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What makes Twitter influential?

An analysis of Twitter content, user behavior, and correlation to Bitcoin market value.

Table of Contents

[1 Introduction 4](#_Toc36231780)

[2 Background 5](#_Toc36231781)

[2.1 The Boom of Social Media Influencers 5](#_Toc36231782)

[2.2 Different Platforms with Different Affordances 6](#_Toc36231783)

[2.3 The Voice of a Million Tweets 6](#_Toc36231784)

[2.4 Measuring Influence 7](#_Toc36231785)

[3 Twitter 8](#_Toc36231786)

[3.1 Overview 8](#_Toc36231787)

[3.2 The Feed 8](#_Toc36231788)

[3.3 User Profile 9](#_Toc36231789)

[3.3.1 Followers 9](#_Toc36231790)

[3.3.2 Following 9](#_Toc36231791)

[3.3.3 Tweet Volume 10](#_Toc36231792)

[3.3.4 Verified User Status 10](#_Toc36231793)

[3.3.5 Location 10](#_Toc36231794)

[3.4 Tweets 11](#_Toc36231795)

[3.4.1 Character Limit 11](#_Toc36231796)

[3.4.2 Links 11](#_Toc36231797)

[3.4.3 Media 11](#_Toc36231798)

[3.5 Interactions 11](#_Toc36231799)

[3.5.1 Likes 11](#_Toc36231800)

[3.5.2 Retweets 12](#_Toc36231801)

[3.5.3 Comments 12](#_Toc36231802)

[3.5.4 Engagements 12](#_Toc36231803)

[3.6 Finding Content 12](#_Toc36231804)

[3.6.1 #hashtags 12](#_Toc36231805)

[3.6.2 Trending Topics 13](#_Toc36231806)

[3.6.3 @mentions 13](#_Toc36231807)

[3.6.4 Keyword Search 13](#_Toc36231808)

[3.6.5 Promoted Posts 13](#_Toc36231809)

[4 Bitcoin 14](#_Toc36231810)

[4.1 Background 14](#_Toc36231811)

[4.2 Elements affecting value 14](#_Toc36231812)

[4.2.1 Scarcity 14](#_Toc36231813)

[4.2.2 Mining & Energy Prices 15](#_Toc36231814)

[4.2.3 Adoption & Use Cases 15](#_Toc36231815)

[4.3 Historical Events 15](#_Toc36231816)

[4.3.1 2018 Crash 16](#_Toc36231817)

[4.3.2 COVID-19 16](#_Toc36231818)

[4.4 Trading 16](#_Toc36231819)

[4.4.1 Exchanges 16](#_Toc36231820)

[4.4.2 Expressing Value 17](#_Toc36231821)

[5 Sentiment Analysis 18](#_Toc36231822)

[5.1 Methods 18](#_Toc36231823)

[5.1.1 Natural Language Processing 18](#_Toc36231824)

[5.1.2 Lexicon Based 18](#_Toc36231825)

[5.1.3 Method Selection 19](#_Toc36231826)

[5.2 Data Cleaning 19](#_Toc36231827)

[5.2.1 Daily tweet rate 20](#_Toc36231828)

[5.2.2 External links 20](#_Toc36231829)

[5.2.3 Hashtags 20](#_Toc36231830)

[5.2.4 Lemmatization 20](#_Toc36231831)

[5.2.5 Stop Words 20](#_Toc36231832)

[5.2.6 Follower to Following Ratio 20](#_Toc36231833)

[5.3 Uncertainty 20](#_Toc36231834)

[6 Correlation 21](#_Toc36231835)

[6.1 Volume 21](#_Toc36231836)

[6.2 Sentiment 21](#_Toc36231837)

[6.2.1 Filtering 21](#_Toc36231838)

[6.2.2 Weighting 22](#_Toc36231839)

[6.3 Calculating Correlation 23](#_Toc36231840)

[6.3.1 Pearson Correlation Coefficient 23](#_Toc36231841)

[6.3.2 Time Lagged Cross Correlation 23](#_Toc36231842)

[6.3.3 Variable Selection & Manipulation 24](#_Toc36231843)

[7 Bibliography 25](#_Toc36231844)

# Introduction

In 2019 US digital advertising revenue surpassed $100 billion (Winterberry Group 2020). In the same year, nearly one in five digital marketing agencies spent over half of their annual budget on social media influencers (SocialPubli 2019). Celebrity endorsements can cost upwards of $1 million dollars per post, but companies can expect a five-fold average return on investment (Influencer Marketing Hub 2020) including Twitter, where users report a 5.2X increase in purchase intent when exposed to influencer marketing (Annalect 2016).

Influencer marketing is not restricted to consumer products and its successful use can be observed across many industries including finance. During 2017, previous antivirus inventor and CEO, John McAfee was famed for the ‘McAfee Effect’ in relation to the influence of his tweets appeared to have over cryptocurrency (a new form of digital currency that is traded in a similar manner to traditional stocks) value (Toshi Times 2018). While the effect did not sustain over time, the short-term positive influence can be witnessed on several cryptocurrencies with MacAfee’s backing. Twitter based support from McAfee could reportedly be purchased for the cost of 25 bitcoins (Twitter 2017); a USD value at the time of more than $200,000.

The high cost of a single cryptocurrency related tweet by an influencer is understandable when put into the context of the cryptocurrency market. With over 5000 different cryptocurrencies, and a total market capitalization of more than $200 billion (reaching a peak of over $795 billion in January 2018), cryptocurrency is a popular and growing technology. The leading (and first ever) cryptocurrency, Bitcoin, has a market share of over 60% of all combined cryptocurrency values. It’s huge popularity and market dominance has resulted in all other cryptocurrencies being known as altcoins. Bitcoin’s dominance also has effects on the general cryptocurrency market trend, where the direction and movement of Bitcoin value can be observed in the value of the other altcoins.

Existing studies have shown a clear relationship between social media sentiment and financial markets (Phillips and Gorse 2018) including the successful implementation of trading algorithms (Garcia and Schweitzer 2015). This project builds on the aforementioned studies to investigate which specific elements of social media content, and user behavior has the greatest correlation with cryptocurrency value. This is achieved through a focused case study of one social media platform and one cryptocurrency coin.

While more in depth online conversations surrounding cryptocurrencies happen on social media sites such as Reddit (Phillips and Gorse 2018), Twitters additional features of verified status’, retweets, likes and comments offer a wider variety of variables that may affect influence. In addition to these features, the ease, speed, volume and length of messages (33 characters average, 280-character limit) reverse chronological order, and public profile focused approach makes Twitter the ideal planform to observe rapid sentiment changes surround cryptocurrency.

This project tracks the messages of Twitter uses discussing Bitcoin (selected as the leading cryptocurrency coin), using hashtags and key terms over a period of one month. Multiple sentiment analysis methods are applied, taking into consideration multiple filtering methods, to only consider users of a particular user groups (for example only those users with verified status) and consider weighted models where different user groups contribute more to the overall sentiment score.

The sentiment analysis is then compared to the changes in Bitcoin value over the same time period, calculating a correlation coefficient and considering time lag to account for any delay between sentiment and the market value.

The resulting visualization demonstrates the effect of each element of Twitter in relation to a filtered or weighted sentiment analysis model. The variations in sentiment score are displayed in relation to Bitcoin market value to show which combination of filters and weights have the greatest correlation with Bitcoin market trend. Each stage of the visualization is interactive to allow the user to explore the full range of possibilities. Due to the high volatility of Bitcoin price, the visualization is not designed to be used as a prediction tool but is an in-depth exploration of the elements of Twitter have the greatest impact on influencing user behavior.

# Background

## The Boom of Social Media Influencers

Since 2017, influencer marketing has doubled in size to over $6 Billion per year (Influencer Marketing Hub 2020). The market has shifted from product placements from celebrities and public figures who found popularity from outside of social media, to now include people who have grown a follower base for the purpose of generating income through online promotion. The shift is so much that audiences are more receptive of social media influencers than traditional celebrities (Mediakix 2019). One of the most successful influencers, Kylie Jenner, has over 165 million followers on Instagram. The image centric social media platform allows users a preview of her lavish lifestyle, luxury products and exotic holiday destinations. For anyone that dreams of sharing any piece of that lifestyle, the regular additional of paid product placement guide the way to find it.

The use of social media influencers has a strength above traditional digital advertisement; the advertisements are not totally unsolicited; for the majority of cases the user has made the conscious effort to follow or view the influencers profile. As people look to Jenner for lifestyle aspirations, other social media users look for guidance and advice on a wide variety topic. These topics could range from inspirational quotes to health advice or financial planning. Many of these topics do not need to visual centered focus of platforms such as Instagram and are more suited to text based platforms that allow the addition of links and attached media (something that Instagram does not allow). Twitter, with 330 million active monthly users (Report 2019) is a clear example that there is still a desire for such a primary text-based platform.

## Different Platforms with Different Affordances

In comparison to Facebook’s 2.45 Billion monthly active users, Twitter may at first appear to be largely insignificant in relation to digital marketing, however the two platforms have a different focus.

While Facebook promotes user privacy (now a default setting) and sharing between friends and family, only 13% of Twitter users have their profile set to private. Twitter has a greater public focus, where the majority of users share posts openly to the any interested party. Links between Twitter users can also be a one-way link. Unlike Facebook’s ‘friendship’ system, a Twitter user can follow any public profile without any requirement for the other user’s prior agreement and without the other user reciprocating. This results in celebrities such as Donald Trump gaining over 70 million followers. In comparison to Facebook, the links between users of Twitter have a much broader reach, with the average twitter user having 707 followers (Kick Factory 2016), vs the average Facebook users 338 friends (Smith 2014).

Another element of Twitter that makes it desirable to marketing and influencers is that the information that users see is not restricted to the individual posts (tweets) from users they follow. The process of ‘retweeting’ a message is to post another users message onto your profile for your followers to see, therefore spreading a message to a larger audience (discussed further in section 3.5.2). Messages that resonate with a large enough audience can quickly turn ‘viral’ and receive millions of retweets. Quantifying what will result in a viral message is difficult (Cha et al. 2010), however they can spawn from any account regardless of the number of followers and can resonate for positive or negative reasons. Retweets allow for semi-unsolicited (the user has chosen to follow the user who retweeted but may not have directly followed the original creator of the post) messages to reach a user’s profile. This aspect of Twitters platform makes it possible for users to be influenced by messages from users they do not directly follow.

## The Voice of a Million Tweets

During the 2016 presidential election campaign, the affordances of the Twitter platform made it ideal for manipulation in the hopes to influence users voting intentions.

“Highly automated accounts—the accounts that tweeted 450 or more times with a related hashtag and user mention during the data collection period— generated close to 18 percent of all Twitter traffic about the Presidential election”

(Kollanyi, Howard, and Woolley 2016)

With an average of 1300 tweets per account per day and messages with pro Trump hashtags reaching over 150,000 each day, automated (‘bot’) accounts were used heavily to spread messages throughout the social media platform. Without speculating on the impact these messages, this suggests that influence through social media may not only come from a few influential users with high follower numbers, but also from a large body of accounts discussing a similar topic.

There are many other aspects to Twitters platform that can impact the level of influence. User interactions with tweets can take several forms, including retweets, comments, and favoriting. The profile of users not only vary in the number of followers, but also in the number of users they follow back, the frequency that they tweet or if they have been granted a verified status by Twitter (all discussed in detail in section 3). It is not a clear case that user with the most followers have the most influence.

“…popular users who have high indegree are not necessarily influential in terms of spawning retweets or mentions.”

(Cha et al. 2010)

## Measuring Influence

With the large returns on product placements by influencers and the extreme effort and money spent on digital political campaigns, there is little doubt that Twitter as a body of users can have a large amount of influence, not only over individual buying or voting patterns, but on a scale where it can impact larger markets and events.

When evaluating the sentiment of Twitter discussions surround the stock market, specifically the Dow Jones Industrial Average (DJIA), there was an 86% accuracy in predicting the daily rise and falls in value (Bollen, Mao, and Zeng 2011). Twitter sentiment analysis has also been used to create an algorithmic cryptocurrency trading bot where they confirm “the long-standing hypothesis that trading-based social media sentiment has the potential to yield positive returns on investment” (Garcia and Schweitzer 2015).

When considering the influence of social media in these studies, both the DJIA and cryptocurrency have additional factors that affect their price fluctuations. Each company in the DJIA has physical assets and balance sheets to be taken into consideration for company valuation; cryptocurrency in comparison is not tied to a physical entity. Cryptocurrency is however affected by the current energy price due to the large power consumption that underpins how the technology functions, and can also be affected by discussion of legislation.

In March 2017 the Security and Exchanges Commission (SEC) disapproved a proposal for a Bitcoin (the largest valued cryptocurrency coin) ETF (investment vehicle), citing price volatility and the price being driven by speculation as two concerns (Security and Exchanges Commission 2017). With no inherent value, the largest cause of price changes in cryptocurrency is market supply and demand, driven by speculation and discussions, that happen in part in the public domain via social media websites. This makes cryptocurrency a topic where the effects of social media influence can be witnessed and have a significant impact.

# Twitter

To inform this project, we will first break down the Twitter platform into individual elements and evaluate how they may impact the level of influence and the justification for their inclusion or dismissal in this project.

## Overview

Twitter, similar to most social media platforms, can be used in two main different way, either to consume information or to create and share information. Often users interchange and combine these uses within one session. These different uses each have their own dedicated sections within the platform, with overlap when viewing other users’ interactions on your own content.

## The Feed

When acting as a consumer, the main view (and default view when logging into the platform) is the Twitter feed which focuses on the content of other users of the website. The feed is a reverse-chronological display of all of the tweets created by other users that the current user has chosen to follow. In 2016, a significant change took place that affected the way that users receive their content. On the initial load of the page (after a period of not viewing the website), the feed no longer displays tweets in a reverse-chronological order, instead displaying tweets according to Twitters ‘relevance model’ that shows ‘top-ranked’ tweets first, with subsequent tweets being in reverse-chronological order (Twitter 2016). The thought process behind this implantation was to drive user engagement through identifying relevant tweets they may have missed (Koumchatzky 2017). In 2018 Twitter users were given the option to control the order of their feed, switching between the two ordering approaches (Twitter 2016).

## User Profile

Each user has a profile page. If the user has a public profile that allows other users to follow their tweets, then their profile page is also public. Public profile pages are available to view everyone and are not restricted only viewers with a Twitter account.

A profile page contains a feed of all tweets by a user, including additional lists of any media they have included in their posts. The relevance of the user profile page to this study is that the profile also contains additional information about the user that can be used in making a judgement about their social status and influence level as detailed below.

### Followers

A list of who is following a user is publicly available via the profile page. Every time a user tweets, each of these followers will receive the tweet via their feed (discussed in section 3.2). The likelihood of these tweets being seen by all of their followers is determined by the amount of time each user spends on viewing their feed and the number of users they have chosen to follow. With the average user following 707 people (MacCarthy 2016), a large volume of tweets are queued in each users twitter feed at any moment in time. Combined with the different approaches to feed ordering as discussed in section 3.2, it is difficult to determine the exact reach and consumption of each individual tweet using public information, however this information is available through the engagement API (section 3.5.4). While the use of the engagement API is beyond the scope of this project, the number of followers of each user is still be a relevant and useful indicator for assessing the potential level of influence.

### Following

While the volume of followers should be a clear indication of the number of users interested in the tweets of a user, this is not always the case. The desire that many users have to feel popular has resulted in two user behaviors. The first behavior is that some users may try to manipulate their follower volume through the purchasing of followers from external agencies (Nicholas Confessore 2018). These followers are usually blank accounts or bot-based accounts that can be purchased in thousands at a time. The second is a phenomenon known as like for like (or in relation to Twitter, follow for follow) and academically is discussed as part of the million followers fallacy (Cha et al. 2010). The premise of the act is that a user will follow another user in the hope or agreement that the other user will reciprocate.

In the same respect as the list of followers, the list of everyone that a user follows is also publicly available. While this does not have an effect on who sees a user’s tweets, it can be used in conjunction with the number of followers to create a ratio of followers to following. A higher ratio may be an indication that the user has not gained a higher follower count from the follow for follow phenomenon. Further uses for the following to follower ratio are discussed in section 5.2.6.

### Tweet Volume

Irregular or new Twitter uses can be a red flag when calculating the sentiment of a body of tweets, however the same can be observed in accounts with a high volume of tweets. Twitter accounts are free and quick to setup and tweets can be placed through a number of different methods, including the web interface, mobile application, desktop applications, SMS and programmatically through the use of the Twitter API. This allows for tweets to be posted easily, from a wide range of unrestrictive locations on a regular basis.

A high daily number of tweets can be a sign of an enthusiastic user, but can also be an indicator that the messages are from a computer generated (bot) source (Kollanyi, Howard, and Woolley 2016). Both the total number of tweets and the age of the account are available on the user profile page. These two elements can be combined to create a daily average which can be used as an indicator to the different types of users and accounts (discussed further in section 5.2.1).

### Verified User Status

One method of identifying users that are not bots and whose popularity is likely not to be due to manipulation either through purchased followers or ‘follow for follow’ is through the verified user status. This status is given to accounts of celebrities, public figures and influencers through an application directly to Twitter. The verification is not automatic and is investigated and verified through a human process. While these accounts may avoid some of the previous mentioned concerns, less than 1% of active monthly users have a verified status, so are not a representative sample of the twitter population. They may however be useful in a weighted model when investigating influence as these users have usually gained their verified status due to their position in society.

### Location

Location data is available on some user profiles. While geolocation could be an interesting element to investigate in the effect on influence, location information is provided by the user with no verification and is not available on a large proportion of user accounts. Using this information would require the exclusion of a large proportion of relevant tweets and would be trusting the user input location which would create a large skew on the results.

Verified location information is available on some tweets (individual to the tweet) that have been created via the mobile app. While this would be excellent information to use, the location information is only included with the user’s permission and is only on a low percentage of messages resulting in the same issue as above.

## Tweets

In addition to the sentiment of the written text in each tweet, there are other characteristics that may have an impact on the level of influence it has.

### Character Limit

One of the most defining characteristics of Twitter in relation to other social media platforms is its character limit. Originally 140 characters, and then doubled in 2017 to 280, the limitation promotes short and to the point messages. Users must consider the content of each message carefully to ensure it stays within the limit or alternatively break the message into separate tweets which can cause some users to not receive the message coherently. While using tweet length on its own as a characteristic to determine influential effect may be difficult, its relationship to the number of hashtags (discussed in section 3.6.1), links and other media may give an indication of content quality.

### Links

Links can be included in the body of a tweet to an external source (internal sources are dealt with through a number of different interactions discussed in section 3.5). Twitter provides its own link shortening service due to the short character limit; however, links still take up valuable characters that may affect the user’s ability to provide additional content. Their inclusion may be an indication of spam or links to promote external sources. As an argument against this, a link may indicate an especially credible message that is supported by sources links. The evaluation of the credibility of individual links is beyond the scope of this project, however the inclusion of links as a filter will be included.

### Media

Additional media items such as images, animations and videos can also be included in tweets (originally as linked content and now embedded within the tweet). In a similar respect to links, evaluating the quality of the included media would be difficult within the scope of this project, however the inclusion (or absence) of media items can be used as a filter property.

## Interactions

Interactions refer to any way in which a user can interact with another user’s tweet. The process of interaction demonstrates user engagement with the content, therefore displaying some level of influence over the user.

### Likes

A like is a single click interaction. The process of liking a tweet shows an appreciation for the post by incrementing a counter displayed at the bottom of the tweet (denoted by a heart symbol). Originally intended (and still referenced within the API) as a favorite button, liked tweets can easily be revisited by the user (and viewed by others) via a link on the users own profile page.

### Retweets

A retweet is another single click interaction. Retweeting places a copy of the original tweet on the users own timeline and in the feed of the people who follow them. The tweet is displayed in the same format as if the user has followed the original content creator. Retweets are important within this project as it immediately increasing the potential reach (and therefore potential influence) of the message. This feature allows the potential for a snowball effect and to create a ‘viral’ message if the message resonates with other users and they continue to retweet.

### Comments

The most time consuming of interactions is to reply, comment or quote (no differentiation is given to these terms within the Twitter platform) a Tweet. Due to the additional time cost of this interaction it is less popular than the other methods, however it shows a higher level of engagement (compared to likes or retweets) with the original tweet. Unlike retweets or likes, comments do not necessarily signify an agreement with a tweets content and may in fact be a form of rebuttal or argument against the content.

### Engagements

While the total number of interactions discussed above are displayed at the footer of each tweet, additional engagements (a term used in Twitters API) are also possible. Each tweet can be clicked on to view the comments and who liked and retweeted the tweet. In addition to this, Twitter also stores how many times the tweet has been viewed (known as impressions), and how many clicks on all media (including links, hashtags and video plays). While these engagements would certainly provide valid variables to consider in influencing outcomes, this information is only available via the enterprise API at a large financial cost and not available through the public API. There are therefore deemed outside of the scope of this project.

## Finding Content

All information thus far has focused on sharing and receiving information within a specified social group; however, Twitter includes many features designed to broaden a user’s network, both in relation to sharing and receiving information. The features discussed within the section benefit both consumers and content creators are used throughout the Twitter platform.

### #hashtags

Introduced in 2007, Hashtags are commonly included at the end of a tweet (although can also be placed within a sentence). A hashtag is a single word (sometimes multiple words concatenated to achieve a single word) denoted using the hash symbol and designed to highlight the topic or topics of the post. Hashtags are clickable links that allow a user’s fast access to a feed of other tweets that have used the same hashtag regardless of the follow status between the two users. The popularity of hashtags has grown significantly, and many other social media platforms have adopted a similar process.

### Trending Topics

Twitter’s trending topics list builds on the success of the adoption of hashtags and displays a ranked list of the most used hashtags. The trending topics list is easily accessible from multiple pages (depending of viewing platform) and gives the user an immediate overview of popular worldwide discussion topics. Due to the clickable attribute of hashtags, a single click will allow the user to view a feed of all of the tweets with that hashtag.

Similar to the issues discussed with users that have a follower volume, the inclusion of a trending topic hashtag is not always a positive sign for a quality user or tweet. The inclusion of trending topic hashtags is often done in an attempt to gain additional exposure on an unrelated topic. The use of a high number of hashtags can also be an indication of a tweet that does not have a single topic or a focused statement.

### @mentions

On signing up to Twitter, each user selects a username. This username can be used by others within tweets (preceded with an @ symbol) to mention (also called tag) the user. Users are notified of these mentions through a separate mentions feed. By default, a user will be alerted to any @ mention by any user regardless of follow status, however this setting can be changed to only show mentions by people that the user follows (popular with celebrities and other popular users). Mentions can be used in detecting if a message is directed to the general public or to a specific person (tweets that start with an @ will not appear in other people feeds but will show on the users profile page), in a similar way to the comment / reply feature discussed in section 3.5.3.

### Keyword Search

Tweets containing both keywords and hashtags can be found through a common search feature that will display a feed of all tweets matching the search criteria. The format of the feed abides to the same ordering as the main feed as discussed in section 2.2. The keyword search is available through the Twitter API and is the main endpoint used to gain information for this project. Tweets that are gained using the keyword search API are not subject to the relevance algorithm used for ordering feeds.

### Promoted Posts

In April 2010 Twitter introduced its first feature to provide a large revenue stream, the promoted post. Promoted posts, which are now commonplace in social media platforms allow for business or individual to pay for a tweet to appear in users feeds that do not follow them. Promoted posts can be targeted to key demographics and are displayed to the user in a similar fashion to a standard tweet, however they are labeled as promoted. Promoted posts are a clear factor in influencing outcomes, however the information on their individual use is not made publicly available. It is important however to highlight their existence as an additional factor in influencing outcomes including their potential to affect Bitcoin price.

# Bitcoin

## Background

Originating in 2008, Bitcoin was the first cryptocurrency; a digital asset that was designed as a medium of exchange that is not tied to a central authority. The currency, built on a technology called blockchain, gained popularity in its early stages due to its ability to keep the users anonymous, as payments are tied to a digital address (free for anyone to obtain) and do not require any human identification process. Bitcoin works on a public distributed leger (everyone can view every transaction ever made) and transactions are verified by bitcoin miners (to stop potential fraud or double spending), who are rewarded for their work with new bitcoins. As bitcoin is not a physical object, such as a coin or bank note, readers who are unfamiliar with its concept can consider each coin to be similar to the serial number on every banknote, where everyone can see who (which digital address) owns each number.

Already this description is an oversimplification containing cryptocurrency specific technical language. While the technical details of the implementation of Bitcoin and other cryptocurrencies are not important within the scope of this project, we must understand some principals that affect the value of Bitcoin (and all other cryptocurrencies) in order to consider the affect that social media plays in influencing a change in value.

## Elements affecting value

### Scarcity

How scarce an item is can affect its value. A clear example of this is the value of precious metals and gems such as silver, gold and diamonds. While these materials are still being mined and new gems are constantly coming into the market, the flow of new material is slow, and the items are still considered rare. This helps keep their value high due to supply and demand.

This same process is true of Bitcoin. As the popularity of Bitcoin grows, more bitcoins are released as part of the mining process. While this increase in volume of available coins should lower the price, the introduction of new coins is very slow and on a decreasing rate (due to a technical implementation known as block reward halving). Meanwhile, the popularity and adoption of Bitcoin is increasing at a growing rate.

### Mining & Energy Prices

The process of Bitcoin mining can be compared to guessing a very complex number (a process called proof of work). The complexity of this number is based on previous transactions, and how many transactions there currently are to be verified. The current probability of guessing the correct number is around 1 in 15 trillion. The current level of computation needed is very high and takes dedicated computer setups which use a large amount of energy. This high energy consumption is a factor that must be calculated into a Bitcoin miner’s profit margin, therefore changes in energy price can attract or detract people from mining, which is an underpinning element of the cryptocurrency ecosystem.

The amount of energy used is also a concern on a global scale, in 2018 the energy consumption of the Bitcoin network (34.86 TWh) was more than the whole of Denmark (33TWh) (Digiconomist 2020). This has caused questions over Bitcoins ongoing viability and potential regulation, which is also an area of contention that causes fluctuations in Bitcoin value (Congressional Research Service 2019).

### Adoption & Use Cases

2011 saw the introduction of alternative cryptocurrencies (known as altcoins) that attempted to address some of the limitations and pitfalls of Bitcoin. Other altcoins were created with specific use cases, such as Ripple, a currency designed to improve the speed of interbank monetary transfers. As of 2020 there are over 5000 different cryptocurrencies (CoinMarketCap 2020).

The wide variety of possible use cases for the blockchain and cryptocurrency technology resulted in some investment firms holding cryptocurrency as part of their investment portfolio, in the hope that the technology would find a mainstream, regulated use.

This interest was not only limited to investment firms. The ease of purchase and lack of regulation also saw a growing interest from the general public. Bitcoin’s lead on the competition due to being first to market and the most easily accessible through multiple markets and exchanges (discussed in section 4.4.1) made it a popular choice for first time cryptocurrency investors. Bitcoin has remained the cryptocurrency leader, responsible for over 50% of market capitalization (market cap) (CoinMarketCap 2020). By 2017 interest had grown substantially where due to supply and demand the value of a single coin grew from $900 to over $20,000.

## Historical Events

Many of the aspects that make cryptocurrency unique, are the same aspects that can be a cause for concern when considering its regulation and use. The SEC’s 2017 denial of regulation due to concerns of speculation driving Bitcoin value can be clearly observed through Bitcoin’s price volatility. An example of this is October 25th 2019, where the Bitcoin value grew by over 40% where only two days earlier it reached a 5 month low.

### 2018 Crash

The largest example of Bitcoin price volatility is January 2018 where between January 6th and February 6th, the value of Bitcoin dropped 65%. This was not an unpredicted event, with many analysts predicting the fall due to rise of cryptocurrency popularity being similar to the dot com bubble. With no intrinsic value and the Chicago Board Options Exchange allowing the ability to ‘short’ (a financial bet against a market) Bitcoin only a month prior; the demand for bitcoin dropped dramatically starting a chain reaction. The Bitcoin bubble was driven by emotion, fear of missing out and the hope of making a fast and substantial profit.

As part of the huge growth in popularity of Bitcoin, new terminology was born including ‘to the moon’ and HODL, originally presumed to be a misspelling of hold, now widely accepted to mean ‘hold on for dear life’ due to cryptocurrency price volatility.

### COVID-19

In March 2020 the worldwide pandemic COVID-19 caused the stock market to drop over 25%. In the same timeframe Bitcoin value dropped 55%. While this is another clear example of the volatility of cryptocurrency value, it is also an important demonstration of the link between bullish and bearish stock market positions and their effect on cryptocurrency value.

## Trading

The buying and selling of cryptocurrency can be broken down further into the initial purchase of a cryptocurrency from a fiat currency (a currency where the value is backed by a government) and trading between various cryptocurrencies. In order for either of these events to happen, an cryptocurrency exchange must be used in a similar process to using foreign exchange for fiat currencies.

### Exchanges

Multiple cryptocurrency exchange websites are available, each offering different availability to buy cryptocurrency from different fiat currencies and the ability to exchange between different cryptocurrency pairs. Not all cryptocurrency pairs can be directly traded, especially between altcoins, and Bitcoin is often used as an intermediary currency. The price of each cryptocurrency will vary slightly between exchanges but not by a large amount. It is important to understand the need and role of the exchange and variations between exchange for this project, as a single exchange (Binance) is used to provide the valuation data for Bitcoin. Binance has been chosen for its popularity, free and well documented API and its ability to offer expansion to a wide variety of altcoins in the future if the project is expanded.

Additional services such as CoinMarketCap are available that can offer average pricing across multiple exchanges, however, this is a paid services and does not offer a significant benefit to the project considering the low variation in price between exchanges.

### Expressing Value

While Bitcoin price can be expressed as a single monetary value (usually in USD) at any single moment in time, there are several values that can be used to express its current market position, strength and volatility. Many of these values are similar to trading traditional stocks and they will all play a role in determining correlation between Bitcoin value and Twitter influence within this project.

#### Candlestick Values

When using a trading platform, a user will view the changes in values between a pair of currencies. For this project we will use the BTC/USD pair (Bitcoin value in relation to the United States Dollar). The user is presented with time series data called candlesticks. A candlestick is similar to a box and whisker diagram in appearance but do not represent the same values. In a candlestick chart, each candlestick represents a user specified time interval. The selectable values are usually between 1 minute, through to 1 day, with intermediate points of 30 minutes & 1 hour. The top and bottom of the lines on the candlestick represent the highest and lowest points (respectively) the currency value reached during the time interval. The top and bottom of the ‘box’ represents the value of the currency at the start and close of the time interval, however the order depends on a value increase or decrease. If the value increased the bottom of the box presents the open value, if the price decreased the bottom of the box represents the close value. While this may seem complicated for the user to understand quickly, a green / red color coding is used on the box (or a fill / stroke in black and white publications) to show an increase or decrease.

#### Volume

In addition to the candlestick values, an additional bar chart is displayed below the main chart (on the same X axis) to show the relative volume of purchases and sales of the currency. This does not show direction on its own but can be used as a strong variable within this project to measure against Twitter volume (discussed in section 4.4.2.2).

#### Market Capitalization & Market Share

In addition to the value of a single coin, another valuation of the strength of Bitcoin is its market capitalization (market cap). This is the total value of all bitcoins in existence at the current market value. This is important for direct comparisons between different cryptocurrencies. While direct comparisons between Bitcoin and altcoins is not the focus of this project, Bitcoin’s relative market share against all other coins is an indication of its growing strength or decline. This is a strong indicator that can be used to determine correlation to Twitter influence.

# Sentiment Analysis

The process of sentiment analysis is to classify text into a series of emotional states, usually for the purpose of analyzing a body of responses. Sentiment analysis does not have fixed classes and is dependent on the subject of the information, however it will usually create a spectrum of results between negative, neutral and positive. Demonstrating correlation between Bitcoin value changes and accurately detected sentiment from Bitcoin related tweets will give the strongest evidence of twitters influence not only over Bitcoin change in price, but also the direction of the price movement.

## Methods

### Natural Language Processing

Natural language processing (NLP) is a branch of Artificial Intelligence that focuses on making sense of human language. There are many different approaches to NLP with many employing supervised machine learning techniques. Understanding the specific details of these techniques is not required for the scope of this project however a basic understanding a few principles are needed to understand NLP’s relevance and suitability for the project.

Supervised machine learning requires a training set of data. This is data that has been labeled in a particular way usually by a human driven process. In the context of this project, a training set would be a collection of thousands (or hundreds of thousands) of tweets that have been labeled by a human with their judgement of the sentiment of the message. This could be a Boolean (true or false) label or a numeric value. This labeled data then has features extracted from it that the computer uses to ‘learn’ what positive or negative sentiment looks like. A feature can be anything from the total number of words in each tweet, to the frequency of particular words, the use of punctuation, the list is very long.

Pretrained NLP applications are available and are very successful in accurately predicting sentiment, however the accuracy of these models is dependent on the strength and breadth of the training set.

### Lexicon Based

The most basic form on sentiment analysis is the use of a sentiment lexicon or sentiment dictionary. These can both be complied by humans or as a result of machine learning and natural language processing. They are lists of key value pairs that link a word with a sentiment or sentiment value. In its most basic form, a sentiment lexicon could be represented as two lists, one list of positive words and one list of negative words, or with each word being given a value or either +1 for positive or -1 for negative. To use such a list, each word in a body of text would be compared to the list and the score totaled.

In reality the process is more complex, with the words in the lexicon usually being assigned a wider range of values (than simply -1 or 1) as some words can be perceived to be more positive or negative than others. Summation of values is not always the best method of creating an overall score, so a comparative score is usually provided that creates an average sentiment value for each word in the body of text. To ensure an accurate score, the text must first be cleaned including the removal of stop words and lemmatization (discussed in section 5.2).

There are a wide variety of pre-existing sentiment lexicons that are free to use; the most popular being the AFINN-165 library that is available in multiple languages and contains 3382 words.

### Method Selection

The performance of machine learning based NLP models on average is more accurate than lexicon-based approaches. It’s downfall with relation to this project is the specific language used surround cryptocurrency (and to a larger extent, financial terminology in general). The sentiment of words used within general conversation may have a different sentiment (or strength of sentiment) when used in relation to discussing cryptocurrency. As an example, a term discussed earlier of ‘to the moon’ may be judged to have no specific (neutral) sentiment, however when discussing Bitcoin this has a strong positive sentiment. Other terms such as bullish or bearish will be rare to be seen in general conversation but have important connotations within financial conversations. Training a machine learning model on a training set of labelled tweets discussing cryptocurrency would provide the most accurate results. This however would require manually labelling a high volume of tweets, which is beyond the scope of this project.

As a compromise, combining both lexicon and NLP approaches has been successfully explored to combine the strengths and weaknesses of both methods. One popular existing system with a specific focus on social media sentiment is VADER (Valence Aware Dictionary and sEntiment Reasoner). While the results of VADER are strong, Lexicon based approaches may still have the ability to provide more accurate results by using finance specific lexicons such as the one created in 2011 by Loughran and McDonald. This popular financial lexicon was further improved upon with a specific focus on social media analysis with the NTUSD-Fin Sentiment Dictionary (Chen, Huang, and Chen 2018). These different methods and models will be explored within the context of this project to find the which translates the best to identifying sentiment within cryptocurrency specific tweets.

## Data Cleaning

The selection of Twitter as the source for this project is due to its high data volume, userbase that spans a wide demographic (that matches closely to the same demographic that invests in Bitcoin) and ability to represent current trends. The broad scope of Twitter can also be problem area in contrast to other platforms such as Reddit that have separate subreddits for specific subject discussions. In order to successful analyses the sentiment of Twitter in relation to Bitcoin, the information must be filtered and cleaned to remove unrelated or programmatic (bot) content.

### Daily tweet rate

Detection of high-volume accounts which is an indication of bot accounts. This does not have to be a restrictive cut off as bot accounts usually have very high tweet volume. A limit of 50 tweets a day should ensure that a low number (if any) genuine twitter accounts are filtered out.

### External links

Links are not processed during sentiment analysis and therefore would not directly impact a sentiment score; however, they may be an indication of tweets that’s are promoting external sources and not general discussion around the topic of bitcoin.

### Hashtags

Hashtags are used within the project as one method (combined with a general text-based search) to find Bitcoin related tweets. Hashtags can also be used as a filter method to discard tweets that contain a high level of hashtags (showing no specific topic or an attempt to gain additional attention and promotion) or hashtags that related to

### Lemmatization

Lemmatization is the process of combining groups of inflections of words so they can be processed together as one. This is an important step in the use of sentiment lexicons to ensure that words are correctly identified and scored.

### Stop Words

Stop words are commonly used words that do not add to the sentiment of the message. If they are not removed before lexicon-based sentiment analysis, then comparative (average based) scores will lower.

### Follower to Following Ratio

The details of this metric have been discussed in section 2.3.2 and are hard to regulate as the ratio does not always indicate a potential issue. However, in a similar respect to the daily tweet limit, a high filter cut off of 1:10 (1 follower for every 10 accounts followed), would likely filter out accounts whose primary focus is to garner unwarranted attention.

## Uncertainty

Comparative scores allow the comparison of sentiment between each individual tweets, however, they also create a single value for text that may contain mixed sentiment. The additional information output by most sentiment analysis tools that allow the full range of sentiment to be displayed should not be dismissed. An important element of this project will be to represent the uncertainty in the sentiment analysis and the spectrum of sentiment in the tweets. In addition to the range of sentiment within a single tweet, it is also important to represent the range of results when aggregating tweets into a time interval when they are compared as time series data against Bitcoin value.

# Correlation

In order to detect if Twitter is having an influence over the Bitcoin value, a correlation must be observed in a quantifiable way. What differentiates this project from previous studies who have already observed a correlation between cryptocurrency price and social media signals is number of different variables being examined and their effect on the strength of the correlation.

## Volume

As a baseline variable, both Twitter and Bitcoin can be quantified as a volume amount for a given period of time. Evaluating volume does not give an indication of movement (either price change direction or change in sentiment) but can indicate a level of general interest. Observing correlation by comparing volume is a useful baseline as the only additional variables are the candle size interval (i.e. 1 minute) and the selected period of time being observed (i.e. from January 1 2020 to January 31 2020). With no additional variables, a strong correlation can be used as an indicator to the strength and effectiveness of the other sentiment related correlations and potential patterns in time lagged correlation (discussed later).

## Sentiment

The specific analysis and scoring of the sentiment of individual tweets is discussed in section 4, however additional options are available when evaluating a aggregation of tweets. For a correlation to be calculated, both the Bitcoin data and Twitter data must be examined for the same interval, to achieve this multiple tweets and multiple sales must eb grouped together. This process is commonplace in regard to Bitcoin data and is provided in this format as candlestick data. Individual Tweets and their sentiment values must be aggregated manually. The simplest approach is to take average sentiment scores of each tweet and keeping track of the highest and lowest values to demonstrate a range of results. The resulting sentiment scores from Twitter aggregation can however change dramatically when considering the question *‘is everyone equal and relevant?’*

### Filtering

In section 2 many different individual elements were discussed and their potential role in affecting the level of influence on Bitcoin price. Allowing live filtering by user input will enable the user of the project to see the effect that each of these has on both the overall Sentiment and how it impacts the correlation value. Filtering can be applied to number of followers, retweets, likes, comments and verified status. Filtering can also be extended to exclude tweets with a close to neutral sentiment value.

Filtering out some of the lowest values should help to remove additional noise that is masking the more influential messages. If we have already accounted for cleaning data that may be affected by social systems, such as follow for follow then it is reasonable to assume that accounts with a large follower counts are popular due to user choice meaning that other users wish to view their content, read their opinions and facts. A large number of followers may not directly correlate to a higher influence, but in combination with the number of retweets, will result in a larger reach than accounts with a smaller follower group and a lower number of retweets.

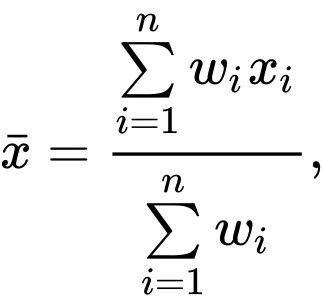
### Weighting

In addition (or as a replacement) to filtering, a weighted method can be employed. A weighted method allows for the potential that every person has the ability to influence, however it is likely not that everyone has the same level of influence.

It is easy to understand that an account with 1 million followers has a larger chance of influencing the Bitcoin value when compared against someone with 1 follower. A closer comparison in reality would be to compare the single user with 1 million followers, against 1 million accounts that only have a single follower each. The potential social reach is the same, but is the level of influence?

A weighted model adds a multiplier to the value of each tweet’s sentiment value. This multiplier can be any of the numeric variables discussed in section 2. This approach allows the inclusion of all tweets (but still allows filtering if required) with tweets with the highest multiplier value (for instance the highest number of followers) to contribute to the overall score more.

In the same format as filtering, the user will be able to change the weightings and combine weightings to visualize the effect on the sentiment score and correlation to Bitcoin value. For this project we will use the weighted arithmetic mean formula below.

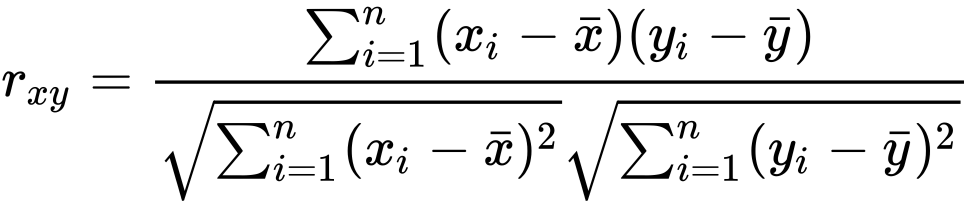
[[1]](#footnote-1)

## Calculating Correlation

A calculated correlation value will be the basis of identifying if the selected body of Tweets (as a collection) are influencing the Bitcoin value. A positive correlation in relation to this project would mean that when the sentiment value is positive, the value of Bitcoin increases and vice versa. A negative correlation would mean that when the sentiment is negative, the price of Bitcoin increases (the variables move in opposite directions).

### Pearson Correlation Coefficient

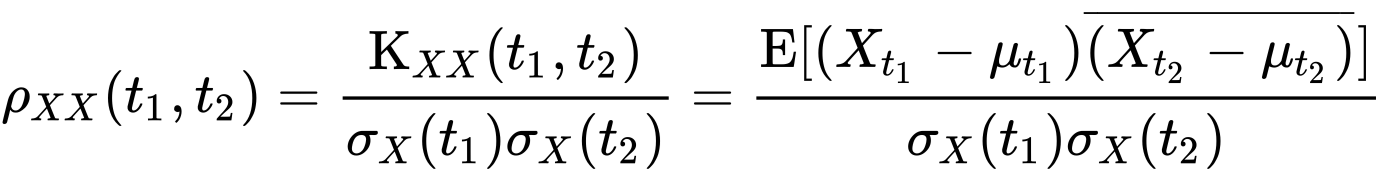
The Pearson Correlation Coefficient (Pearson’s R) is a measure of linear correlation between two variables. The output of the Pearson’s R formula is a value ranging from -1 (negative correlation) to 1 (positive correlation) with 0 representing no correlation.

[[2]](#footnote-2)

Pearson’s R is a popular method for calculating linear and directional correlation in time series data. The issue with its use in this project is that even if there is a perfect correlation (value of 1), it is unlikely that the increase and decrease in both sentiment and Bitcoin value will happen at the same time. For Twitter to have had an influence, people must react to the sentiment and act by buying or selling Bitcoin. The delay between changes will result in Pearson’s R giving a low or null correlation result.

### Time Lagged Cross Correlation

A time lagged cross correlation function (CCF) allows for a correlation to be calculated at different lag (offset) amounts. When normalized, CCF will provide a Pearson’s Correlation Coefficient and will provide a lag amount.

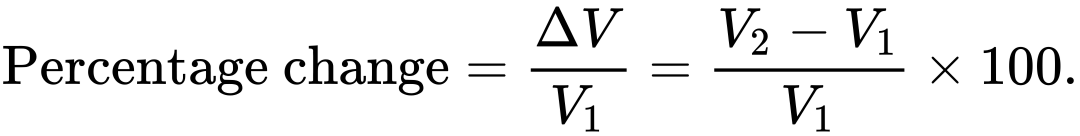
[[3]](#footnote-3)

A negative lag and positive coefficient would mean that a positive correlation is being observed where the direction of the Twitter Sentiment is being followed by the same direction in Bitcoin value. A positive lag value would mean that Twitter is reacting to Bitcoin value changes, which would not infer any influence.

### Variable Selection & Manipulation

Correlation can be calculated using the baseline data for both sentiment (a value between -1 and 1) and Bitcoin value (either open or close price for each interval). The issue with this approach is that each sentiment value (an aggregation a sentiment values over a set interval) is not related to the previous sentiment value, where the Bitcoin price value is a continuation from the previous candlestick.

If a percentage change is calculated for each candlestick, then it is no longer a continuation of price and can help to identify correlation between price and sentiment direction.

[[4]](#footnote-4)

As an additional step both the sentiment and Bitcoin value can be converted in Binary or Categorical datatypes to represent a similar positive or negative sentiment and a rise or fall in value. This would not show if the strength of sentiment is related to the amount that Bitcoin has changed in value, however this is not necessary to show a correlation and infer a level of influence.

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1. https://en.wikipedia.org/wiki/Weighted\_arithmetic\_mean [↑](#footnote-ref-1)
2. https://en.wikipedia.org/wiki/Pearson\_correlation\_coefficient [↑](#footnote-ref-2)
3. https://en.wikipedia.org/wiki/Cross-correlation [↑](#footnote-ref-3)
4. https://en.wikipedia.org/wiki/Relative\_change\_and\_difference [↑](#footnote-ref-4)