Impacts of Positive and Negative Comments of Social Media Users to Cryptocurrency

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***Abstract*—Blockchain implementation brought several benefits to many areas. One of the usages of blockchain is in digital currencies. Digital currency (cryptocurrency) is a new era for the global financial system. Cryptocurrencies draw significant attention from researchers because of their advantages. Although there are several risks (e.g., speculation, 51% attack) related to cryptocurrency, billions of dollars are invested in them, because of their transparency, traceability, low transaction cost, and highly profitable potential. In December 2017, the most famous cryptocurrency, Bitcoin, has reached almost $20,000.00 per coin. Such short-term, high gain potential attracts many new small investors. However, speculative movements raise many questions related to the safety and privacy of investors, just to name a few. To understand public opinions about cryptocurrency and speculative movements to protect small investors financial interests, sentiment analysis can be done by using social media activities of individuals who are interested or investing in cryptocurrencies. It is also one of the essential steps in the analysis to understand the profiles of the users. Therefore, in this paper, we determine the attitudes of social network users by analyzing the positivity and negativity of the comments about six cryptocurrencies. Results show that the positivity is higher than negativity, and there exist relations between price changes and attitudes. However, relations vary according to currency types. The results and analysis, which are provided in this paper, help new investors and developers to obtain opinions of social network users who are interested or investing in cryptocurrency.**

***Index Terms*—Cryptocurrency; Social Media; Attitude Analysis; Sentiment Analysis.**

I. Introduction

Blockchain brings in a new era for the global financial system with the advent of digital currency, and its impact can be felt in other related industries [1]. With its ongoing development and increased number of implementations, it draws significant attention from researchers. One of the most important benefits of the blockchain, particularly with financial systems, is the use of cryptocurrency. Although there are a number of risks (e.g., taxation, speculation, pseudo-anonymity, and 51% attack) related to cryptocurrency [2], billions of dollars are invested in it [3], [4] largely due to its permanent transparency, traceability, low transaction cost, pseudo-anonymity transactions [1], and high-profitable profiles. In December 2017, the most famous cryptocurrency, Bitcoin, had reached almost $20,000.00 per coin [4], which is ten times higher than its price in the previous year. Such a short-term, high gain venture attracts many new small investors. However, speculative movements have caused cryptocurrency bans [5] and brought several investment questions, such as safety and privacy, just to name a few. In order to understand the public opinion of cryptocurrencies and also protect new investors, sentiment analysis can be implemented using the social media activities of cryptocurrency-related forums. This is because small investors and interested parties follow and actively enroll in social media, including Twitter [6], Reddit [7], YouTube [8], and many other social media platforms to get more information about the features of coins and future gain possibilities [9].

Text analysis in social media is widely used to understand the trends of users [10], [11]. As a result of text analysis of users' comments on cryptocurrency subjects, researchers have identified a strong interaction between the social media sentiment and the Bitcoin price, and a tendency for investors to overreact to the news on social media within a short period [9]. However, a social marketing strategy can negatively affect investors [12] in the long term. Therefore, it is crucial to analyze and identify profiles of cryptocurrency investors and those who are interested in it to protect new investors from financial losses and provide profile information to new investors and interested parties.

There are several works which analyze cryptocurrency in terms of security, privacy, applications, usability, regulations, and technology [1]–[3], [13], [14]. Although there is no text mining analysis specifically on profile analysis of cryptocurrency activities, there are text mining research works on price predictions [9], [15], [16]. In [15], social network data is analyzed to understand better the factors underlying the price and other trends in emerging cryptocurrency markets. Similarly, in [9], social network data is studied to understand the relation between bitcoin price and social activities. In [16], keywords are extracted from Bitcoin-related user comments posted on the online forum to analytically predict the price and extent of the transaction, and fluctuation of the currency. The previous works mostly focus on price predictions of cryptocurrencies, especially Bitcoin, by using text analysis. On the other hand, this paper *aims* to examine profile information. In our previous work [17], we investigate the education levels of users from their comments. Conversely, in this paper, we are interested in the attitudes of the users who are active in social media, which is related to cryptocurrencies and their attitudes changes relating to price fluctuations.

The *objective* of this paper is to analyze the comments of the users who are active in six cryptocurrency subreddits (Bitcoin, Bitcoin Cash, Dash, Ether, Litecoin, and Ripple) in terms of positivity and negativity by using users' comments for each coin subreddit on Reddit. The key *contributions* of this paper can be listed as follows:

- The six cryptocurrencies are investigated in terms of users' positivity and negativity attitudes, and the mood change effects on the price according to all comments and the most upvoted posts.
- The relation between six cryptocurrencies prices and the number of comments are investigated.
- By using Valence Aware Dictionary and Sentiment Reasoner (VADER) [18] over five million comments of the users on cryptocurrencies mentioned above have been thoroughly analyzed to determine the attitude changes for short and long terms.

The *results* show that the almost 75% of comments are neutral, and positivity is higher than negativity. Moreover, there exist relations between price changes and attitudes. However, the relations vary according to the currency type. The results and analysis, which are provided in this paper, help new investors and developers to obtain public opinions and attitudes towards to cryptocurrency.

The rest of the paper is organized as follows: In Section II, the system model and assumptions are explained. Section III explains the selected coins. In Section IV, the analysis and results are presented, and finally, Section V has the concluding remarks with future works.

II. System Models

In this section, we introduce two data collection models which have been used in this paper.

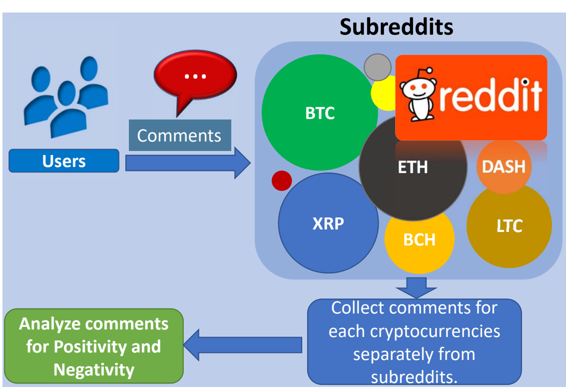

Fig. 1: Illustration of data gathering model from Reddit for cryptocurrencies by considering all comments.

Fig. 1 shows the data collection process for each digital currency from Reddit. Reddit can have one or more subreddits for each cryptocurrency, and each cryptocurrency can have several posts in each subreddit. Moreover, each post can have many comments from many users because users

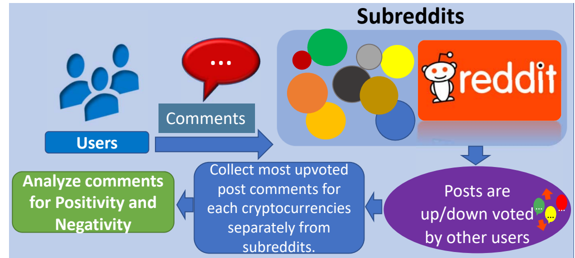

Fig. 2: Illustration of data gathering model from Reddit for cryptocurrencies according to the most upvoted posts.

tend to respond to posts that match their interests. We use subreddits for each cryptocurrency to collect distinct comments. Because of the Reddit API limitation, we instead used https://pushshift.io/ [19]. We assume that if a user comments on a subreddit post which belongs to a coin, either the user is an investor or they are interested in the currency or they want to speculate. Moreover, because of the informal structure of the comments (no or missing punctuation, shortened words, and other informal writing styles), and the low number of comments in a day or desired time range, the comments are pre-processed. Therefore, the pre-process helps to better approximate to the attitude of the users. Moreover, as shown in the second model 2, we also collect data from the most popular post created on each day in the subreddits. The model then grabs user comments replied within 10 hours of the submission's created time. Therefore, the differences between all comments and only the most upvoted comments can be compared.

III. Selected Cryptocurrencies

In this section, we explain why these particular cryptocurrencies have been selected. Although there are more than 1000 types of coins and tokens, we have selected Bitcoin (BTC), Bitcoin Cash (BCH), Litecoin (LTC), Ethereum (ETH), Lumen (XLM), Monero (XMR), Dash (DASH), and Ripple (XRP) for this study not only because of the 75% of total market cap in digital currencies as shown in Fig. 3 but also their development purposes regarding privacy, security, finance and transaction speed. More details about the selected currencies can be found in our previous work [17] and the above-cited websites.

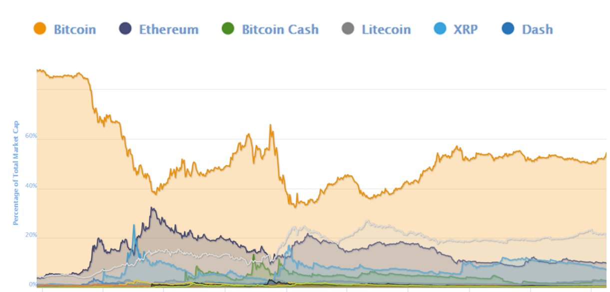

Fig. 3: Market share of cryptocurrencies from 2017-2019 [20]

IV. Analysis of Comments for the Currencies

In this section, we present the results in terms of three different perspectives. First, we explain the number of comments and price relation, and the mood and price changes. To have reliable results, more than five million comments, made in 2017 and 2018 regarding six digital currencies, have been analyzed.

A. *Positivity and Negativity of the Comments*

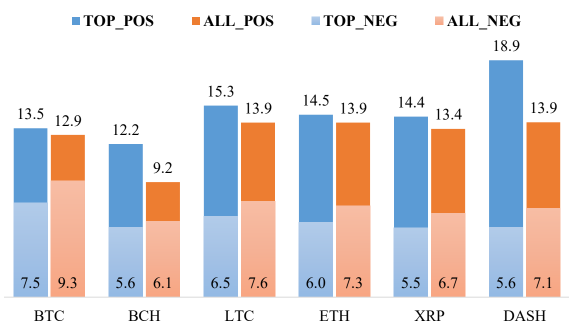

Fig. 4: The average positivity and negativity of the top most post and all comments for each coin.

B. *The Average Positivity and Negativity*

Fig. 4 shows the average positivity and negativity level of topmost post and all comments. The positivity of top post comments is higher than positivity of all comments and negativity of top post comments is lower than the negativity of all comments for each coin. When only all comments are observed, the comments of LTC, ETH, XRP, and DASH have similar positivity level (13), and XRP has the lowest negativity out of four coins (6.7). It is interesting to see that BCH has the lowest positivity (9.2) and negativity (6.1) comparing to all coins according to all comments, and BTC has the highest negativity (9.3). When top post comments are observed, XRP, DASH and BCH have almost the same lowest negativity ($5.5 - 5.6$), and DASH has the highest positivity with 18.9. BTC also has the highest negativity (7.5) according to top post comments. This figure does not contain the neutrality of comments. However, it can be measurable by subtracting the sum of positivity and negativity from 100. Thus, the neutrality of comments approximately varies between 75% and 85% for coins.

C. *The Number of Comments and Price Relation*

Figs. 5 to 10 show the 15-day averaged price and the number of comments changes for six coins. The price and amount of comments percentage measured by using daily changes rather than cumulative changes to observe the relation. As shown in Fig 5, BTC price and the number of comments have an obvious relation until May 2018, and the number of comments increases or decreases according to the price changes. Although there is a relation between price and the number of comment changes until January 2019, the significance is not clear due to the frequent fluctuation. We found out that if the price changes are lower than 4%, the number of comments are not affected. Most interestingly, in January 2019, changes in the number of comments happen before the price change, which may be used for price prediction for 15 days. Moreover, the maximum price changes are almost 12% although it is 18% in the number of comments (See the changes from January 2018 to March 2018.)

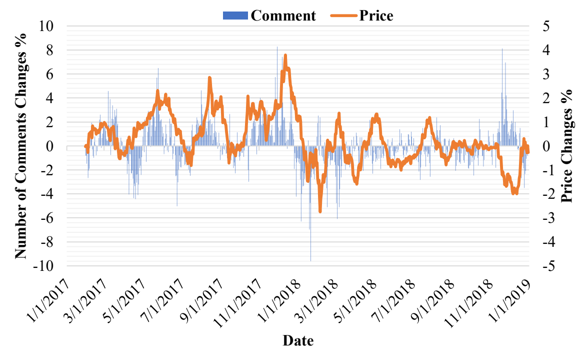

Fig. 5: BTC price changes with the number of comment.

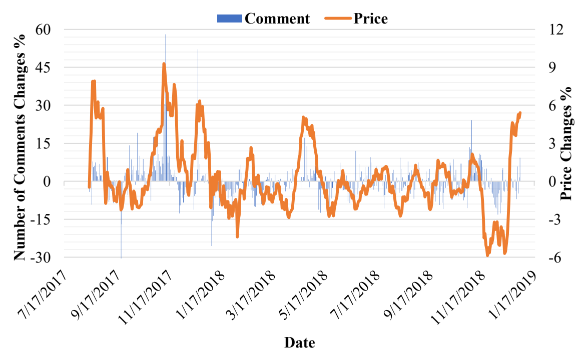

Fig. 6: BCH price changes with the number of comment.

Fig. 6 shows the BCH prices changes with the number of comments. BCH price and the number of comments follow the same patters except between September 2018 and November 2018, and the number of comments increase or decrease according to the price changes. However, the increment and decrement percentages are significantly higher than changes in BTC such that the maximum price alteration is almost 12% although it is 85% in the number of comments (See the alteration with number of comments in December 2017 and price changes in December 2018.) Similar to BTC, after May 2018, the relation between price and the amount of the comments is not well-recognized although the relation exists with the smaller percentage.

Fig. 7 depicts the ETH price changes with the number of comments. Unlike the BTC and BCH, the relation between the number of comments and price exist and easily recognizable during two years. The maximum price and the number of comment changes are 15%.

LTC (Fig. 8) follows similar paths as BTC except for the January 2019 case, and it is not significant. Moreover,

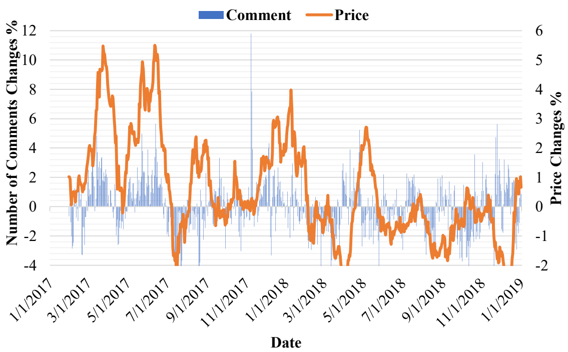

Fig. 7: ETH price changes with the number of comment.

the maximum difference between increment and decrement percentages is much higher than BTC with 80% in the number of comments and 9% in price.

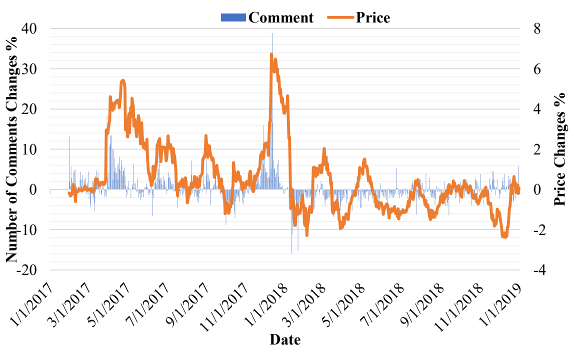

Fig. 8: LTC price changes with the number of comment.

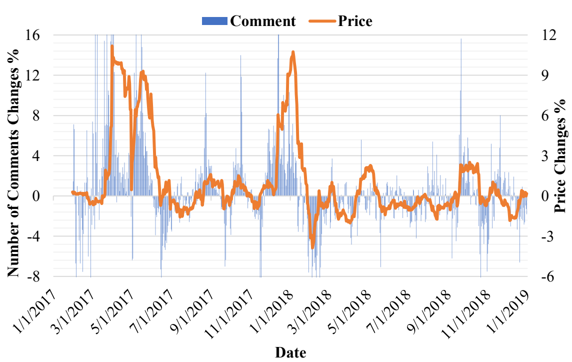

Fig. 9: XRP price changes with the number of comment.

Figs. 9 and 10 show the prices changes with the number of comments for XRP and DASH, respectively. Similar to ETH, (Fig. 7), XRP (Fig. 9) and DASH (Fig. 10) have the similarity with the price and the number of comments during two years. However, XRP has more often sudden high increases and decreases comparing to DASH and other coins.

D. Mood and Price Relation

In this section, we explain the effects of the mood changes of users on the price and vice verse. Initially, the effects of the positivity and negativity on the price changes were investigated. However, we found out that the changes from negativity to positivity requires time to progress. Therefore, during those stages, the effects are not analyzed correctly if only one of positivity and negativity is used for the relation. Therefore, in this paper, we consider both positivity and negativity at the same time by renaming as "mood." Simply mood is measured by subtracting negativity from the positivity. However, mood and price are averaged to 30-day due to the high fluctuations in mood changes that cause unreadable format in the figures. Moreover, we observe the mood changes based on all comments ($MoodAll$) and top post comments ($MoodTop$) to observe the relation between price and moods.

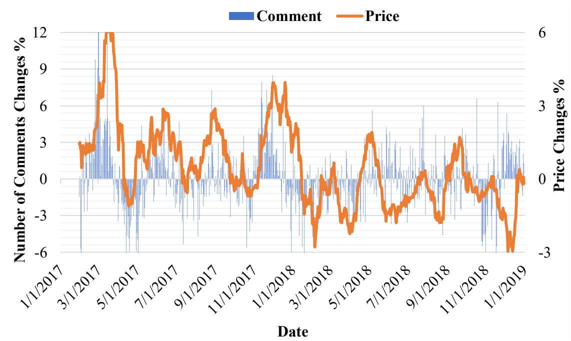

Fig. 10: DASH price changes with the number of comment.

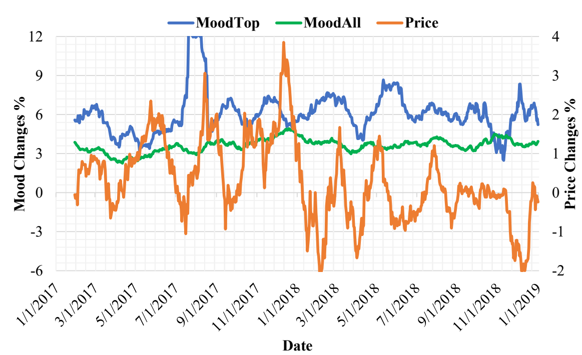

Fig. 11: BTC price movements with mood changes from January 1, 2017 to January 1, 2019.

1) Bitcoin Price with Mood Changes: Fig. 11 shows the price and mood changes for BTC from January 2017 to January 2019. While $MoodAll$ varies between 2% and 5%, $MoodTop$ varies between 2% and 12%. The reason is that top posts in BTC affect the changes positivity and negativity attitudes more. Therefore, $MoodAll$ and price changes relation is not understandable. Moreover, the sudden changes in the price are not seen in $MoodAll$. On the other hand, $MoodTop$ follows the price changes as seen between March 2018 and September 2018. More interestingly, $MoodTop$ increases or decreases before the price movements as seen in July 2017 and November 2018. Although it is not reliable all the time, as shown in Fig. 11, the $MoodTop$ can be used to predict the price movement direction better than $MoodAll$ for BTC.

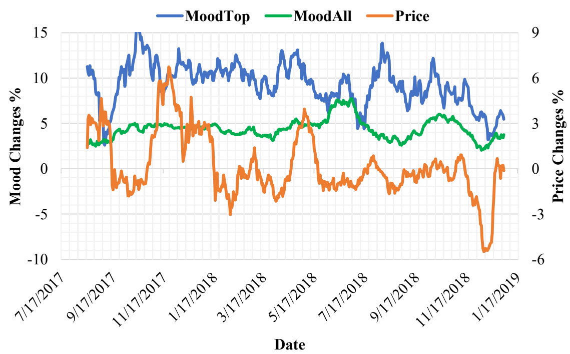

Fig. 12: BCH price movements with mood changes from July 17, 2017 to January 17, 2019.

2) Bitcoin Cash Price with Mood Changes: Fig. 12 shows the price and mood changes for BCH from July 2017 to January 2019. Due to its initial forked in July 2017, the data before July 2017 does not exist. While $MoodAll$ varies between 2% and 8%, $MoodTop$ varies between 2% and 15%. Fluctuations in $MoodTop$ and $MoodAll$ are higher than BTC. We believe the reason is that BCH was recently forked and the users' expectation is high. Moreover, $MoodAll$ in BCH is stable on 5% from October 2017 to February 2018. As similar to BTC, the sudden changes in the price are not seen in $MoodAll$ most of the time except between July 2018 and January 2019. Interestingly, $MoodTop$ movements are not well suited as BTC, although there is a clear indication for relations after March 2018. Moreover, $MoodTop$ sometimes contradicts with $MoodAll$ as seen in August 2018, and price movements are parallel to $MoodTop$ during August 2018.

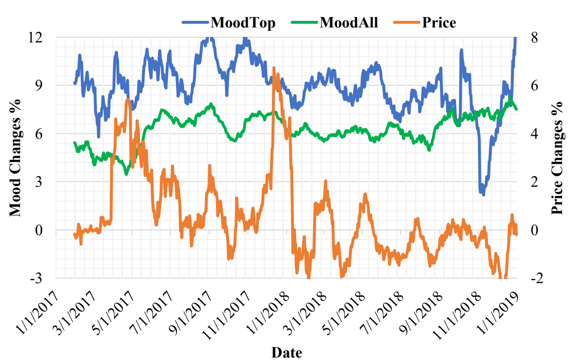

Fig. 13: LTC price movements with mood changes from January 1, 2017 to January 1, 2019.

3) Litecoin Price with Mood Changes: Fig. 13 shows the price and mood changes for LTC from January 2017 to January 2019. Until November 2017, $MoodAll$ and $MoodTop$ follow the price movement. However, both $MoodAll$ and $MoodTop$ increase before the sudden increment in price in January 2018 although the price increases in April 2018 and June 2018 do not significantly affect $MoodAll$. On the other hand, as similar the other coins, $MoodTop$ is affected by most of them before or after the price movements.

4) Ether Price with Mood Changes: Fig. 14 shows the price and mood changes for Ether from January 2017 to January 2019. Ether is the only coin out of the analyzed coins that $MoodAll$ and $MoodTop$ are closer to each other most of the time, although some slight differences exist such as in March 2017 and September 2018. Moreover, though 15% price changes in January 2018 and June 2018, neither $MoodAll$ nor $MoodTop$ are affected. We believe the reason could be the users' motivation and trust to Ether future after November 2017.

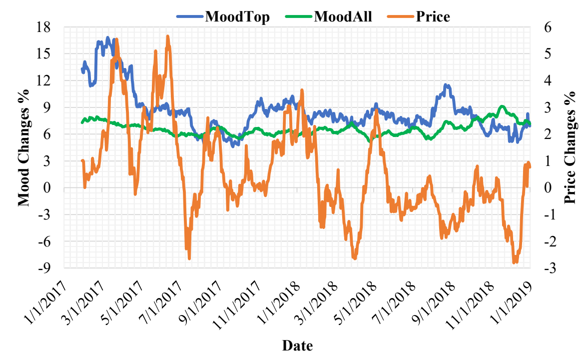

Fig. 14: ETH price movements with mood changes from January 1, 2017 to January 1, 2019.

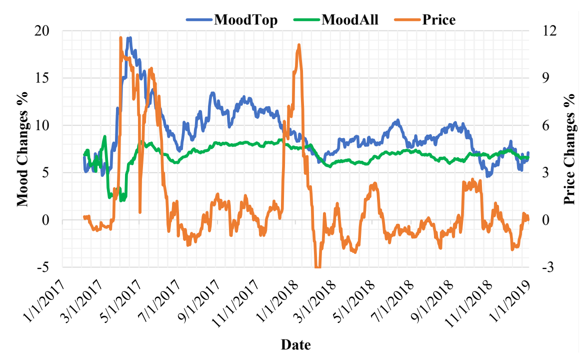

Fig. 15: XRP price movements with mood changes from January 1, 2017 to January 1, 2019.

5) Ripple Price with Mood Changes: Fig. 15 shows the price and mood changes for XRP from January 2017 to January 2019. XRP has two significant price changes March 2017 and January 2018. Although the price movement affects both $MoodAll$ and $MoodTop$ in March 2017, the price change in January 2018 does not impact the $MoodAll$ and $MoodTop$ because both moods started to drop while the unanticipated price increment happened. Except for the second price changes, the other small changes impact $MoodTop$. Therefore, they follow a similar pattern.

6) Dash Price with Mood Changes: Fig. 16 shows the price and mood changes for DASH from January 2017 to January 2019. DASH has the most stable $MoodAll$ values out of the investigated coins, and the values approximately change between 6% and 8%. Although there is an indication for the effects of price on $MoodAll$, it is not as significant as other coins. However, $MoodTop$ closely follow the price movements except for some minor cases such as March 2017.

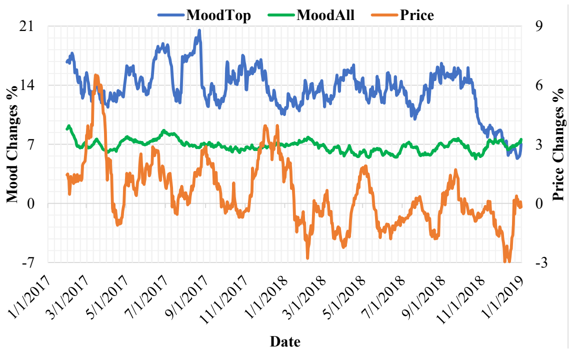

Fig. 16: DASH price movements with mood changes from January 1, 2017 to January 1, 2019.

E. Summary of Results

The results which have been obtained from Reddit comments can be summarized as follows:

- According to positivity and negativity analysis, the positivity is higher than negativity in all digital currencies. It is worth to note that the neutrality of comments approximately varies between 75% and 85% for coins.
- According to the average of positivity and negativity analysis in terms of all and top post comments, the positivity of the topmost comments is higher than the positivity of all comments while the negativity of the topmost comments is lower than the negativity of all comments.
- There is a relation between the number of comments and price movements for all coins.
- Price changes affect mood measured by using topmost comments in a day more than mood measured by using all comments in a day. Additionally, the effects of mood changes on price movements are also observed for some coins like BTC.

V. Conclusion and Future Works

In this paper, we analyze the attitudes of users who are interested in cryptocurrencies to provide information about users' positivity and negativity. To obtain the perspectives of users, we use Reddit.com to collect and classify the gathered comments data from subreddits of six cryptocurrencies and analyze the data according to the sentiment analysis. The results which we obtained from distinct cryptocurrencies show some similarities in terms of the amount of positivity and negativity. We also observed that the positivity is higher than negativity in all investigated digital cryptocurrencies, and there exist relations between price and mood changes. However, the relations vary according to cryptocurrency type. The results and analysis, which are provided in this paper, help new investors and developers to learn the users' positive and negative attitudes towards the digital currencies.

In the future, we would like to extend this work by obtaining not only attitudes but also the characteristics of users from multiple social media platforms. Moreover, we will investigate the moods of each class of users towards digital currencies.

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