion), and others. But considering the fact that the crypto currency partially fulfill and, in the future can fully fulfill the role of money, further growth of the capitalization can carry certain risks for monetary policy of the central banks.

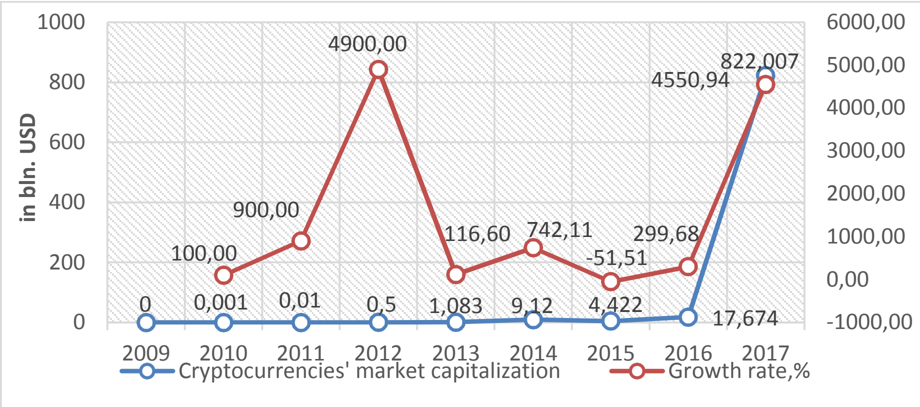

Fig. 2. Cryptocurrencies' market capitalization and growth, 2009-2017.

Exploring the capitalization of the crypto currency market in comparison with the money supply of the developed countries, the capitalization of cryptocurrency is higher than monetary aggregate M0 (money outside banks (cash)) or M1 (depending on methods of calculating of monetary aggregates), and higher than aggregate money supply of more than 100 countries of the world. Fig. 2 reflects the growth of the cryptocurrencies market over the last 9 years.

4 Data

We gathered the data on the Bitcoin exchange rate from the website of http://markets.businessinsider.com/currencies/btc-usd.

We collected the Twitter data for the research purposes. The timespan includes the period between January 2014 to September 2017. We use simple combination for the key word "Bitcoin + "exchange rate". This combination intends to capture the most pertinent tweets usually posted by the professionals or those interested in trading. We collected the tweets only in English to simplify further sentiment analysis. In total, we contained almost 2.5 million tweets for more then 2,5 years. Table 1 provides the descriptive statistics on the average number of tweets per day, standard deviation, and the example of the scrapped tweets.

Similarly to [7] we created three following data sets:

set 1: the historical data on Bitcoin exchange rate to US Dollar;
set 2: the sentiment score of the pertinent tweets
set 3: the combination of the first and the second sets.
These sets are divided into training and testing subsets at the ratio 90:10.

Table 1. Some descriptive statistics on available tweets and the scrapped examples

MEAN	2482	TWEET1	Why Nobel Winning Economist Joseph Stiglitz is Wrong about Bitcoin
SD	548	TWEET2	Massive offloading of #Bitcoin detected - Mt. Gox selloff suspected

5 Methodology

In this section we explain the developed deep learning method to predict the daily directional change of the Bitcoin exchange rate, methods of performance evaluation, and the methodology of the sentiment score calculation.

5.1 Deep Learning Setup

Among the deep learning methods convolutional neural networks (CNNs) are discriminant models apt for classification problems. Moreover, CNNs address dimensionality. CNNs have been successfully used for unsupervised extraction of abstract input features for prediction problems [1]. The approach has also proved effective in financial predictions [8, 9]. It motivates us to use CNNs to predict the daily directional change of the Bitcoin exchange rate (BTC). Units in the CNNs receive inputs from small contiguous subregions of the input space, called a receptive field, that collectively cover the entire set of input features [9]. We use maximum pooling for down sampling and reducing dimensionality. We employ a dropout as regularization technique to avoid overfitting in the training phase. The output of a convolution layer is obtained by applying a rectified linear unit (ReLU). The softmax function is applied at the output generation stage. We use Keras Python Library with Tensorflow framework to run the experiments. In the first series of experiments with only time-series data on the target exchange rate we obtain the best prediction results with the following CNN architecture: width: 4; height: 1; depth: 1; stride: 2; padding: 0. In the second series with inclusion of tweets we obtain the best prediction results with the following CNN architecture: width: 5; height: 1; depth: 2; stride: 1; padding: 0.

Experimental setup to evaluate our method

In accordance with best evaluating practices the predictive accuracy of developed models are compared to those of baseline models and best available existing methods on out-of-sample data to determine if the improvement in predictive accuracy is statistically significant. We will test the hypothesis that *"the proportion of correctly* *classified observations"* measure resulting from our model is higher than those obtained using alternate methods. We now expand on the candidate models we propose to use for comparison.

Random walk. Following standard evaluation practice in financial economics (see [2]), we will evaluate the prediction accuracy of our model by using random walk without a drift (RW).

ARIMA. Integrated Moving Average (ARIMA) is commonly used time series model for foreign exchange rate forecasting. We use auto.arima () from the library "forecast" function with default parameters to get prediction results. Then we implement the function to calculate the proportion of correctly classified observations.

Shallow neural networks. A standard multilayer perceptron (MLP) with 1 hidden layer of neurons is used as a prediction model to compare with CNNs. The logistic activation function is used for the neurons in the hidden layer and the output neuron. We use standard back-propagation training algorithm with fixed training speed for training. We conduct experiments using the Tensorflow framework. The output layer contains 1 neuron with the forecasted value. We obtain the best prediction results with 10 neurons in the hidden layer.

Sentiment score

As in the study of [6], we usethe Pattern Package with Python programming environment to compute the sentiment score. "Pattern" (BSD license) is a Python package for web mining, natural language processing, machine learning and network analysis, with a focus on ease-of-use [13]. The results are the values in the range [-1; 1]. The most negative tweets have the score (-1) and positive incline to 1. These values are the polarity scores for the pertinent tweets. The polarity score is negative when the tweet content is pessimistic or aggressive. The tweets with polarity score close to 1 reflect the positive expectations about Bitcoin and may be treated as the incitation for the bullish strategy of the user if he/she participates in the cryptocurrency trading. Table 2 includes the descriptive statistics on the sentiment score findings. Fig. 3 depicts the distribution of the tweets with different 'mood': [-1; -0.1) – negative, [-0.1; 0.1] – neutral, (0.1; 1] – positive. The downside of the method is that it uses the polarity score of the adjectives to assess the tweet 'mood'. The tweets without the adjectives are then recognized as neutral.

Table 2. The sentiment score, daily score

Variable	Mean	SD	MIN	MAX
Aver. Polar.	0.12	0.08	-0.57	0.68

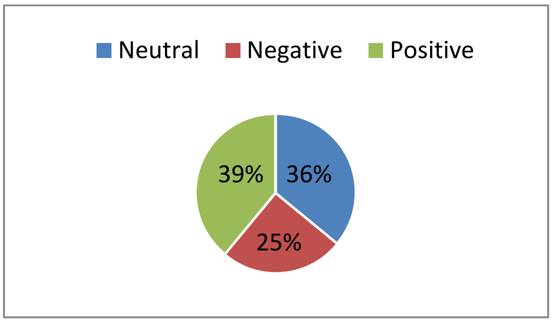

Fig. 3. The distribution of the positive, negative and neutral tweets over the sample

6 Results

The results (Table 3) prove the empirical evidence for the CNN superior performance in forecasting the Bitcoin direction of change in comparison with the other methods using the set 1. However, the findings indicate that even the best available methods do not yield the accurate results with the crypto currencies' historical data. Recall that we assess the classification accuracy of the point estimate forecasting technics to evaluate the developed model. The results with ARIMA, one-layer neural network and the convolutional neural network provide only marginally better forecasts than the simple random walk. The possible explanation is in the high volatility of the Bitcoin exchange rate in 2017 with the moderate interest to the crypto currency before. The results obtained with sentiment score as the input data improved the accuracy of the method drastically. Fig. 4 displays the training accuracy of the CNN with the set 3. The accuracy rate reaches around 95 % on the training data and 68.6% with the test inputs. Fig. 5 depicts the training loss decrease during the CNN training visualized with Tensorboard. In the experiments, we do not anticipate the lag between the Bitcoin rate change and the tweet news following the idea that with the daily window the news influence is absorbed by the market participants within an ongoing day.

Table 3. Classification accuracy of the developed model on the test data.

FX/method	RW	ARIMA	MLP	CNN*	CNN**
BTC/USD	46.2	47.2	47.5	52.6	68.6

*CNN with set1 as an input data

** CNN with set 3 as an input data

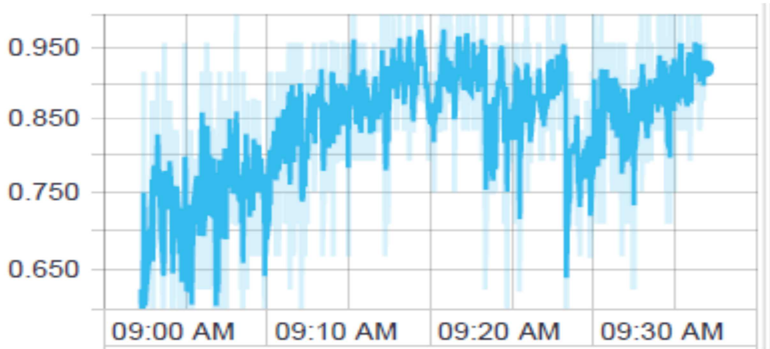

Fig. 4. The CNN accuracy on the training data from the set 3.

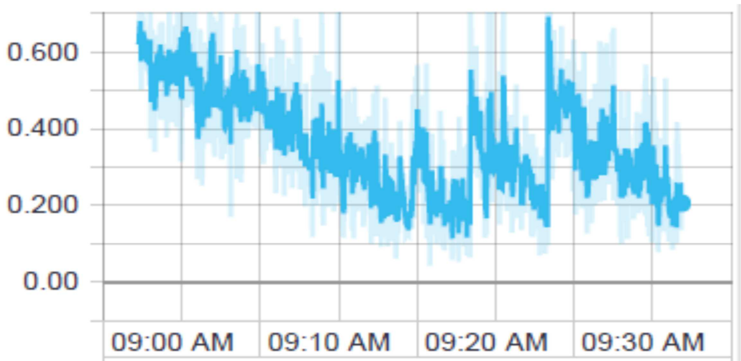

Fig. 5. The CNN loss decrease on the training data from the set 3.

7 Conclusions

The Bitcoin is among the most popular crypto currencies. However, it does not represent the legal tender. There is no evidence about the underlying conditions that lead the Bitcoin market participants. We made the hypothesis about that the behavioral signals make the most significant contribution to the Bitcoin fluctuations. The hypothesis is tested with the developed model together with the traditional methods. Our findings prove the significant influence of the Twitter signals on the Bitcoin fluctuations. The sentiment score included as an input data much improved the prediction accuracy for the Bitcoin directional changes. Thus the tweet sentiment data may be further exploited in the developing of the trading strategies. Further research studies will devote special attention to the periods when some regulations concerning Bitcoin legitimacy are adopted.

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