Relations between Reputation and Social Media Marketing Communication in Cryptocurrency Markets: Visual Analytics using Tableau

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Abstract: Visual analytics is an emerging research field that combines the strength of electronic data processing and human intuition-based social background knowledge. This study demonstrates useful visual analytics with Tableau in conjunction with semantic network analysis using examples of sentiment flow and strategic communication strategies via Twitter in a blockchain domain. We comparatively investigated the sentiment flow over time and language usage patterns between companies with a good reputation and firms with a poor reputation. In addition, this study explored the relations between reputation and marketing communication strategies. We found that cryptocurrency firms more actively produced information when there was an increased public demand and increased transactions and when the coins’ prices were high. Emotional language strategies on social media did not affect cryptocurrencies’ reputations. The pattern in semantic representations of keywords was similar between companies with a good reputation and firms with a poor reputation. However, the reputable firms communicated on a wide range of topics and used more culturally focused strategies, and took more advantages of social media marketing by expanding their outreach to other social media networks. The visual big data analytics provides insights into business intelligence that helps informed policies.

Keywords: cryptocurrency; marketing communication; semantic network analysis; sentiment analysis; visual analytics

1. Introduction

The telescopes and microscopes have helped pioneer new scientific discoveries in physics and biology. Similarly, new research tools create research practices that are different from the past, and contribute to improving the overall research process. Some scholars warned that the proliferation of new analytical tools has rendered traditional methodologies useless [1]. In particular, data flooding requires new techniques such as visualization, rather than conventional scientific methodologies. There is also a claim that “there is no better theory than a good method” of research [2].

Not only scholars in natural and engineering science but also humanists and sociologists have faced the challenge of exploding data. Thanks to increasing use of abstract and indexing databases including Web of Science and Scopus, they can easily access a large amount of information. Although the methodology itself is not regarded as ultimate goal of academic endeavor, it enables a systematic awareness of important but elusive phenomena. The humanities, as its nickname ‘soft science’ implies, rely much less on structured and objective methods, academic exchanges among their sub-disciplines are difficult. However, a better communication can be accomplished, if new data analysis tools are used to present highly subjective and descriptive results in photographs, graph charts, and network diagrams. Therefore, data analysis is designed to facilitate interdisciplinary research.
There has been increasing interests in visual analytics in data science. In spite of its value and utility, visualization analysis has been relatively limited to bar graphs and simple plots for researchers in the humanities background [3, 4]. Recently, as various tools and open data sources with affordable prices are developed, data visualization has become popularly used in the industry and other fields of research beyond computer science and engineering areas [5]. Among the many visual analytics tools, Tableau is particularly useful for uncovering multidimensional relational data, visualization, and statistical analysis [6]. Tableau is based on a database visualization language VizQL (Visual Query Language), which converts users’ actions into database queries that result in a broad range of graphics through relatively simple and easy steps [7].

The aim of this study is to demonstrate visual analytics and semantic network analysis for determining how popular cryptocurrency companies strategically communicate their coins on social media. We comparatively investigate the sentiment flow over time and language usage patterns between companies with high reputation and firms with low reputation. In addition, this study explores the relations between reputation and marketing communication strategies in terms of emotional intensity of expressions and language usage patterns.

2. Understanding Cryptocurrencies in the Digital Economy

Bitcoin's price has been rapidly changing. There are also mixed interpretations of the cause. It is important to note that these changes are not sudden phenomena. Economists attribute the so-called ‘don’t ask’ investment to the Dutch tulip crisis in the 1630, dot-com bubble in the early 2000s, and the global housing crisis in 2007. Shiller [8] also warned of a sharp fall in the global stock market in his latest edition of the ‘Irrational Exuberance’. Theoretically, this phenomenon is a type of the ‘herding behavior’ that occurs when people make an investment decision without seriously considering economic fundamentals [9]. In other words, they act like a flock of sheep in cryptocurrency market [10]. However, economists have often overlooked the important role of social media that can affect the inexperienced investors in the cryptocurrency market [11].

This study builds on the ideas of research on using Twitter to predict the cryptocurrency market. Consumer decisions were shaped by non-economic fundamentals such as emotions [12, 13] and information available on social media [14]. Previous studies in this field have focused on the predictive power of web metrics and social media such as Twitter for cryptocurrency usage, adoption, and valuations. Empirical studies suggest that social media contributes to understanding the voices of influential people and organizations that affect cryptocurrencies prices. For example, web search traffic such as Google Trends predicts cryptocurrency prices [15, 16]. In line with this, the web citations of cryptocurrency sites reflect financial performance of the cryptocurrencies such as market capitalization, price, and trading volume [17, 18]. Social media also serve as social signals of cryptocurrencies. For example, Barth et al. [19] discovered that frequent unethical discussions of cryptocurrencies on Twitter negatively related to prices of cryptocurrencies. On the contrary of this, ethical discussions were positively associated with prices. Garcia et al. [20] found that the volume of users’ information search and word-of-mouth communications of Bitcoin in social media affected not only its price growth, but also changes in price.

Moreover, previous studies highlight the importance of information availability in cryptocurrencies’ traction and valuation. For instance, Jahani et al. [21] contends that along with higher level of technical innovation availability for coins, information availability determines the success of the cryptocurrency ecosystem. Similarly, Johansson and Tjernström [22] suggest that information demand is a positive predictor of Bitcoin volatility.

As reviewed above, existing studies on uses of social media in the cryptocurrency market have heavily focused on the function of Twitter in predicting cryptocurrency prices and valuations. However, there is a dearth of work on organizational activities that can shape and influence the value of cryptocurrencies within social media communities. Although there was little study showing empirical exploration about the impact of cryptocurrency firms’ marketing behaviors on its reputation, few studies found how firms’ word-of-mouth communications impact on investors’ perception and behaviors in stock market. Equity issuing firms’ languages that implied sentiments used in the disclosing documents influenced the performance of the corporation [23] and investors’ emotions [24]. Moreover, this sentiment changes affected buying or selling the stock [25]. A recent study investigated the effects of cryptocurrency issuers’ sentiments via Twitter on cryptocurrency price and market reactions. It was found that positive emotions implied in a cryptocurrency firm’s official Twitter account increased the coin’s return [26]. The investors reacted accordingly to the sentiments of the firms as they considered firms’ sentiments as credible information.
Such few empirical evidence suggests that word-of-mouth communication affects diffusing, promoting, and shaping users’ perspectives and purchasing behaviors [4, 27]. To fill this gap in the literature, this study aims to explore the role of marketing communication activities of cryptocurrency companies using social media by analyzing how they manifested key issues and sentiments in their promotional contents.

This study is an initial attempt to determine how cryptocurrencies are promoted on social media and the relations between reputation and marketing communication strategies. This study contributes to understanding effective Twitter marketing strategies in terms of expressions of sentiments and language uses on social media by comparing communication of high- and low-reputation firms in cryptocurrency markets. In order to achieve this, this research collected all the tweets from accounts operated by top cryptocurrencies and employed traffic analysis and text analytics combining sentiment analysis and semantic network analysis.

3. Materials and Methods

We collected a total of 74 popular cryptocurrencies in terms of the credit rating reported by WEISS as of February 20, 2018 (See table 1) [28].

<table>
<thead>
<tr>
<th>WEISS ratings</th>
<th>Cryptocurrencies</th>
</tr>
</thead>
<tbody>
<tr>
<td>B, B- (N = 5)</td>
<td>Ethereum, NEO, EOS, Cardano, Steem</td>
</tr>
<tr>
<td>C+ (N = 9)</td>
<td>Bitcoin, Dash, NEM, BitShares, Ark, Decred, Litecoin, Byteball Bytes, I/Ocoin</td>
</tr>
<tr>
<td>C (N = 32)</td>
<td>Ripple, Monero, Verge, Stellar, Dogecoin, Ethereum Classic, Lisk, Qtum, Stratis, Waves, Nxt, Vertcoin, Komodo, Neblio, Syscoin, Zcash, PIVX, NAV Coin, Zcoin, Peercoin, BlackCoin, Counterparty, Bytecoin, Burst, Nexus, Blocknet, Shift, Smartcash, XTRABYTES, AEon, Asch, RaiBlocks</td>
</tr>
<tr>
<td>C- (N = 13)</td>
<td>DigiByte, Electroneum, BitcoinCash, ReddCoin, Ubiq, Viacoin, Feathercoin, CloakCoin, Namecoin, Zencash, Whitecoin, DigitalNote, Skycoin</td>
</tr>
<tr>
<td>D+ (N = 8)</td>
<td>BitCoinGold, Einsteinium, GameCredits, MetaverseETP, Gulden, Auroracoin, Pura, Megacoin</td>
</tr>
<tr>
<td>D (N = 7)</td>
<td>Rise, PotCoin, Expanse, Matchpool, Novacoin, SaluS, Quark</td>
</tr>
</tbody>
</table>

All the tweets posted by 74 cryptocurrency accounts were extracted using an API-based tool, Webometric Analyst 2.0 [29]. The intensity of sentiments represented in nearly 10,000 tweets was categorized based on a 5-point Likert scale using SentiStrength software [30]. Sentiment flow of the cryptocurrencies’ profiles over time was analyzed and visualized using the Tableau to draw understandable and longitudinal configuration.

In addition, we also employed a semantic network analysis to compare marketing strategies of companies with high reputation and firms with low reputations. Semantic network analysis is a “meaning-centered network approach” to detect prominent issues, metaphors, and key themes based on the pattern of word co-occurrences in a text corpus [31] and useful to investigate a large scale textual data. First, top 100 key words in terms of the frequency in the tweets of the cryptocurrency firms were generated using TextSTAT [32]. Next, the Fulltext software [33] was employed to generate co-occurrence matrices of top 100 word-pairs in tweets produced by the corporations who received the highest ratings (B and B-) and firms received the worst ratings (D) by WEISS. A core and periphery blockmodeling was conducted to determine overall structure of the semantic networks [34]. The most popular network software UCInet was used for computing network metrics and visualization.

4. Results

First, a time series analysis of tweet traffic and sentiment flow in tweets posted by 74 cryptocurrency firms from 2011 to 2018 indicates that the amount of promotional tweets increased temporarily between 2014 and 2015. Figure 1 shows sentiment flow of tweet traffic over time. The left diagram displays the positive sentiment trend and the right diagram shows the negative sentiment trend. In the graph, the x-axis refers to dates and years, and the y-axis indicates the amount of tweets.

The results suggest that the size of tweets decreased as it moved to 2015 and 2016, but it started to grow again in mid 2016. The traffic increased rapidly as it moved toward the end of 2017, suggesting more marketing
efforts using Twitter by the cryptocurrency firms. This can be attributed to a spike in Bitcoin price, trading volume, and user interests to cryptocurrencies during November and December 2017 [35]. The findings indicate that although a slightly positive value (1) was dominated from 2011 to 2014, the cryptocurrency firms used more positive words over time. In particular, when the trading activities and prices were picked in December 2017, they used extremely positivity strategies.

Similarly, a wide range of negative words were observed from 2011 to 2014 although the twitter traffic during this time period was very small. Not surprisingly, firms used slightly critical words than the intensively negative languages over time from 2014 to 2018. When the price of cryptocurrencies was dropped in 2018, more skeptical voices appeared. Monthly data were also used to examine changes in average strength of positive and negative sentiments over time (see Figure 2). Interestingly, friendly and hostile emotions have stabilized since 2014.

![Figure 1. Sentiment flow of tweet traffic over time](image1)

Next, to investigate the sentiment flow across companies, cryptocurrencies’ positive and negative emotions used in their tweets were analyzed using box plots. As shown in Figure 3, there is no outlier outside the box plot on the -1 point, but on the 1 point the Bitcoin is quite far from the box.
For a close investigation of an outlier Bitcoin’s emotion strategy, we analyzed the frequency and percentage in using positive and negative sentiments of the Bitcoin messages in comparison of a randomly selected cryptocurrency firm, Dogecoin. As displayed in Figure 4, Bitcoin dominantly used slightly positive messages compared to other companies whereas the distribution of sentiments were similar across companies.

As visualized in Figure 5, the intensity of the positive and negative sentiments is represented in two dimensional graphs. Interestingly, Namecoin had the highest variance in sentiments, with an average of +1 and -3.5 points for optimism and negativism respectively. Next, Dogecoin had an average of 2.313 for the positive value and -1.147 for the negative value.
The mean values of Twitter sentiments obtained from different groups per Weiss ratings were compared using analysis of variance (ANOVA). As only several companies received a B or B- rating, these two ratings were integrated for the analyses. As summarized in Table 2, there was no significant difference of emotional language uses among companies in different reputations (p > .05). This result suggests that emotional language strategies on social media did not affect cryptocurrencies’ reputations. According to the results of Pearson correlation analysis, positive emotion was not significantly related to negative emotion, r(72) = .03, p > .05).

We comparatively examined Twitter marketing strategies of high reputation and low reputation firms. Figures 6 and 7 show the semantic network diagrams of the tweets used in highly reputable coin firms and non-reputable coin firms.

### Table 2. Mean difference test of sentiment strength per Weiss credit ratings

<table>
<thead>
<tr>
<th>Division</th>
<th>Grade</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weiss-Positive</td>
<td>B- and B</td>
<td>5</td>
<td>1.438</td>
<td>0.056</td>
<td>1.454</td>
<td>0.217</td>
</tr>
<tr>
<td></td>
<td>C+</td>
<td>9</td>
<td>1.353</td>
<td>0.143</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>32</td>
<td>1.437</td>
<td>0.145</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>C-</td>
<td>13</td>
<td>1.447</td>
<td>0.130</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>D+</td>
<td>8</td>
<td>1.358</td>
<td>0.093</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>7</td>
<td>1.486</td>
<td>0.076</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weiss-Negative</td>
<td>B- and B</td>
<td>5</td>
<td>-1.186</td>
<td>0.004</td>
<td>1.079</td>
<td>0.380</td>
</tr>
<tr>
<td></td>
<td>C+</td>
<td>9</td>
<td>-1.200</td>
<td>0.084</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>32</td>
<td>-1.196</td>
<td>0.079</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>C-</td>
<td>13</td>
<td>-1.178</td>
<td>0.063</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>C-</td>
<td>8</td>
<td>-1.188</td>
<td>0.056</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>7</td>
<td>-1.130</td>
<td>0.071</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 6. Semantic network of cryptocurrency firms with high reputation
Figure 7. Semantic network of cryptocurrency firms with low reputations

Node sizes are proportional to the frequency of words and the ties between nodes refer to co-occurrence of the words. As most of these words were connected to each other, we only display word relations that were more frequently occurred together, which is above the network density value. The size of the tie is also proportional to the frequency of co-occurrence. The color of nodes refers to groups of nodes in accordance with the results of core-periphery blockmodeling. A red color denotes nodes in the core group and a yellow color refers to nodes in the periphery group in the network.

The results suggest that 2 cores and 98 peripheral nodes were observed with the final fitness of 98.1% and 88.3% respectively in both the highly reputable companies’ network and the network of companies with low reputation. The core terms in the reputable companies’ network were the terms “RT” and “blockchain” in that these terms were closely connected to each other. For the companies with low reputation, the terms “RT” and “new” were in the core group.

To compare the pattern of language usages between high reputation and low reputation firms, the density between core-periphery classes were computed, which suggests the strength of ties between groups (see Table 3). As expected, there were strong connections between core-core classes in both networks. Interestingly, the terms between the core classes and the periphery classes were paired highly compared to the rate of density between the periphery classes and the periphery classes in both networks. This suggests that most of the words were strongly associated with the core words in the tweets of both reputable firms and non-reputable firms.

<table>
<thead>
<tr>
<th></th>
<th>Firms with high reputation</th>
<th>Firms with low reputation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Core</td>
<td>Periphery</td>
</tr>
<tr>
<td>Core</td>
<td>2965688.000</td>
<td>158926.594</td>
</tr>
<tr>
<td>Periphery</td>
<td>-</td>
<td>6414.797</td>
</tr>
</tbody>
</table>

Both semantic networks represent hub-and-spoke distributions, suggesting central nodes played roles as hubs in the network (Park, Hoffner, 2020). The central nodes in terms of eigenvector centrality were RT (0.637), blockchain (0.489), new (0.277), cryptocurrency (0.146), and update (0.134) in the reputable firms’ network. RT (0.628), new (0.312), blockchain (0.231), marijuana (0.224), and coin (0.190) were central nodes in the non-reputable firms’ network.

For reputable companies, words related to coin transaction such as “wallet”, “token”, “exchange”, “quote” were strongly associated to each other. Terms, indicating the security of the services, such as “security”, “cryptocurrency”, “development”, “developer”, and “technology” were also frequently appeared. Social media platforms such as “social media”, “Youtube”, “Facebook” were closely connected to “RT”, requesting
stakeholders’ word-of-mouth efforts. Cultural-oriented terms such as “food” and “travel” were also observed. Interestingly, some East Asian countries such as “Korea”, “Japan”, “Tokyo” and “Chinese” were presented in the context of popular international marketing and services in these regions.

In the network of companies with low reputation, it is very interesting that a signal of marijuana marketing was detected (e.g., “marijuana”, “weed”, “legal”, “buy”, “legalize it”, “business”, and “merchant”). This is attributed to the PotCoin (POT)'s marketing strategy who is a pioneer in the cannabis-focused cryptocurrency industry. PotCoin has attempted to support banking issues for those looking for legal marijuana transaction [37]. Similar to reputable companies, non-reputable companies also promoted their service advantages (e.g., “safe”, “secure”, and “easy”) and infrastructure system based on blockchain technology (e.g., “decentralized”, “trade”, “cryptopionner”, “skill”, “mining”, and “development”).

5. Discussion

Visual analytics is an emerging research field that combines the strength of electronic data processing and human intuition-based social background knowledge [3]. Business applications of visual analytics is crucial to understand and monitor stock market in real time and obtain insights to implement informed decision making and develop future necessary actions [5, 18]. As social media is one of the primary marketing platforms in today's industry, this study demonstrates a useful visual analytics in conjunction with semantic network analysis using examples of sentiment flow and strategic communications strategies via Twitter in a blockchain domain.

In line with previous studies, the findings of tweet traffic analysis suggest that cryptocurrency firms more actively produced information when there was an increased public demand and increased transactions and when the coins’ prices were high [35]. To extend the discussion on the role of social media in cryptocurrency valuations [19], this study determined the impacts of marketing communication activities on cryptocurrency reputation using textual analytics. Emotional language strategies on social media did not affect cryptocurrencies’ reputations. There was no significant difference of emotional language uses between companies with high reputation and companies with low reputation.

In addition, the results of this study indicate that key strategies in highly reputable companies were providing information about coin transaction, the security of their products and services, innovation in technical infrastructure, and word-of-mouth promotion on other social media platforms. It is also noteworthy that they focused on outreach to and regional marketing in East Asian countries, including Korea, Japan, and China. In addition, they shared cultural information of travel and food as well as blockchain technology conference information held in these countries.

Similar to reputable companies, cryptocurrency companies with low reputation also communicated their service advantages and superior infrastructure system. We noticed that PotCoin’s marijuana marketing was active on Twitter. While the pattern in semantic representations of key words were similar in both networks, the reputable firms communicated on a wide range of topics and used cultural marketing strategies and took more advantage of social media marketing by expanding their outreach to other social media networks.

6. Conclusions

The main contribution of this study is to demonstrate useful visual analytics to collect, represent, and analyze longitudinal Twitter data with Tableau. This study also provides insights on business intelligence into the domain of blockchain technology and cryptocurrencies, which is a new social phenomenon that still needs exploratory studies to establish informed policies [18]. There are limitations that need to be acknowledged and improved in future studies. First, although Twitter is a major marketing outlet in the cryptocurrency industry [4], we found that reputable companies also utilized other social media platforms such as Facebook and YouTube. This factor limited the study results’ generalizability. Thus, to improve generalization, future studies need to expand the scope of the research to other social media channels as well. Second, while we comparatively investigated the emotional strategies and language usage patterns between companies in different reputation, we did not verify the customers’ reaction on these different marketing strategies. Thus, the flow of sentiment and content marketing strategies do not explain their effects on consumer perceptions directly. This calls for future studies on the effects of distinct language uses and marketing strategies on consumer behaviors by implementing surveys or interview of the message recipients. Lastly, this study only analyzed the word-of-mouth communication of cryptocurrency corporations. Future studies should also investigate the word-of-
mouth communication of customers that can influence the Twitter dialogue and critical issues related to the societal values of cryptocurrencies.

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Conflicts of Interest: The authors declare no conflict of interest.

References


