Studying the Evolution of Bitcoin-related Topics Extracted from an Online Forum

by

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The undersigned recommend to
the Faculty of Graduate Studies and Research
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Abstract

Besides all uncommon events of 2020, Bitcoin finally passed 20,000 USD in this year, and grabbed more attention about what is going on cryptocurrency and what will happen next? So far, several researchers used social media data in their works and the role of public opinion especially in the specialized forums on Bitcoin price was proved. To have a better understanding about the discussions in a Bitcoin specialized forums, in this thesis we studied the evolution of discussions in `bitcointalk.org`, as the main references of discussions related to Bitcoin over the past 10 years. We found 31 different topics in the forum by applying *LDA topic modeling* and categorized them into 6 categories: *Future*, *General*, *Mining*, *Monetary*, *Regulations*, and *Technical*. Our investigation on this work finds relation between Bitcoin price and the sentiment polarity of selected categories of discussions in the forum.

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Chapter 1

Introduction

In this chapter, Section 1.1 opens describing the idea of this thesis and highlighting the role of public opinion in cryptocurrency studies. Section 1.2 presents our motivation for this work. Section 1.3 outlines our research questions, while Section 1.4 highlights the key contributions. Section 1.5 describes the organization of the thesis.

1.1 Public Opinion in Cryptocurrency Studies

Cryptocurrencies have emerged in the past decade as alternate forms of exchanging value [2]. The demand for cryptocurrencies has been increasing rapidly in the world, as they are accepted and used for many different types of payment and trading [3]. Cryptocurrencies, from the earliest years of their birth, were different from Fiat Currencies and have some distinct differences with traditional currencies. They are decentralized, and their distributed nature has resulted in the fact that up until now, almost none of these cryptocurrencies has been supported by a central government or international institution. Their ownership is anonymous as it is not possible to track the real ownership of an asset, and they are mainly traded online.

Based on the state-of-the-art research literature, the price of cryptocurrencies is volatile and fluctuates more than the traditional monetary items [3, 4]. The price of

Bitcoin, the largest cryptocurrency by market capitalization [5], has been fluctuating from less than 1,000 USD at the beginning of 2017 to more than 19,000 USD in less than nine months. But it has dropped to around 6,000 USD in the middle of 2018 and continues to fluctuate since [6]. Even, at the time of writing this thesis, in December 2020, it has reached again 19,000 USD and is highly likely to hit 20,000 USD before the end of this year. As we describe in Section 2.1.4, cryptocurrencies’ valuation, analyzing their price volatility and analysing their prices is an open research question, and numerous research studies have been conducted in this area [7].

Social media data is one of the important sources of information for analyzing the cryptocurrencies’ price [8]. Public opinion in the Bitcoin-specialized forums such as `Bitcointalk.org` or `Reddit.com` has been used for analyzing the impact of users’ discussions on Bitcoin’s price in recent papers [6–8]. In this work, we will investigate the data extracted from social media within a long period of time (past 10 years) to gain a comprehensive view about this domain and the role social media plays in the world of cryptocurrency. In order to do that, first we determine discussion topics from the online forum and study the topic evolution over time. Then, we apply the sentiment analysis on the posts and determine how sentiment evolves over the time. Finally, we explore the correlation between the discussion topics and their sentiment and the price of Bitcoin.

1.2 Motivation

With the increasing prevalence of Bitcoin in trades, a growing number of people participate in online discussions on forums to share their knowledge. Bitcoin is usually traded online, and it is the common practice for the traders to make their trading decisions based on the information they gain on the online discussion forums [9]. Users of these forums and websites tend to share their opinions, reasoning and concerns

which in a long term create a rich source of information.

The previous research in this area has already recognised the importance of public opinion in future price of Bitcoin and involved this factor in their price analysis models. However, to the best of our knowledge, virtually almost all of them have considered the effect of social media content as a static factor and because of the change in the public opinion about a topic, these models tend to lose their accuracy over time. The aim of this research is to study and analyze the changes in the discussion topics and see how these topics evolve over time. We are interested in highlighting the changes that happened in the past to show the effect of the changes in discussions on the traditional predictive models.

Cryptocurrency, in general, is a new term and it takes a lot of time and effort to be well understood by people. Considering this fact, in this research we study discussions and posts in online forums to provide a new insight about Bitcoin. We collect and categorize the online debates, interpret them and link them to the Bitcoin price fluctuation. The result of this work can be used in cryptocurrencies' price analysis. Moreover, the final findings of our work can be helpful for gaining a better perception about different aspects of this domain.

1.3 Research Questions

The goal of this thesis is to gain new insights about Bitcoin by mining and investigating `bitcointalk.org`. Figure 1 illustrates the road map that we followed to provide answers to the following research questions:

1. **RQ1: What topics are discussed in a Bitcoin specialized forum?** On `bitcointalk.org`, users who are interested in cryptocurrency share their ideas and seek feedback from others. Over the past decade, many different topics have been discussed in this forum. In RQ1, we detect and classify all the discussed

Figure 1: Research roadmap.

topics in this forum. This classification provides comprehensive metadata about the discussions in the cryptocurrency domain and helps researchers to have a better understanding about the domain and its discussion topics.

2. **RQ2: How do the discussion topics on the forum evolve over the time?** The social media data affects cryptocurrency price, and it is used as an input factor in cryptocurrency's price analysis. In this research question, we study the patterns of the topics, when the new topic emerges and how long it lasts. These findings highlight the evolution patterns of the topics in the forum. The result of this research question can help the designer of current models to consider the evolution of topics in their models and reach higher performance.
3. **RQ3: How does the topic's volume of posts change over time?** As we mentioned in the previous RQ, some topics are used in the price analysis models. In this research question, we study the changes in the number of posts over time. The result of this RQ can offer new insights into the discussion trends of the topics over time. We can gain insights into what topics are heavily discussed during the past decade. The results can be also useful for tuning the price analysis models as the change in the discussion topics could be taken as an effective input parameter in the model.
4. **RQ4: What sentiment is associated with each discussion topic?** The sentiment is measured as sentiment polarity of the posts in the forum, and can be used as a feature to be added to the model for analyzing the future price of cryptocurrencies. Previous research has considered sentiment as a factor in their price analysis models. In this research question, we analyze the sentiment similarity between different discussion topics. We try to find how different discussion topics in the forum are similar in terms of their sentiment polarity, as well as the way these polarities change over the time. It's important to

understand what topics carry a more positive or negative user opinion. The results of this RQ can highlight the difference in sentiment across various topics, and lays the foundation for the researchers to study sentiment in different topics. To the best of our knowledge, most works that use sentiment analysis only analyze the sentiment polarity of the full data set, yet presenting the difference of sentiment weights in different topics makes it possible to design more accurate models.

5. **RQ5: Is there a correlation between the evolution of the Bitcoin-related discussion topics and the Bitcoin price volatility?** In previous research questions we try to determine factors related to the discussions in the forum. For the final research question, we try to identify the correlation between Bitcoin's price and these factors. The goal of this RQ is to identify what factors have relation with Bitcoin price. This work explores and highlights the major criteria which can help experts design better price analysis models by focusing on determining factors. Furthermore, this study introduces a number of parameters that may affect Bitcoin price. This, in turn, helps different stakeholders within the Bitcoin community pay attention to these parameters and be informed on the determining factors for making better long-term goals and plans.

1.4 Contributions

The contributions of this research study are as follows:

1. A longitudinal analysis of the discussion topics extracted from the online forum during the 10-year time period.

2. Extraction of 31 topics related to various discussions about cryptocurrency classified across 6 categories.
3. Analysis of the evolution of topics in the forum.
4. Sentiment analysis of the discussion and the study of sentiment changes over the past 10 years.
5. Analysis of the factors related to Bitcoin price.
6. A dataset of the discussions on the Bitcointalk forum.

1.5 Organization of the Thesis

The structure of the remaining chapters in this thesis is as follow: Chapter 2 offers background and presents key concepts related to Bitcoin. It also introduces topic modeling, as well as reviews relevant related work in this area. Chapter 3 presents methodology and describes data collection methods and data analysis techniques used in this work. Chapter 4 reports the results and answers to our research questions, while Chapter 5 discusses implications of our work. And finally, Chapter 6 concludes this thesis by offering the summary and discussion of future directions for this line of research.

Chapter 2

Background and Related Work

In this chapter, we first provide background on cryptocurrency and Bitcoin in Section 2.1. We then present topic modelling in Section 2.2. Finally, in Section 2.3, we discuss the previous works related to our research and highlight the novelty of our work in this domain.

2.1 Cryptocurrency and Bitcoin

The goal of this section is to describe the role that our results can play in the cryptocurrency domain. We start the item with the “Story of Bitcoin” in Section 2.1.1 and then continue the text with a brief review on blockchain technology and its applications in Section 2.1.2 and Section 2.1.3. Then, we discuss the valuation of cryptocurrencies in Section 2.1.4 and discuss the effects of public opinion on cryptocurrencies in Section 2.1.5.

2.1.1 Story of Bitcoin

The story of Bitcoin began with a paper titled “Bitcoin: A Peer-To-Peer Electronic Cash System” published by a person or group named Satoshi Nakamoto, the identity is yet to be confirmed, in 2008. The paper described a method of direct online payment

without the need for any financial institution to be involved in the process. Some months later on January 2009, an open source program which implemented this new protocol was released and the story of Bitcoin began. As the leading cryptocurrency, Bitcoin, has had its ups and downs over the past decade. Playing a major role in Silk road black market, rising its value by nearly 2000 percent in 2017 are among the most mentionable points in the history of this popular cryptocurrency. Right now with over 400 billion CAD, Bitcoin owns nearly 60 percent of the whole cryptocurrencies market values.

As the main focus of this study will be on the discussions on social media, we reviewed some of the previous works and prerequisites for it. We will start with a brief description of blockchain as the main technology behind Bitcoin and other cryptocurrencies and describe the way they work. In the later sections, we present applications of cryptocurrencies and continue with the valuation of Bitcoin and the effects of public opinion on it.

2.1.2 Blockchain Technology

Like all other digital currencies, Bitcoin is not saved on any specific database, and the records of all activities are stored on a blockchain [3]. A blockchain is a distributed database of public ledger/records that have been executed and shared among different participating parties [10]. Generally, users of a system are required to be authenticated in order to insert a new record into the database. Similarly, any new piece of information or transaction needs to be validated by the majority of the peer-to-peer network to be saved in a blockchain. Blockchain uses public and private keys for verification of information and saves the data in an encrypted format. Like all other cryptocurrencies, Bitcoin uses “blockchain technology”, we explain this technology on the example of Bitcoin transactions. Assume Alan wants to transfer one bitcoin to Bob in his “Wallet”. Alan prepares a new block with the “public key” of

Bob (receiver) and his own “private key” (sender) and broadcasts it to the network. The network validates the transactions by checking two criteria: first of all it checks whether the sender account actually belongs to Alan by checking his digital signature, and secondly, it verifies whether he has sufficient bitcoins in his account by reviewing his previous transitions. If these steps are passed, this transaction will be saved as a new chain in the ongoing blockchain, and from that time on, Bob will be considered as the owner of the transferred bitcoin.

We now provide the definitions of the terms used in the above example [11]:

- **Wallet:** A Bitcoin (cryptocurrency) wallet on the Bitcoin network is similar to the physical wallet in daily life. It involves “private key”, which is the element that enables users to make a transaction in the blockchain. A wallet shows the total balance and enables users to pay some bitcoins to any other member in the network.
- **Blockchain:** is a record of all previous records for the cryptocurrency and is publicly available. Blockchain verifies the validity of a transaction, and also is used for preventing “double spending”.
- **Double-Spending:** if one user tries to spend one bitcoin for two different payments simultaneously, it is called double-spending, and is stopped with the help of mining in a blockchain.
- **Mining:** each new transaction needs to be verified in the network, and cryptocurrencies use mathematical calculation to do it. That is, only the miner, who solves the latest problem, is allowed to add the block to the blockchain. For instance, in the above example, the first miner who solves the problem will be able to transfer the ownership information of the transferred bitcoin from Alan to Bob and will earn some bitcoins as a reward of its work.

In conclusion, blockchain plays the role of a trustworthy intermediary party like banks in traditional transactions, and provides a reliable environment with a peer to peer (P2P) network. Given the fact that the data is decentralized and distributed in different nodes on a network, it is safeguarded against being stolen or lost, like what it used to be in the traditional databases. Furthermore, since the responsibility of storing and processing data is distributed among some parties, it is highly unlikely to be dependent on any central authority or government. Having said that, there is only one special and hypothetical case that might threaten a cryptocurrency which is known as 51 percent attack. This attack happens when a number of miners gain the control of more than 51 percent of the network, thereby being able to apply any change they want in the blockchain. The blockchain technology has revolutionized the world of finance and opened new doors to state-of-the-art applications without the need for any governmental or central unit to be involved in the process. We present some of its most important applications next.

2.1.3 Cryptocurrencies Applications

Blockchain has laid the foundation for many services to be delivered in a decentralized manner. The range of these services is so wide that many specialists such as professor Tapscott called the technology as “blockchain revolution” [3]. Cryptocurrencies have numerous applications and in this section we review six distinct categories of them suggested by McKinsey & Company [12].

1. **Static registry:** it is a distributed database for storing reference data which are the information that enable users to have an estimation of ownership’s properties.
2. **Identity:** the next is related to storing personally identifiable information which can be used in elections or identification processes.

3. **Smart contracts:** smart contracts are self-executing and automatic transactions which occur between buyer and seller based on a decentralized consensus record [13].
4. **Dynamic registry:** for keeping records of the current owner of an asset, i.e., a shipping material in supply chain or stocks.
5. **Payment infrastructure:** the way people can transfer money without the need for any third party to transfer the money, either locally or internationally.
6. **Others:** there are many other applications. For example, by using smart contracts, many IoT devices are able to directly trade between themselves. As an illustration, a traffic camera can earn the cost of its electricity bills by selling some information to traffic monitoring apps.

2.1.4 Bitcoin Price and Cryptocurrencies Valuation

One of the most controversial questions in the world of cryptocurrencies has been about the intrinsic value of Bitcoin and the possible ways to calculate it. Finding the ways to predict the future value of Bitcoin and the determining factors has been quite interesting and even crucial for different stakeholders [9]. Investors, for instance, require predictive models to plan for their investments and calculate the expected return. Policymakers, on the other hand, need some means by which they can take proper measures to minimize financial risks and increase stability in the world of cryptocurrencies [14]. The price of Bitcoin at the time of its launch was less than 1 USD, and about one decade after its launch time, this value reached 20,000 USD. The price of this currency has experienced many fluctuations, and doubling or losing half of its value during only one season has been quite common. Only at the time of writing this thesis, the price of Bitcoin fluctuated between 7,500 and 23,000 USD [15].

There must be far more explanations for Bitcoin price fluctuation and this phenomena cannot be sufficiently explained by standard macroeconomic theories [7, 16–19]

Finding a proper answer to this question along with analysing Bitcoin price and predicting its future value is a challenge in the world of economics and many papers have targeted this domain. Given the wide range of these researches, we only mention [20], [21], [22], and [23] as few examples among hundreds of works. One of the matters about evaluation of Bitcoin price that has attracted attention in many papers is the effect of social media on Bitcoin price. Not only the change in price causes many debates in social media, but some discussions result in change in the price of Bitcoin. We will discuss this matter in Subsection 2.1.5 with more details.

2.1.5 Public Opinion effects on Cryptocurrencies

A variety of stakeholders are involved in cryptocurrency communities such as traders, miners, users, developers and so on. There are a number of platforms that provide the possibility of discussing cryptocurrencies. The most familiar forums for these discussions are official forums such as bitcointalk.org and reddit.com, as well as social media such as Facebook and Twitter [24]. From the past, a number of research studies have been carried out in this domain to determine whether social media can affect the price of Bitcoin and reveal their relation [9]. Some studies have adopted Wikipedia and Google Trend in public opinion analysis, for instance, Kristoufek et al. [25] and [18] surveyed the correlation between Bitcoin price and the information on the above mentioned examples, or Jin et al. [26], worked in the Google Trends data to predict ICO¹. Several other researchers have adopted Wikipedia and Google Trend in their works [25], [27], [6].

The other source of data that has been used in public opinion analysis widely is Twitter. Twitter posts have been the source of data for many stock analysis papers

¹Initial Coin Offering

such as [28] and [29]. Given the similarity of Bitcoin and stocks as an asset, Twitter has been widely adopted in the Bitcoin price analysis. For instance, the sentiment weight of tweets has been used to analyze Bitcoin price [30], and [31], [32].

Another adoption in the Bitcoin price analysis is the use of the information on specialized forums, and the two major sources in these works are Reddit and Bitcointalk [8], [6], [7].

Existing state-of-the-art research highlights the key role of social media in Bitcoin price prediction. Moreover, posts in forums usually affect Bitcoin price more strongly compared to tweets [33]. Based on this evidence, in our research we focus on specialized forums that are dedicated to the Bitcoin discussions and try to answer the questions related to the Bitcoin discussion and social sentiment (as presented in Section 1.3). In order to become more familiar with the existing research literature, we study the state-of-the-art and discuss previous works in Section 2.3.2.

2.2 Topic Modeling

Topic models are a modern class of text analysis methods that have been embraced by a range of scholars in the social sciences, humanities and beyond. The most peculiar feature of topic models is that they remove the need for a supervisor to provide initial insights for the model to be trained. In other words, topic models facilitate an automated procedure for coding the content of a corpus of texts into a set of substantively meaningful coding categories called “topics” [34].

What made topics models unique among previous models is that they minimize the need for an intelligent agent (like humans) to be involved in the process which caused a revolution in a number of branches of science [35]. Unlike traditional approaches in text processing such as BOW [36], topic models take into account the semantic context of words in their unsupervised training steps [37, 38].

In this section, we describe Latent Dirichlet Allocation (LDA) in Section 2.2.1 and explain how it works in Section 2.2.2. Section 2.2.3 highlights the good number of topics in an LDA model, while Section 2.2.4 explains its validation. Section 2.2.5 describes key text pre-processing techniques for LDA, and finally, Section 2.2.6 discusses the reason why we selected topic modeling rather than self-organizing map technique.

2.2.1 Latent Dirichlet Allocation

The origin of LDA dates back to the 1980’s when there was a need for a means to retrieve text information more accurately. The oldest member of the topic modeling family is called Latent Semantic Analysis (LSA) which was introduced by Deerwester, Dumais, Furnas, Landauer, and Harshman [39]. LSA enabled researchers to cluster documents with similar words considering the theory that words with similar semantic ranges are highly likely to be seen together. Several years later, in 2003, Blei, Ng, Jordan, and Lafferty adopted the main idea of LSA and developed another algorithm for topic modeling called Latent Dirichlet Allocation (LDA) [40]. LDA is a generative probabilistic model for a collection of discrete data, for instance, a collection of documents. The basic idea behind this model is that documents of a corpus are represented as random mixtures over latent topics [40]. A topic in this definition is considered to be a distribution over words. This gained a lot of attention and inspired many researchers and academics in their works. LDA represents topics by word probabilities. The words with the highest probabilities in each topic usually illustrate the main concept of the topic. For example, a topic consisting of the words such as “Bitcoin”, “digital currencies”, “blockchain”, and “wallet” that have the highest probability is more likely be labeled as “cryptocurrencies”.

Figure 2: A graphical representation of the distribution of topics in a document in an LDA model [1].

2.2.2 How LDA Model Works

LDA follows a generative approach to find the parameters which are used in the model. The primary assumption is that there are k latent topics according to which documents are generated, and that every topic is represented as a multinomial distribution over the $|v|$ words in the vocabulary. A random document is created by sampling a mixture of the above-mentioned topics and then sampling words from that mixture [40]. After training a LDA model on a set of documents, every document could be represented as a distribution over topics, but the point is that the probability of topics varies in different documents based on their main semantic context, Figure 2 represents a sample graphical distribution of topics in a document. In order to be trained on a collection of data, LDA models require four fundamental parameters:

1. α : indicates the document's prior distribution. This parameter is generated from a Dirichlet allocation distribution on a random base and with α hyper-parameter.
2. β : indicates the topic's prior word distribution. This parameter is generated from a Dirichlet distribution on a random base and with β hyper-parameter.
3. k : indicates the number of topics that we expect the model give us after

training phase.

4. *The number of iterations* which specifies the maximum number of runs that the model is allowed to pass to converge.

In a LDA model a document which consists of N words $w = (w_1, \dots, w_n)$ is generated according to the following steps:

First, the model makes a sample for θ from a Dirichlet $(\alpha_1, \dots, \alpha_k)$ distribution. Thus, we can say that θ lies in the $(k - 1)$ dimensional simplex: $\theta_i \geq 0, \sum_i \theta_i = 1$.

In the next step, for every single word among N words in the corpus, a topic $z_n \in \{1, \dots, k\}$ is sampled from a Mult(θ) distribution $p(z_n = i | \theta) = \theta_i$.

Finally, each word w_n is sampled, conditioned on the z_n th topic, from the multinomial distribution $P(w | z_n)$

According to the above definitions we can write the equation for a document's probability in Formula 1:

$$p(w) = \int_{\theta} \left(\prod_{n=1}^N \sum_{z_n=1}^k p(w_n | z_n; \beta) p(z_n | \theta) p(\theta; \alpha) \right) d\theta \quad (1)$$

In the above equation $P(\theta; \alpha)$ indicates Dirichlet, $p(z_n | \theta)$ is a multinomial parameterized by θ , and $P(w_n | z_n; \beta)$ is a multinomial over the vocabulary of the corpus [41]. Figure 3 shows an overall schematic of these parameter assignment.

2.2.3 How many topics a good LDA model should have?

In order to have concrete topics in a topic model, it is of great importance to choose the right number of topics according to the nature of the corpus. Some academics take this as one of the shortcomings of topic modeling as determining the number of topics is usually a challenging task [43]. While other researchers believe that the right number of topics should be guessed by evaluating the real performance of the model [44]. That is why most of the researchers empirically try several numbers of

Figure 3: An overall scheme of parameter assignment in a LDA model. The boxes are plates indicating replicates. The outer plate indicates documents in the corpus, while the inner plate is an indicator for the repeated choice of topics and words in a document [42].

topics to determine the best number of topics that suits their data. Carron-Arthur et al [45] examined the performance of the topic model by trying different number of topics known as k . The number of topics varied between 10 and 100 as they monitored the performance of the model by investigating the top words in every topic. They concluded that models containing more than 30 topics tended toward duplication. On the other hand, having less than 20 topics did not lead to satisfactory results as some independent and distinct topics merged together. Yau et al. [43] tested a number of different values for k ranging from 50 to 200 but ended up using only 50 since interpreting the results can be handled easier and more effectively. These studies do not explicitly indicate how one should choose the number of topics when training a topic model. However, it can be concluded that several tries and errors are required to find the optimum number of the topics. Furthermore, we can say that the right number of topics for a model should strike a balance between topics which are too general (choosing too few topics) and topics which are too specific (choosing too many topics).

2.2.4 Validation of LDA models

One of the most important questions that should be answered after building a topic model on a text corpora is how good the model is? The minimal expectation of an acceptable topic model is that it must have topics which are semantically related. In order to measure coherence level among topics, there are both qualitative and quantitative measures, however, most of the researchers prefer to use qualitative evaluations of the coherence of topics in a topic model [8, 46]. For qualitative evaluation, researchers can manually investigate the topics and check if the top words in a topic actually are related and belong to the same context semantically. Martin and Johnson [47] comment that the top words in a topic must not be ambiguous nor be without an interpretable theme. Chang, Boyd-Garber, Gerrish, Wang, and Blei [48] propose a “word intrusion test” to measure the consistency of words in topics. In their experiment, they selected some topics and replaced one of the top 10 words of these topics with another word calling it “intruder” word. Their judgement about the quality of the model depended on the participant’s ability to find this replaced word. If the participant distinguished the intruder word without trouble, the model was considered to be coherent. Carron-Arthur et al. [45] mention the significance of “domain knowledge” in this domain. That is some words might be taken as intruders to a topic by the in-charge participant, while they are actually related to the topic from the specialists in the subject. Researchers have already adopted other methods to validate how precise the topics of a topic model are. Agrawal et al. [49] measured the quality of topics using the words that overlapped in different topics. The overlap metric used was *Jaccard similarity*. To sum up, we can say that a good topic model must be practical and applicable. A topic model which is useful for gaining an overall insight over a huge corpus of text documents may not be ideal for one which is going to be used for classifying documents precisely. That is why defining strict measures to

examine the performance of a topic model is not easy nor helpful, and the researchers should decide on some aspect of the model based on their own requirements and expectations.

2.2.5 Text Preprocessing for LDA

Pre-processing is a vital step in almost every text processing task including building a topic model. In order to achieve good results and coherent topics, documents should be prepared in a way that the most influential features of the corpus could be extracted and interpreted by the computer [50]. This pre-processing step might include a number of similar tasks such as normalizing the data, tokenizing the documents, removing stop words, stemming, lemmatization, etc.

In *normalizing* step characters with different written forms will be converted to the same form. For instance “is not” and “isn’t” should be considered one word. Furthermore it is of great importance to correct spelling errors in a corpus as much as possible since a machine considers miss-spelled words as nonsense which reduce the quality of the model [51]. Researchers could place a premium on text normalization, especially when the data comes from noisy sources such as social media, text messages and comments on blog posts and web pages, since the use of informal language, abbreviations and misspellings are common in these cases. In a social media corpus removing hashtags, punctuations, users, and other unimportant signs and words forms a great part of the work.

The *lemmatization* and *stemming* are two common ways to reduce the number of words in a corpus which belong to the exact same semantic family. For example after lemmatizing a document “see”, “saw” and “seeing” would be converted to the same form (i.e., “see” which is the root of the verb). The same rule is adopted in finding the stem of plural words. That is, the word “books” will be converted to “book” after lemmatization [52]. Not only does this reduce the number of words

which should be processed in a corpus thereby reducing processing time and resource, but the performance of the model is highly likely to increase as the words with the same context are already introduced to be the same. Lemmatization and stemming each normalize the text in helpful ways, but more work may need to be done in this regard. *Removing stop words* is a standard practice in preparing a corpora for the further processing tasks. The main idea behind this step is that words which are so repetitive and do not have much information could be removed to give the model the opportunity to only concentrate on real informative vocabulary. Furthermore, according to the nature of the corpus, other words may need to be removed as well. For instance, the corpus of scientific journals processed by Suominen and Toivanen [44] tended to have acknowledgment sections which were not informative for their project and they decided to omit these sections in their work. Some of the words that are usually taken as stop words in English documents are “that”, “is”, “are”, etc. In an LDA model, for instance, the existence of such words in a document does not help the model to link the document to the correct topic as they do not have a special meaning.

Apart from removing stop-words which are usually quite repetitive in a corpora, one might decide to remove very rare words in their work as they distract the topic model. In fact, there is not a standard guideline for removing words and researchers usually do apply this based on their experience. Székely and vom Brocke [50] deleted words that appear in fewer than two documents, Carter et al. [53] removed words that exist in fewer than 50 documents or that exist in more than 50 percent of the corpus. Mimno [54] suggests that there could be called a 5-10 rule: remove words that appear fewer than 5-10 times and remove words that appear in more than 5-10 percent of the corpora.

Although these recommendations and experience can give us a good insight, they cannot be applied without paying attention to the objective of the final model. Some

researchers such as Székely and vom Brocke [50] suggest that in order to make sure that nothing has slipped in the pre-processing step it might be a good idea to check the corpus manually in the final step.

Researchers already have adopted some other techniques to reduce the number of words in a collection of text documents. For example, Martin and Johnson ignored all words except for nouns in their work [47]. They developed three topic models each one based on three different versions of the same news corpus. The first one is the original version of the corpus without any pre-processing, the second is a lemmatized version, and in the third copy of the corpus they only include the lemmatized version which had only noun words. The final result of the experiments revealed that the topic model trained on the third version of the corpus was the most coherent one. In other words, according to their experiment lemmatized nouns are the most informative members of a corpora and omitting other words (verbs, prepositions and adjectives) can help the model to find the semantic relations far easier.

2.2.6 Topic modeling vs. self-organizing map

Self-organizing map (SOM) is a type of artificial neural network (ANN) that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretized representation of the input space of the training samples, called a *map*, and is therefore a method to do dimensionality reduction [55]. A SOM can parse the entire dataset in different groups according to the similarity of the features of input data. SOM is useful for visualization of complex or high dimensional data in a low dimensional map typically with two dimensions [56]. Since the goal of our research is studying the evolution of topics, SOM cannot elaborate on the topics of discussions like LDA. When applying SOM, we would need to find the topic of each cluster.

In our work, for finding the evolution of topics, we split our dataset into 22 six-month periods and ran the LDA model for each period separately. According to Rzeszutek et al. [57], it is possible to apply LDA-SOM for finding the evolution of topics. In this method, researchers initially run topic modeling over the entire dataset and then use SOM (clustering technique) for studying the evolution of topics over the time.

We provide the following justification for the choice of leveraging topic modelling over SOM in this work:

- Since previous works have used topic modeling, we decided to be consistent with the selection of our methods to be able to compare our results and findings with the state-of-the-art research.
- Both methods are simply different machine learning techniques. Our choice of LDA vs. LDA-SOM is subject to the following pros and cons:

– **Pros:**

- * LDA models are trained for each of the 22 datasets, thus, reducing the time to train each model on a smaller data compared to the entire dataset that SOM is using for training.
- * Topic modeling finds similar sets of words across different discussion posts. For example, both CPU and GPU are frequent words in the same “Mining” topic. Since SOM is trained on the entire data, different words would be treated as different topics. However, training LDA on smaller datasets would allow us to put these two words into one topic.
- * Parameter optimization is essential for LDA, as well as manual inspection of the topic numbers since some topics only exists in very limited series. It is possible to miss such topics with SOM.

– **Cons:**

- * Our method includes manual topic labeling. SOM is more automated and can reduce human errors.
- * A new LDA-based topic model needs a new customized preprocessing prior to training, while SOM can handle live data for training a model.

According to Section 2.3.2, previous works in this domain used topic modeling and thus, to be consistent with the previous research, we apply topic modeling in our work.

2.3 Related Work

We review previous research that adopted topic modeling in Section 2.3.1 and then discuss previous works on social media analysis related to Bitcoin in Section 2.3.2.

2.3.1 Application of Topic Modeling

Topic modeling has been a hot topic over the past decade and it has won over many researchers who work on natural language processing tasks. Many articles have been published based on topic modeling approaches in a wide range of subjects such as linguistic science, social network, software engineering, etc. Chen et al. [58] have studied the possible ways by which topic models can play a constructive role in software repositories. They provided a collection of articles which were published between Dec 1999 and Dec 2014. Aiming at finding the works related to software engineering that applied topic models, they identified and demonstrated the research trends in mining unstructured repositories using topic models. They found that many software engineering tasks were neglected and only basic topic models were adopted in these works [34].

An important challenge in the natural language processing world is text summarization which takes the most important parts of a document and creates an informative summary from a document automatically. Arora and Ravindran [59] used LDA to find latent variables in word level and SLDA (sentence-based latent Dirichlet allocation) to do the same thing in sentence level. They used Document Understanding Conference (DUC) which is a news corpus in their work and managed to achieve higher precision and recall and F-measure compared to other methods. Zhai et al. [60] aimed at adopting topic modeling in opinion mining with a focus on product reviews. The problem that this work tries to resolve is the wide range of words used in reviews to describe the same feeling. In other words, reviewers express the same opinion with diverse phrases and words which makes the further processing tasks challenging. This work used topic modeling to group semantically related words together. Furthermore, it suggests that pre-existing information can help the topic model to gain better results. Nolasco et al. [61] designed a modular algorithm which works based on topic modeling and introduced a new term called “sub-event”. In order to address the problem in previous works (existing models assumed an event to be a single entity ignoring that it can be composed of other events over time), they suggested a model that identifies sub-events and creates labels to represent them more accurately. They evaluated their proposed method using two large-scale Twitter collections. Their approach detected several sub-events, most of them were related to real sub-events. Naskar et al. [62] tried to focus on discussions on social networking websites to find the sentiment behind sentences in online conversations. Their goal was to identify users’ feelings in the social network through their conversations. They conducted a study to determine whether users of social networks (Twitter, in particular) have a tendency to form gatherings based on their common interests. Jin et al. [63] introduced Targeted Aspects Oriented Topic Modeling (TATM) to find better-oriented topics in documents where short length of text is a concern. The benefit of their

proposed strategy is that the topics which are generated using their model are more focused and homogeneous as each topic has its focus on a specific aspect. After training their model on a real-word database they ended up producing more concrete and complete topics.

2.3.2 Cryptocurrency Analysis in Social Media

Social media messages are one of the predictor parameters in Bitcoin valuation [9] and the majority of investors develop their investment strategies on cryptocurrencies considering the resources they find on the Internet [7, 64].

This area has gained increased attention in many research works related to cryptocurrencies. Many researchers focus on quantitative data and search engine information by studying Google trends, Wikipedia, or quantitative statistics of social media, mainly Twitter, in their recent research [9, 16, 18, 31, 65, 66].

Although the content of popular social media such as Twitter has been the main source of analysis in many research works, there are some concerns about the quality of these data [8]. First of all, many researchers put forward the argument that many tweets might be spam thus worthless. And secondly, people talking about cryptocurrencies usually do not discuss other topics, thus, analyzing their opinion on the specialized forum related to Bitcoin may provide better results.

To the best of our knowledge, there are only a limited number of research works that have performed some explorations of the social media that focus on cryptocurrencies such as www.bitcointalk.org and www.reddit.com. In this section, we review these works in more detail and discuss their findings.

Kim et al. in 2016 [64], tried to provide a predictive model for cryptocurrency using the related discussions about Bitcoin, Ethereum, and Ripple, three cryptocurrencies with big market size and dedicated public discussion forums on that time. They developed a web crawler to collect comments from web forums and tagged

them using a sentiment analysis tool called VADER. This tool proposed by Hutto et al. can be used for classifying comments in online communities [67]. It assigns all comments with a score in the range -1 to 1 for negative and positive ones.

For the next step, they applied the Granger causality test to find the correlation between the fluctuation in cryptocurrencies' prices and comments in forums. This test has been already adopted in many researches related to market shares and currencies [68]. The input data are online comments, the price of cryptocurrencies and the number of transactions of cryptocurrencies. The findings of this paper suggest that user comments and replies can be a source of data for price prediction, there is a relation between positive vs. negative comments on price change but the pattern is different for each cryptocurrency, and there is a positive relationship between the number of transactions and replies in the forums. All in all, this work was one of the earliest researches on the role of public opinion on cryptocurrencies, but it studied a limited history of cryptocurrencies at that time.

Lee et al. [6] have tried to build predictive model with deep learning using the comments in an online forum. They used the comments on www.bitcointalk.org as their main source of input data and scrapped the content of this website between December 2013 and September 2016. They also used Google daily Trends and Wikipedia daily usage for Bitcoin for training of their learning model. For their analysis, they first used Nonnegative matrix factorization (NMF) algorithm of topic modeling for creating an initial lexicon. For the next step, they expanded the corpus using kernel density estimation (KDE). They had selected 10 concepts among items and provided scores for all of them per topic. Finally, they applied a deep learning model based on the above mentioned KDE-based topic scoring and other quantitative data such as the number of topics, the sum of replies, the sum of views, Google Trend Value, and Wikipedia Pageviews. The best prediction result was achieved when they used a three-layer neural network which had an accuracy of more than 80 percent.

Kang et al. [7] have tried to recognize the influencer groups in social media who mainly discussed Bitcoin. They used the online discussions on www.bitcointalk.org as the input dataset for their paper. They crawled all discussions from November 22, 2009 to February 2, 2018 and categorized the users by applying a hypertext-induced topic selection (HITS) algorithm into two groups: opinion leaders and majority users. The authors used Pareto's principle (proposed by Koch et al. [69]) and considered the top 80 percent of authority scores for classifying these two groups. Opinion leaders formed around 11 percent of the members with an overall 49 percent of the total posts and comments in the dataset, and the remaining 51 percent posts and comments were from the 89 percent remaining members. For analyzing the role of influencer, they analyzed the comments in three different groups such as opinion leaders, majority users, and total users. The paper applied the topic modeling technique (NMF) to analyze the comments between June 1, 2015, to February 1, 2018. The findings of the research group are as follows:

- The majority group mainly focused on price, transaction, and investment while the opinion leaders discussed technical terms in addition to their discussion on financial matters.
- There is a similarity between the topics in the opinion leaders and the total members. So it is possible to evaluate only the topics from the opinion leaders group to analyze the entire community.

Philips et al. [8] have focused on determining the relation between the change in the price of cryptocurrency and the topic of discussions in social networks. This research employed the discussions about Bitcoin and Ethereum in a Reddit forum, in technical and trading subreddit forums for Bitcoin and Ethereum. They first applied a dynamic topic modeling approach (an extension of LDA) to retrieve information from social networking websites and then adopted the Hawks model to find the relation between

the retrieved topics and cryptocurrency prices. The results of their work introduce a direct relationship between the discussions in social media and the change in the price of cryptocurrencies. They claim that some items could be taken as an indicator for increase or decrease in the price. For instance, items such as risk, investment, or trading can indicate price reduction. Conversely, items such as “substantial price movement” indicates price fluctuation, and “fundamental cryptocurrency value” is a signal for a rise in prices. One main limitation of this research is they used four different subreddit forums, and some of the results were not consistent. Therefore, it is essential to investigate the process using a better dataset to enhance the reliability of the results.

Chapter 3

Methodology

This chapter describes the approach we adopted to extract and analyze the evolution of topics on social media discussions. In Section 3.1 we describe the datasets we collected and used in this thesis, while Section 3.2 presents the data preprocessing, modelling, and analysis techniques. Section 3.3 reports on the software and tools used in this work.

3.1 Datasets

In this work, we extracted and collected the discussion data from `bitcointalk.org` and gathered the historical price data from `coindesk.com` and `bitcoincharts.com`. Since researchers have used Twitter, Reddit and/or Bitcointalk data in their works, we offer several reasons justifying our choice of the data source.

- The goal of this research is to study the evolution of discussions related to Bitcoin over time. Thus, we opted for mining the data from a publicly available specialized forum, rather than Twitter data since historical data for Twitter (i.e., past 10 years) is not freely available.
- Twitter data is typically less formal, contains hashtags, slang, and informal

words. Since topic modelling is sensitive to the quality of the input data, training a reliable topic model is essential for our work.

- Comparing Bitcointalk and Reddit, researchers have worked with Bitcointalk in the past. To be able to compare our findings with previous research, we have decided to mine Bitcointalk for our longitudinal analysis of the discussions.

3.1.1 Bitcointalk Data

Bitcointalk.org is a forum website in which users share their opinions on different topics related to the cryptocurrency. The forum is divided into five different sections: Bitcoin, Economy, Local, Alternate cryptocurrencies, and Other. Each section has its own subsections. In this work, we collected all the discussions of the “Bitcoin” section. We used the BeautifulSoup library of Python and crawled all the 48,819 discussion subject posts and 511,233 replies which were posted between December 16th, 2009 and October 1st, 2020. Apart from the main content of the posts, our dataset includes information about their authors, the date and time of the post, and all the replies which were related to the post. This dataset is made available on GitHub¹ for future studies.

3.1.2 Bitcoin Price

In this work, we collected the daily price of Bitcoin by downloading the data from [coindesk.com](https://www.coindesk.com)². This website only contains the data from October 1st, 2013. Since we were analyzing the evolution of discussion topic for a longer period of time, we collected the older daily price data from bitcoincharts.com³. This website offers a range of exchange prices, we used Mt. Gox Bitcoin Exchange as the base for Bitcoin

¹<https://github.com/saljouhi/Evolution-of-topics-of-discussion-on-Bitcointalk.org>

²<https://www.coindesk.com/price/bitcoin>

³<https://bitcoincharts.com/charts/mtgoxSEK#tgSzm1g10zm2g25zv>

price. Mt. Gox Bitcoin Exchange was one of the most important Bitcoin exchanges which became obsolete in 2014.

3.2 Data Modelling and Processing Techniques

We now describe the step-by-step procedure we followed in this work for answering the research questions. Section 3.2.1 presents our preprocessing, followed by our approach for determining the suitable LDA model in Section 3.2.2. Then, we describe our models and their evaluation in Section 3.2.3. We explain the process of our manual topic labeling and semantic analysis in Section 3.2.4 and Section 3.2.5, respectively. Finally, Section 3.2.6 describes the data analysis techniques used for interpreting the results. The resources and documentations of this work can be found in a GitHub repository⁴ for the future works.

3.2.1 Data Preprocessing

`Bitcointalk.org` offers a wide range of topics on the main page and users can choose any topic to explore, different subjects, as well as the replies to the original subject. For keeping the role of the main title in our analysis, we added the title of each subject to the main post, and for the replies we only used the body of their post to avoid entering noise in our input data with some fixed repeating phrases. We stored all the posts along with the time on which they were published sorted by their publishing date; we excluded the posts prior to 2010. Then, we separated the posts into 6 month long periods, resulting in 22 different datasets.

As mentioned in Section 2.2.5, we took the following steps to preprocess our data:

1. *Data cleaning and tokenization*

⁴<https://github.com/saljoughi/Evolution-of-topics-of-discussion-on-Bitcointalk.org->

We removed URLs and emails as they provide little information about the context, then we deleted all non-English characters and numbers, and removed all the posts that were shorter than 6 words. Then, we split the text into the sentences and sentences to the words and converted all characters to lowercase form and removed all the punctuation. Finally, we tokenized the corpus using `gensim` library’s `simple_preprocess` [70].

2. *Building bigram and trigram models*

The main idea behind using n-grams is that they can help text processing models gain an insight about the language structure. Bigram and trigram are the sequence of two and three words that are frequent in use at the same time [71]. We built and incorporated bigrams and trigrams to our input data to improve the model’s performance.

3. *Lemmatization and stop word removal*

For removing the stop words, we used the standard stop-word library of Python and added some additional words from our own corpus to it, e.g., “bitcoin”, “quote”, “subject”, “edu” or names of week days and months. Then, we lemmatized the comments using `spaCy` [72]. As suggested by prior work [8, 47], we only kept nouns and adjectives as input to our LDA model.

4. *Removing short words*

It is common practice to delete short words with a length of three or less characters or repetitive words that appear in more than 50 percent of data points, as well as those with very low frequency. In this work, we only delete the words with a length of less than three characters, because there are many common abbreviations with a length of three characters which are related to cryptocurrencies. In addition, we did not delete any word because of its low frequency.

Since we were building 22 different corpuses, if we set any limitation for the number of appearance of any word, we would miss the track of evolution of some words in different times.

3.2.2 Evaluating LDA models

In order to determine the quality of the model and measure its performance, we used the topic coherence score. Topic coherence itself refers to a set of statements or facts that support each other. In the LDA topic modeling domain, topic coherence measures the semantic interpretability of the topics by considering the similarity of the top N most repeated words, i.e., 10 frequent words in each topic [73]. Based on the study of Röder et al. [74], a number of coherence metrics can be used for assessing the quality of LDA models such as C_V , C_P , C_{UCI} , and C_{NPMI} , with C_V performing better than others. Therefore, we have used C_V metric as the topic coherence measure in this work.

C_V coherence is based on applying four steps [75]: 1) segmentation of data in the pair of words (top N words for each topic), 2) calculating the probability of occurrence of the word and pair of words in the whole documents, 3) calculating a confirmation measure about how every two words in every topic support each other based on the similarity of all words in that topic, 4) and finally, the C_V coherence score is equal to the mean of all values measured in step 3.

According to Röder et al. [74], C_V score is in the range of 0 to 1, where higher C_V score illustrates the better implementation of topic modeling. To the best of our knowledge, no minimum is set for the acceptable coherence score, while previous works report the coherence scores of around 0.5 or higher [75–77].

To determine whether all the words (regardless of their part of speech) should be included in training, we run the model using two different sets of words for training the LDA model: 1) all the words in the corpus, and 2) only nouns and adjectives.

Table 1: Coherence score of topic modeling with different K.

Number of Topics (K)	All POS Tags	Nouns and Adjective Tags
5	0.47	0.50
10	0.38	0.38
15	0.40	0.40
20	0.31	0.35
25	0.34	0.35
30	0.40	0.40
40	0.38	0.38
50	0.42	0.40
100	0.47	0.37

Table 2: Coherence score of Mallet implementation of topic modeling with different K.

Number of Topics (K)	All POS Tags	Nouns and Adjective Tags
5	0.60	0.59
10	0.60	0.60
15	0.58	0.60
20	0.55	0.57
25	0.55	0.54
30	0.53	0.52
40	0.48	0.50
50	0.47	0.48
100	0.40	0.40

Figure 4: pyLDavis visual with 10 topics.

As we can see in Table 1, the LDA model produced a better result when we only used nouns and adjectives as the principal components of the posts. In order to investigate an improvement, we applied Mallet implementation to identify whether it can increase the performance of the LDA model. The results are presented in Table 2. By comparing Table 1 and Table 2, we can say that using the Mallet implementation can have a positive effect on the coherence score of the generated topics. So we decided to use this implementation in our work.

To determine the right number of topics for our experiments, we trained two LDA Models using Mallet implementation, one with 10 and the other with 15 topics. Moreover, we compared their pyLDavis visuals to analyze the distribution of topics and the number of occasions on which topics overlap with each other. As shown in Figure 4 and Figure 5, the LDA model produced a better result when we set the number of topics to 15.

Figure 5: pyLDavis visual with 15 topics.

3.2.3 Training Models

After setting the initialization, we worked with 22 datasets that we had generated for each 6 month period. We trained a separate LDA model for each one of these 22 datasets. Table 3 presents the number of posts in each set and the coherence score of our model on each set.

After training each model, we collected some analytical information about the corpus including the summary table, Pyldavis chart and table of all posts for each dataset.

- **Summary table** provides valuable information about the distribution of topics in the corpus (the number of posts that are assigned to a topic, the probability of seeing this topic in the whole corpus), as well as the 10 most frequent words and their probability for each topic. A sample of this table is presented in Figure 6.

Table 3: Number of posts and coherence score for each set

Serie	All Posts	Posts (after cleaning)	Coherence Score
2010a	515	495	0.45
2010b	5,402	5,213	0.42
2011a	32,660	30,744	0.59
2011b	28,848	27,341	0.59
2012a	14,902	14,036	0.53
2012b	12,855	12,132	0.49
2013a	25,327	23,744	0.54
2013b	25,384	23,809	0.55
2014a	46,018	43,636	0.56
2014b	33,100	31,624	0.56
2015a	29,197	28,401	0.54
2015b	27,818	27,240	0.56
2016a	25,700	25,252	0.53
2016b	17,416	17,283	0.49
2017a	30,375	30,105	0.53
2017b	64,354	63,683	0.61
2018a	55,390	54,906	0.60
2018b	24,205	24,094	0.56
2019a	18,277	18,211	0.51
2019b	18,570	18,515	0.48
2020a	15,507	15,459	0.50
2020b	7,949	7,935	0.42

Topic_Num	Count_of_Comments	Perc_Contrib	Topic_Keywords
0	2419	0.0804	0.044**technology" + 0.037**news" + 0.035**great" + 0.026**article" + 0.019**interesting" + 0.018**blockchain" + 0.016**place" + 0.015**potential" + 0.012**adoption" + 0.012**medium"
1	1940	0.0644	0.027**opinion" + 0.025**side" + 0.023**idea" + 0.022**point" + 0.021**thread" + 0.017**reason" + 0.015**fact" + 0.015**group" + 0.014**guy" + 0.013**mind"
2	1940	0.0644	0.079**address" + 0.041**site" + 0.039**user" + 0.034**person" + 0.031**key" + 0.028**public" + 0.027**satoshi" + 0.025**information" + 0.021**project" + 0.020**website"
3	2356	0.0783	0.089**exchange" + 0.072**payment" + 0.068**bank" + 0.049**money" + 0.043**service" + 0.030**account" + 0.028**business" + 0.023**cash" + 0.020**merchant" + 0.019**trading"
4	952	0.0316	0.055**number" + 0.047**amount" + 0.047**time" + 0.034**large" + 0.022**rate" + 0.020**order" + 0.019**huge" + 0.017**point" + 0.017**volume" + 0.017**term"
5	3068	0.1019	0.164**price" + 0.061**market" + 0.050**coin" + 0.039**altcoin" + 0.028**gold" + 0.025**investment" + 0.019**investor" + 0.018**demand" + 0.016**profit" + 0.016**alt"
6	1806	0.06	0.106**money" + 0.040**real" + 0.023**thing" + 0.022**question" + 0.021**rich" + 0.020**stuff" + 0.018**worth" + 0.017**life" + 0.016**good" + 0.015**kind"
7	2881	0.0957	0.279**transaction" + 0.193**fee" + 0.032**confirmation" + 0.031**pay" + 0.030**high" + 0.024**hour" + 0.022**day" + 0.021**fast" + 0.017**minute" + 0.017**cheap"
8	1984	0.0659	0.116**wallet" + 0.081**coin" + 0.028**safe" + 0.025**store" + 0.022**paper" + 0.021**security" + 0.020**online" + 0.019**internet" + 0.016**access" + 0.015**private_key"
9	1949	0.0647	0.136**block" + 0.069**node" + 0.065**chain" + 0.057**fork" + 0.055**network" + 0.043**hard" + 0.038**size" + 0.035**full" + 0.020**pool" + 0.017**increase"
10	1561	0.0519	0.128**miner" + 0.062**mining" + 0.035**power" + 0.035**attack" + 0.025**network" + 0.022**user" + 0.020**work" + 0.016**change" + 0.014**mine" + 0.014**reward"
11	1347	0.0447	0.153**time" + 0.073**problem" + 0.067**year" + 0.049**solution" + 0.044**long" + 0.042**issue" + 0.029**thing" + 0.026**future" + 0.020**current" + 0.017**situation"
12	2247	0.0746	0.082**core" + 0.071**segwit" + 0.034**support" + 0.028**code" + 0.026**unlimited" + 0.026**developer" + 0.019**consensus" + 0.018**uas" + 0.016**dev" + 0.016**litecoin"
13	1062	0.0353	0.057**system" + 0.020**important" + 0.017**top" + 0.017**future" + 0.017**decision" + 0.016**work" + 0.015**idea" + 0.015**part" + 0.014**free" + 0.014**thing"
14	2593	0.0861	0.112**currency" + 0.072**country" + 0.064**government" + 0.056**world" + 0.023**digital" + 0.017**crypto" + 0.015**financial" + 0.014**dollar" + 0.014**control" + 0.013**legal"

Figure 6: Sample summary table for 2017a dataset.

- **Pyldavis chart** This chart shows the 30 most frequent words in each topic and their presence in the rest of corpus.
- **Table of all posts** In this table we can see all the posts of the corpus and the major topic that could be assigned to each one of them, as well as the probability of this major topic for this specific post.

3.2.4 Manual topic labeling

We performed the topic labeling for all the 330 different topics (15 different sets of words in 22 different datasets) we had. The manual process was conducted by two coders who followed these steps:

- **Step 1:** Reading several documents about the cryptocurrency domain and reviewing them together to gain a similar understanding about the domain.
- **Step 2:** Reviewing list of the most frequent words of topics in two datasets independently and labeling the topics accordingly.
- **Step 3:** Discussing their justifications to come to an agreement for choosing a label for the topics in these two datasets.
- **Step 4:** Repeating Step 2 and Step 3 for two other datasets.
- **Step 5:** Having discussion meetings and summarizing the list of topics that coders had faced while labeling the first four datasets and building a map for the topics.
- **Step 6:** Performing the initial manual topic labeling for another six datasets separately to finalize them in the meeting.
- **Step 7:** Based on the mutual agreement and common point of view in the Step 6, the coders have decided to continue the process together and labeled the rest

of datasets and completed the map of topics by adding new topics when they found new ones.

- **Step 8:** In order to be consist with our labelling, we re-labeled the first four datasets based on the final map of topics.

After the manual topic labeling, we decided to ignore the first dataset(2010a), since there were only about 500 posts in the dataset and we were not able to detect accurate labels for it. We also compared the performance of our topic labeling in different datasets and reviewed the list of frequent words in each topic and revised our topics to make sure that the labels best suited the topics. We checked and finalized the topics for around 40 topic labels that we thought needed a revision.

3.2.5 Sentiment Analysis

Sentiment analysis provides high-level categorization of text in terms of polarity (positive vs. negative) or subjectivity (the level of emotion or neutrality of the text). With the high demand for this technique in industry like analyzing customers emails, comments on social media and websites, many ready to use tools are developed and commercialized [78]. Similar to previous work [64], we applied the Valence Aware Dictionary and Sentiment Reasoner (VADER) sentiment analysis on our dataset and calculated the sentiment polarity score for each post. VADER is a lexicon and rule-based tool which is specially designed for social media data [67]. This algorithm assigns each post a compound score from the range of $[-1,1]$, for highly negative to highly positive posts. For our analysis, we also divided all posts into three groups, i.e., negative, neutral, and positive. For classifying the posts based on their sentiment weight we needed a threshold to place them into three categories (negative, positive, neutral). According to the tutorial of this tool on GitHub⁵, the thresholds are defined

⁵<https://github.com/cjhutto/vaderSentiment>

Table 4: Sentiment compound score threshold.

Sentiment	Scoring
Positive	compound score > 0.20
Neutral	(compound score ≥ -0.20) and (compound score ≤ 0.20)
Negative	compound score < -0.20

as follows:

- *Positive sentiment*: compound score ≥ 0.05
- *Neutral sentiment*: compound score > -0.05 and compound score < 0.05
- *Negative sentiment*: compound score ≤ -0.05

Some researchers [79,80] have already adopted these thresholds. However, considering that using these thresholds for our work, only 8.7 percent of posts were placed in neutral class and this matter made it challenging for us to interpret the results accurately. Therefore, similar to Kim et al. [64], a previous research on `bitcointalk.org` dataset in 2016, we decided to consider 0.2 as the border between neutral and positive posts and -0.2 as the border between negative and neutral posts. Table 4 shows the thresholds we used for classifying posts.

3.2.6 Data Analysis

In order to answer our research questions RQ1 to RQ4, we imported all the findings of previous steps(3.2.3, 3.2.4, and 3.2.5) into a PowerBI so that we can build the connection between different output tables and analyze the results. We first assigned the labels (that we had identified in Section 3.2.4) to each topic. Furthermore, we integrated the sentiment information of the posts with the information of all the topics' tables to lay the foundation for our final analysis and evaluation.

We used Pearson correlation to identify potential relations between topics/sentiment and Bitcoin price. The *Pearson correlation coefficient* is a statistical measure that quantifies the extent to which two or more variables fluctuate together [81]. This metric is sensitive only to a linear relationship between two or more variables. Pearson correlation is usually denoted with ρ or r and it ranges from -1 to $+1$. Therefore, we have three interpretations:

- (a) a correlation close to zero indicates little or no relationship between the two variables;
- (b) a correlation close to one implies that the variables have a tight dependency;
- (c) a correlation close to -1 emphasizes that when one variable decreases, other the one also increases and vice versa

The Pearson correlation coefficient is defined as follows. Consider that there are two variables X and Y , with $X_1, X_2, \dots, X_n$ and $Y_1, Y_2, \dots, Y_n$. Let the mean of X be $\bar{X}$, the standard deviation of X be S_x , the mean of Y be $\bar{Y}$ and, the standard deviation of Y be S_y . Pearson's r is:

$$r = \frac{\sum (\frac{x_i - \bar{x}}{S_x})(\frac{y_i - \bar{y}}{S_y})}{n - 1} \quad (2)$$

In order to calculate the correlation ratio between the input parameters and Bitcoin price, we considered the following inputs to our model: the number of posts, the percentage of posts in its dataset, the average and percentage of positive, neutral, and negative sentiment polarity and, the average Bitcoin price within the time period of the dataset.

3.3 Tools and Libraries Used

All the implementation described in Section 3.2 was done with Python 3.8.3 64-bit in a Jupyter Notebook [82] in Visual Studio Code 1.49.0 [83]. We used the following open source libraries in our implementation in Python: re [84], nltk [85], and spaCy [86] for data preprocessing; gensim [87] and Mallet LDA 2.0.8 [88] for topic modeling; pyLDAvis [89] for topic model visualisation; numpy [90] for Numpy arrays; pandas [91] for dataframe, and Vader Sentiment 3.3.2 [92] for sentiment analysis.

For generating the results we combined and processed all the data with PowerBI version 2.87.923.0 [93] and built the visuals in its environment or in Tableau [94]. For the correlation model we used R programming language version 3.6.1 [95], ggplot2 [96], ggthemes [97], dplyr [98], corrgram [99], and corrplot [100] libraries.

Chapter 4

Analysis and Results

In this chapter, we present the results for the research questions described in Section 1.3. In each section, the results provide the answer for each research questions of this work.

4.1 RQ1: What are the discussions in a Bitcoin specialized forum about?

One of the key results of this work was identifying a variety of distinct topics in the discussions on the `bitcointalk.org` forum. During the process of manual topic labeling as described in Section 3.2.4, we gradually built a map of discussion topics. The definition of these topics is presented in Table 5, and the list of the frequent words for each topic can be found in Table 6.

While we found 33 distinct topics, we eliminated two unrelated topics and classify 31 topics into six categories containing two or three subcategories:

1. **Future:** this category refers to the topics related to the predictions about the future of Bitcoin, the way it might change the finance domain, and the role that this cryptocurrency will play in the world in the future. Three topics belong

Table 5: Map of topics.

Topic	Description
Bitcoin Transaction	How Bitcoin is transferred with Bitcoin wallet in the block chain network.
Bitcoin Alternatives	Discussion related to the other alternative crypto currencies to Bitcoin like Altcoins or Ethereum.
Bitcoin Exchange Rate	What is the value of bitcoin for the purpose of exchange with other assets like gold.
Bitcoin Foundation	The Bitcoin Foundation is an American nonprofit corporation founded in 2012.
Bitcoin Future Price Discussion	Discussion related to the prediction of Bitcoin price in future.
Bitcoin in Illegal Activity	How can Bitcoin used by the criminals in the illegal activity.
Bitcoin Price Discussion	Discussion related to Bitcoin Price in short term.
Bitcoin Price Discussion (Covid)	How Bitcoin price has been effected during the Pandemic.
Bitcoin Regulatory	The law and the rules imposed by the government on the exchange and trade on Bitcoin.
Bitcoin Scam	Discussion related to the exposing the fraud that puts Bitcoin users to theft.
Bitcoin Trading	Discussion related to the risks in trading Bitcoin.
Bitcoin Transaction Cost/Time	The cost/time of sending the bitcoin over the network.
Bitcoin User experience	Discussion of the experiences of each person with using and trading the Bitcoin.
Blockchain Technology	Discussion related how the block chain technology and its applications.
Cryptocurrency Adoption	Acceptance and use of crypto currencies by the public.
Discussion of an Event	Discussion of special/unknown events in forum.
Effect of Bitcoin on Banking	Impact of Bitcoin on banking system, How financial institute act related to Bitcoin.
Effects of Covid on Bitcoin	What are the effects of COVID in the Bitcoin economy.
Financial Return	Discussion related to how much money made or lost on Bitcoin investment over some period of time.
Fork	Discussion related to changes to the blockchain protocol or when a blockchain diverges into two potential paths forward.
Future of Bitcoin	what happens to the value of Bitcoin in future?
Future Role of Bitcoin	The role of Bitcoin in the world, its role in the economy and other fields.
General Bitcoin Discussion	Discussion about the origin of Bitcoin/ Satoshi Nakamoto.
General Network Discussion	Discussion related to the general queries or issues related to network.
Mining: Requirement	What are the hardware and other requierments required for mining. And the financial return of mining.
Mining: transactions	How mining secures the network of block chain and confirms the Bitcoin transaction. The 51% attack in the network.
Network Security	Discussion related to security of network.
Off Topic	Discussion related to the topics that are not relevant to && Bitcoin.
Payment with Bitcoin	How to use Bitcoin for payment and ultimately move that amount to bank account.
Project Development	Organization of Bitcoin and related projects, campaigns, advertising etc.
Technical Issue	Discussion related to the technical issue.
User Security	This topic is about the safety of users wallet, it's security and the way it works.
Wallet Apps	Discussion related to the Software that stores Bitcoin.

Table 6: Frequent words in each topic.

Topic	Frequent words
Bitcoin Alternatives	coin problem price number gold market internet datum
Bitcoin Exchange Rate	money currency price system payment bank dollar
Bitcoin Foundation	work project price source market support idea
Bitcoin Future Price Discussion	price time year long problem number investment profit
Bitcoin in Illegal Activity	user illegal criminal crime drug information issue scam
Bitcoin Price Discussion	price coin currency market increase profit worth crypto
Bitcoin Price Discussion (Covid)	price market time pandemic increase rate stock high
Bitcoin Regulatory	government law country regulation state world legal currency
Bitcoin Scam	scam project website site hack money worth account
Bitcoin Trading	exchange cryptocurrency trading user trade amount Investment profit
Bitcoin Transaction	exchange address payment system site account cryptocurrency money
Bitcoin Transaction Cost/Time	transaction fee payment amount user block service network
Bitcoin User Experience	service person user good trust idea reason part product
Blockchain Technology	technology project blockchain internet indusatry development datum
Cryptocurrency Adoption	adoption future crypto cryptocurrency gold altcoin time news
Discussion of an Event	idea site thread business free question video thread
Effect of Bitcoin on Banking	money currency bank system world financial payment service
Effects of Covid on Bitcoin	news crypto trading situation due altcoin virus pendamic
Financial Return	worth price exchange coin currency market time risk
Fork	block node chain fork core network segwit change
Future of Bitcoin	coin idea time number risk person trust bit
Future Role of Bitcoin	currency crypto money world future time idea
General Bitcoin Discussion	system currency idea coin real work satoshi public
General Network Discussion	internet user client source blockchain software change information
Mining: Transactions	transaction fee mining miner block network cost attack
Mining: Requirement	miner block mining network cost power coin world
Network Security	network time client number node point amount attack
off topic	idea thing thread question video great question world
Payment with Bitcoin	currency service account fee payment service exchange money
Project Development	news site article project website page
Technical Issue	system problem bit time person work issue secuity
User Security	wallet address key public security safe paper information
Wallet Apps	address account password email site website exchange service

to this category such as “Cryptocurrency Adoption”, “Future of Bitcoin” and “Future Role of Bitcoin”.

2. **General:** Some of the general discussions such as introducing blockchain technology, defining Bitcoin or introducing payment and transaction methods are placed to this category. Moreover, this category concerns the topics that discuss the measures that should be taken to increase public awareness about Bitcoin and establishing specific institutions. Some of the topics that could be found in this category are “Bitcoin Transaction Cost/Time”, “Blockchain Technology” and “Effects of COVID on Bitcoin”.
3. **Mining:** This category contains two different topics, one of them is the requirement for mining and the feasibility studies. The other one is related to its role and description during transactions, as well as discussions about the possibility of 51% attacks from miner sides.
4. **Monetary:** A large number of topics are related to this category and we further classify them into three subcategories which are *Currency*, *Financial*, and *Price*. In the *Currency* subcategory, there are some discussions related to the currency feature of Bitcoin (two topics) and one for other cryptocurrencies posts. *Financial* subcategory contains three topics related to the trading and investment of Bitcoin, its risk and financial returns. Finally, the *Price* subcategory is for all topics related to Bitcoin price.
5. **Regulations:** This category contains all the discussions related to the governments, adopting Bitcoin in illegal activities or scamming. The posts in this category of topics are usually related to making new regulations for Bitcoin, concerns and ideas about Bitcoin tax, the situation in different countries and some political events related to Bitcoin.

6. **Technical:** This category contains six different topics, and we classified them in two subcategories, *Wallet* and *Others*. *Wallet* subcategory has two topics, the first one is related to the applications that can be used for managing personal accounts. The other topic is related to the wallet and users' security. The rest of topics are placed in the *Others* subcategory. Here, one topic is related to the technical problems that occurred and the discussions about some technical issues. Two other topics are related to general and security aspects of the network. Finally, the last topic is about the fork conditions in mining and the related discussions.

Figure 7 represents distribution of topics among the above mentioned six categories. We processed 543,363 posts, and as we can see, *Monetary* with around 30 percent of posts is the largest category. The number of posts in this category (162,335) virtually doubles the number of posts in the next major categories which are *General* and *Technical* and posts of these two categories contain around 17 percent and 15 percent of the corpus respectively. Furthermore, *Future* with around only 5 percent of posts is the smallest category and the number of posts in this category is almost half of the posts of the next small categories which are *Regulations* and *Mining* with 9 percent and 10 percent of posts. As Figure 7 presents, there is a un-labeled category with around 15 percent of posts which contains comments that we could not assign to any specific topic and for simplicity we considered them as *Off-topic*.

Table 7 depicts the categorization of topics along with the number of their occurrences and detailed information about the number of posts for each topic. As we can observe, some of the categories such as *Monetary* and *Technical* have subcategories, while categories such as *General* and *Future* do not have any subcategory. We assign each one of the 31 topics to one of these categories. According to this table, we can see that some topics such as “User Security” and “Bitcoin Regulatory” and

Figure 7: Number of posts in categories.

“Bitcoin Exchange Rate” have been quite repetitive in discussions and users of the forum had been continuously talking about them. Some other topics have shown up in more than half of datasets such as “Future Role of Bitcoin” and “Mining: Requirement”. Furthermore, we can see that a number of topics have appeared only over some periods and have a frequency of 6 to 11 times such as “Effect of Bitcoin on Banking”, “Blockchain Technology”, and “Bitcoin Alternatives”. Finally, as Table 7 shows, some discussion topics have been quite uncommon and repeated in only fewer than 5 sets. Our justification is that these topics are related to a specific event or phenomenon that attracted public opinion only for a short period of time such as “Bitcoin Price Discussion (COVID)”.

Answer to RQ1:

In this work, we identified 31 distinct topics in www.bitcoing.org that people talk about and categorized these 31 topics to 6 categories. While some topic categories such as *Monetary* are more common having a considerable percentage of posts (around 30%), several topics are repetitive which means they persist in different time periods and people always discuss these matters, such as *Monetary* or *Technical*. On the other hand, some other topics are not major, consistent and unlikely to appear in many sets and over a long period of time.

4.2 RQ2: How do the discussion topics on the forum evolve over the time?

In the second research question, we study and analyze the evolution of discussion topics over the time. In order to reach this goal, we first present the overall change trend of the six categories which we introduced in the previous section. And then, we investigate the evolution patterns of each category in detail.

Figure 8 illustrates the number of existing discussion topics in each category for each dataset. As we can observe, the most frequent category of the topics is *Monetary* as it forms more than 33% of the debates. *General* category, on the other hand, appears with various frequencies within different time spans. However, it usually appears in at least one of the discussion topics. *Mining* category which has two topics usually can be found in discussions. *Future* and *Regulations* appear in discussions occasionally and sometimes they show up in debates and sometimes they disappear.

In order to explore the evolution of discussion topics more closely, we study the change of discussion topics in each category.

Table 7: Number of posts and frequency of topics in each category.

Category	Subcategory	Selected label	Frequency	# Posts
Future	-	Cryptocurrency Adoption	3	2,299
		Future of Bitcoin	5	4,869
		Future Role of Bitcoin	13	18,157
General	-	Bitcoin Transaction	11	16,246
		Bitcoin Foundation	3	5,224
		Bitcoin Transaction Cost/Time	7	9,183
		Bitcoin User Experience	1	2,030
		Blockchain Technology	8	13,521
		Effects of Covid on Bitcoin	1	847
		General Bitcoin Discussion	11	17,368
		Project Development	13	25,411
Mining	-	Mining : Transactions	17	36,008
		Mining: Requirement	12	16,730
Monetary	Currency	Bitcoin Alternatives	8	15,323
		Bitcoin Exchange Rate	16	28,166
		Payment with Bitcoin	14	30,681
	Financial	Bitcoin Trading	3	3,177
		Effect of Bitcoin on Banking	8	13,989
		Financial Return	10	23,517
	Price	Bitcoin Future Price Discussion	9	13,249
		Bitcoin Price Discussion	10	33,497
		Bitcoin Price Discussion (COVID)	1	736
Regulations	-	Bitcoin in Illegal Activity	4	8,836
		Bitcoin Regulatory	18	37,415
		Bitcoin Scam	3	2,986
Technical	Others	Fork	7	17,637
		General Network Discussion	2	2,689
		Network Security	2	812
		Technical Issue	7	7,080
	Wallet	User Security	20	42,759
		Wallet Apps	7	12,601

Category	2010b	2011a	2011b	2012a	2012b	2013a	2013b	2014a	2014b	2015a	2015b	2016a	2016b	2017a	2017b	2018a	2018b	2019a	2019b	2020a	2020b	Grand Total
Future		2	1	1	2		1	1	1		1		1	2		1	1	1	1	1	3	21
General	2	2	1	1	2	3	3	2	3	2	3	3	3	3	2	3	2	4	4	4	3	55
Mining	2	1	1	2	2	2	1	1	1	1	2	2	2	1	1	1	1	1	1	2	1	29
Monetary	3	4	3	2	2	3	3	4	4	5	3	4	3	3	5	7	5	5	4	5	2	79
Regulations	1	1	2	1	1	1	1	2	1	2				1	1	1	1	1	2	2	3	25
Technical	3	2	2	3	2	1	3	1	2	3	3	3	2	2	3	1	3	2	1	1	2	45
Grand Total	11	12	10	10	11	10	12	11	12	13	12	12	11	12	12	14	13	14	13	15	14	254

Figure 8: Presence of the topics in each categories for each dataset.

Topic Label	2010b	2011a	2011b	2012a	2012b	2013a	2013b	2014a	2014b	2015a	2015b	2016a	2016b	2017a	2017b	2018a	2018b	2019a	2019b	2020a	2020b
Cryptocurrency Adoption																					
Future of Bitcoin																					
Future Role of Bitcoin																					

Figure 9: Topics over the time in *Future* category.

4.2.1 Future

In the *Future* category, we can find three topics and the most repetitive one is “Future Role of Bitcoin”. This topic has been repeated in 13 datasets and could be taken as an ongoing and continuing topic. The next topic is “Future of Bitcoin” which has been repeated in 5 datasets and mostly has appeared in the first years after Bitcoin’s birth during which people discussed the future of Bitcoin. This topic has been replaced by a third topic called “Bitcoin Adoption” in the last 2 years, and we can see that the topics of debates in the forum have changed and instead of discussing the existence or extinction of Bitcoin, people talk about its stability and adoption. The trend of these changes has been depicted in Figure 9.

4.2.2 General

During the earliest years, “Project Development” was the most frequent topic of this category. Although we still can see this topic in the *General* category, its frequency

Figure 10: Topics over the time in *General* category.

has decreased over the time. From 2012, two other topics such as “Bitcoin Transaction” and “General Bitcoin Discussion” have been created and they still remain popular discussion topics. “Bitcoin Transaction Cost/Time” is a topic that has appeared occasionally in some datasets, and we still can find some traces of this topic in the forum discussions occasionally. In 2015 a topic that we labeled as “Blockchain Technology” showed up, and it is still an alive and ongoing topic. As we can see in Figure 10, there is a topic called “Bitcoin Foundation” among the topics of this category. This topic was created following the establishment of a NGO with the same name in the USA in 2013 and 2014. Finally, “Bitcoin User Experience” and “Effects of COVID on Bitcoin” are two topics that have been appeared only once among all the 22 datasets.

4.2.3 Mining

There are two topics in this category, and each one of these topics has been repeated in more than half of the time periods. The topics which are related to transactions and risk attacks have been discussed continuously, but the one which is related to feasibility and requirements has appeared or disappears periodically. The repeating

Figure 11: Topics over the time in *Mining* category.

Sub Category	2010b	2011a	2011b	2012a	2012b	2013a	2013b	2014a	2014b	2015a	2015b	2016a	2016b	2017a	2017b	2018a	2018b	2019a	2019b	2020a	2020b	Grand Total
Currency	3	2	2	2	2	2	2	3	2	1	1	2	2	2	2	3	1	1	1	2		38
Financial		1					1	1	2	2	2	2	1		1	2	2	2	1	1		21
Price		1	1			1			2					1	2	2	2	2	2	2	2	20
Grand Total	3	4	3	2	2	3	3	4	4	5	3	4	3	3	5	7	5	5	4	5	2	79

Figure 12: Topics in *Monetary* category.

pattern of these two topics are also presented in Figure 11.

4.2.4 Monetary

The most frequent topic among all the discussions is related to the *Monetary* category. This category is divided into three subcategories which are 1) *Currency* 2) *Financial*, and 3) *Price*. In this category, we can find an increase in the diversity of topics and the number of topics in each set grows over the time. For instance, while in the first years there were only three or four topics in this category, this value increased to 7 topics in 2018a. Among the three mentioned subcategories the major topic in the discussions used to be in *Currency* subcategory. However, from 2013b, the topic of debates changed and gradually users started discussing about topics in the *Financial* subcategory. This trend still exists in discussions of the forum. The *Price* subcategory started from 2017a and turned out to one of the major discussion topics in the forum; we need to mention that before 2017 this topic appeared occasionally in around 30 percent of discussions. The trend of all these changes are presented in Figure 12.

Figure 13: Topics over the time in *Currency* subcategory.

- **Currency** In the *Currency* subcategory, there are three topics which are: “Bitcoin Exchange Rate”, “Payment with Bitcoin”, and “Bitcoin Alternatives”. The first item of the mentioned list (Bitcoin Exchange Rate) appeared in the discussion constantly. “Payment with Bitcoin” on the other hand, disappeared in some time spans. For instance, while it had been a constant member of discussion topics in 2017, in 2018 there is no trace of this topic in the discussions of the forum after 2018 (the last time that this topic appeared was in 2018a). Discussions about “Bitcoin Alternatives” take place time by time and the only time period in which this topic showed up constantly was between 2016 and 2018. The trend of changes is presented in Figure 13.

- **Financial**

Financial subsection consists of three topics and the major one is “Financial Return” that occurred occasionally in 2011a and continued to appear continuously between 2013 to 2018 (except the one year period between 2016b and 2017a). Similarly, from 2014 to 2019 “Effect of Bitcoin on Banking” has shown up in discussion constantly. From 2019 a new topic which we labeled as “Bitcoin Trading” which in turn indicated the transition of topics from “Financial Return” to this topic. The repetition trend of topics can be found in Figure 14.

- **Price**

Discussion about *Price* occurred occasionally before 2017, however, from 2017

Figure 14: Topics over the time in *Financial* subcategory.

Figure 15: Topics over the time in *Price* subcategory.

“Bitcoin Price Discussion” has appeared in debates constantly. Furthermore, future prices and price prediction has been added to the discussion topics from 2017 simultaneously. At the end of this period we can find some discussions about the “Bitcoin Price Discussion (COVID)”. Figure 15 depicts the repetition trend of these topics.

4.2.5 Regulations

The major topic of this category is “Bitcoin Regulatory” which could be considered as one of the continuing discussions in the forum. Except for a 1.5 year long period between 2015 and 2016, we can find this topic in almost all the time periods. “Bitcoin Scam” debates began in 2019. Moreover, discussions regarding illegal activities using Bitcoin have been found occasionally in four datasets. The trend of changes is presented in Figure 16.

Figure 16: Topics over the time in *Regulations* category.

Sub Category	2010b	2011a	2011b	2012a	2012b	2013a	2013b	2014a	2014b	2015a	2015b	2016a	2016b	2017a	2017b	2018a	2018b	2019a	2019b	2020a	2020b	Grand Total
Others	2			1	1		1		1	2	2	2	1	1	1		2				1	18
Wallet	1	2	2	2	1	1	2	1	1	1	1	1	1	1	2	1	1	2	1	1	1	27
Grand Total	3	2	2	3	2	1	3	1	2	3	3	3	2	2	3	1	3	2	1	1	2	45

Figure 17: Topics in *Technical* category.

4.2.6 Technical

This category has two subcategories which are *Wallet* and *Others*. *Wallet* has shown up in all the time spans, while *Others* can be found in most of the time periods. The change pattern of these subcategories is presented in Figure 17. Next, we elaborate on each one of them.

- **Wallet** We assign two topics in this subcategory which are “User Security” and “Wallet Apps”. The first one has been repeated all the time. The second one used to appear more frequently at first and nowadays, despite being an ongoing topic, it is less likely to show up among discussions. The repetition trend of topics can be found in Figure 18.
- **Others** The most frequent topic in this subcategory is “Fork” which appeared constantly between 2015 and 2018, and after this time span, we can find no trace of this topic in discussions. “Technical Issue” is the next topic that has appeared in debates occasionally. The other two topics of this category which are “General Network Discussion” and “Network Security” have occurred only

Figure 18: Topics over the time in *Wallet* subcategory.

Figure 19: Topics over the time in *Others* subcategory.

twice in the forum and could be taken as the rare discussion topics. The change trend of topic in presented in Figure 19.

Answer to RQ2: During our analysis of the topics, we found that except for some topics such as “Mining: Transactions” or “Bitcoin Regulatory” that showed up in the forum continuously, other topics in the forum have experienced some change over the time which included some alteration in the discussion topics of a specific category and creation of temporary topics over some specific periods or an increase in the number of topics in some categories. Some of the most important changes in discussion topics are an increase in the diversity of topics in *Monetary* category, and creation of more specialized topics such as “Future Price” or “Bitcoin Adoption” in the forum.

Figure 20: Total number of posts over the time.

4.3 RQ3: How do the number of posts in each topic change over the time?

The number of posts in this forum has changed over the time which means the popularity of the forum has varied across the studied timeline. As we can see in Figure 20, the largest number of posts has been written within a one-year long time period (from 2017b to 2018a), and the second period in which we can see the largest number of comments is 2014a. As this figure suggests, the number of posts has decreased in this forum over the past two years, which is most probably the consequence of the emergence of some papers and research work that used `reddit.com` as a forum for evaluating comments [8, 101].

Generally the number of posts in a category changes proportionally to the overall increase or decrease in the number of posts. However, the largest value of increase is related to *Monetary* category and the trend of change in this category is similar to the trend for all the posts. The second large category is *General* that has virtually

the same change trend in the number of posts, except for a period between 2017 and 2018 that despite a general increase in the number of posts in the whole sets, number of posts was constant for this category.

Technical category used to have a larger number of posts during the first years, it reduced in size within the recent years. Considering the fact that we can find a similar trend of change in other categories and in the overall average, we will discuss each one in their own part. We will describe the details using two charts: Figure 21 represents the number of post (numerical values) and Figure 22 represents the percentage of each category in its own set, i.e., in 2012b.

4.3.1 Future

Each one of the topics of this category has appeared in around 5 percent of posts and given the fact that usually only one of them showed up in a dataset, overall, they formed at most 10 percent of the posts. The only exception is 2020b in which the three topics occurred together and formed more than 15 percent of the whole posts. The trend of changes in this category has been depicted in Figure 23 and Figure 24.

4.3.2 General

“Project Development” was one of the important topics in the first years with around 10 percent of all posts of the forum in that time. This topic still could be found in discussions occasionally. The second important topic in this category is “Blockchain Technology” which could be assigned to around 5 percent of the discussions of the forum. The posts that are related to this topic have been written since 5 years ago. The next topic of this category is “Bitcoin Transaction” which again appears in around 5 percent of debates of the forum. The information about the number and the percentage of each one of the topics of this category is depicted in Figure 25 and

Figure 21: Number of posts in categories over the time.

Figure 22: Percentage of categories for discussions over the time.

Figure 23: Discussion topics over the time in *Future* category.

Figure 24: Distribution of topics over the time in *Future* category.

Figure 26.

4.3.3 Mining

During the first 5 years usually both topics of this category which are related to transactions and requirements were present in discussions and frequently more than 10 percent of talks were related to these topics. In 2015 and 2016, the total number of discussions which were related to the topics exceeded 15 percent of the whole topics, however, from 2017b this value decreased to between 5 to 7 percent of the whole topics. The change trend of topics of this category has been presented in Figure 27 and Figure 28.

4.3.4 Monetary

This category is the most repetitive one among all the discussions of the forum. As we can see in Figure 29 and Figure 30, during the first years, a considerable part of the discussions were related to *Currency* and, little by little, *Price* as another topic that has emerged among the debates. From 2014 another subcategory that we labeled as *Financial* was created and even sometimes this subcategory overtook *Currency* in discussions. *Price*, on the other hand, showed up from 2017 and gradually it became the main subcategory of discussion in this category and in forum.

Currency

During the earliest years, the most frequent topic used to be “Payment with Bitcoin” that sometimes formed up to 15 percent of discussions in the forum. This topic gradually faded and was replaced by other topics in other subcategories. The next topic of this category is “Bitcoin Exchange Rate” that appeared in a larger number of datasets, and usually around 5 to 6 percent of debates are related to this topic.

Figure 25: Discussion topics over the time in *General* category.

Figure 26: Distribution of topics over the time in *General* category.

Figure 27: Discussion topics over the time in *Mining* category.

Figure 28: Distribution of topics over the time in *Mining* category.

Figure 29: Discussion topics over the time in *Monetary* subcategory.

Figure 30: Distribution of topics over the time in *Monetary* subcategory.

The last topic in this category is “Bitcoin Alternatives” which has emerged in 2016 and in some periods forms up to 10 percent of talks. Figure 31 and Figure 32 present the change trend of topics of this category.

Financial

The largest number of discussions occurred in the “Financial Return” topic which formed up to 8 percent of debates between 2014 and 2018 in some specific years. This topic was replaced by “Bitcoin Trading” which has virtually the same proportion among discussions. “Effect of Bitcoin on Banking” has been created since 2013 and usually forms around 6 to 7 percent of conversations. The trend of changes in this category has been depicted in Figure 33 and Figure 34.

Figure 31: Discussion topics over the time in *Currency* subcategory.

Figure 32: Distribution of topics over the time in *Currency* subcategory.

Figure 33: Discussion topics over the time in *Financial* subcategory.

Figure 34: Distribution of topics over the time in *Financial* subcategory.

Figure 35: Discussion topics over the time in *Price* subcategory.

Price

“Bitcoin Price Discussion” can be seen in the discussions occasionally before 2017. From 2017 this topic appeared in conversations continuously. This topic, in turn, forms up to 10 to 20 percent of debates in the forum and counts as one of the most important ongoing topics. Simultaneously, from 2017 “Bitcoin Future Price Discussion” was added to the discussion topics of the forum and around 5 percent of discussions are related to this topic. Finally, we can find the impact of the emergence of COVID-19 that has resulted in the creation of a new topic, “Bitcoin Price Discussion (COVID)” which according to the similarity of its pattern and frequency to “Bitcoin Price Discussion”, we can say that it is virtually a substitution for the mentioned topic. The change trend of discussion topics in this category can be found in Figure 35 and Figure 36.

Figure 36: Distribution of topics over the time in *Price* subcategory.

4.3.5 Regulations

The major topic in this category is “Bitcoin Regulatory” which is a constant topic in the forum and expect for a 1.5 year period between 2015 and 2016, we can see this topic among all the discussion. This ongoing topic usually forms 5 to 10 percent of discussions in the forum. “Bitcoin scam” is a new topic in the forum which has emerged in 2019 and appears constantly in 7 to 8 percent of debates. “Bitcoin in Illegal Activity” is a topic that can be found occasionally in 4 sets and probably the number of discussions that are related to this topic varies according to the importance of the topic. For instance, it has the highest frequency in 2014a set. The change trend of discussion topics in this category can be found in Figure 37 and Figure 38.

Figure 37: Discussion topics over the time in *Regulations* category.

Figure 38: Distribution of topics over the time in *Regulations* category.

Figure 39: Discussion topics over the time in *Technical* subcategories.

4.3.6 Technical

In this category, *Wallet* appeared in all of the periods constantly, but *Others* can be found only in some periods occasionally. The trend of changes in subcategories has been depicted in Figure 39 and Figure 40. We should emphasize that the large number of posts which are placed in *Others* indicates their importance in discussions.

Wallet

This subcategory has two topics which are “User Security” and “Wallet Apps”. User Security used to have a larger percentage of discussions during the earlier years, but in later periods it had a virtually constant percentage in the debates of the forum (around 7 to 8 percent). Similarly, “Wallet Apps” showed up in conversations occasionally with the frequency of around 5 to 8 percent. The change trend of discussion topics

Figure 40: Distribution of topics over the time in *Technical* subcategories.

in this subcategory can be found in Figure 41 and Figure 42.

Others

The most frequent topic in this subsection is “Fork” which appeared in the forum only within a specific period (between 2015 and 2018) and disappeared after 2018. In 2017a set, this topic formed 14 percent of discussions. The other topics of this subsection showed up occasionally and formed up to 5 percent of the debates. Figure 43 and Figure 44 present the change trend of topics of this subcategory.

Figure 41: Discussion topics over the time in *Wallet* subcategory.

Figure 42: Distribution of topics over the time in *Wallet* subcategory.

Figure 43: Discussion topics over the time in *Others* subcategory.

Answer to RQ3:

The number of posts in the forum has been considerably varied during different time periods. However, over the past two years, the overall number of posts has decreased in the forum and the number of posts in this period is less than half of the number of posts in 2017 and 2018. The highest growth of post numbers happened up to 2018 in *Monetary* topics, and it is worth mentioning that the discussion topics in this category have changed from general discussions to price-oriented talks. The highest decrease in the discussions is related to *Technical* and *Mining* categories. Furthermore, the percent of discussions about *Regulations* has increased over the past years compared to previous years.

Figure 44: Distribution of topics over the time in *Others* subcategory.

Figure 45: Average sentiment compound score of the total posts over the time.

4.4 RQ4: What is the sentiment polarity of discussions in each topic?

In this question, we evaluated the sentiment polarity of posts in the forum. With a quick glance in Figure 45, we can see that the overall sentiment weight of posts in all years was positive which indicates a general positive tendency in discussions. However, as Figure 46 shows, we can find that the percentage of neutral posts has reduced from around 20 percent to around 10 percent which implies the creation of sentiment polarity among the posts. Respectively, we can find that average compound score in both positive and negative categories has increased gradually.

If we want to evaluate polarity in different categories, we can see in Figure 47 that the situation varies in different categories, for instance, the volume of polarity in *Mining* and *Regulations* is less than other categories. We next present the answer for this question with more detail for every category just like what we did for the previous questions. We describe the details using two charts: similar to Figure 47, each bar chart represents the average compound score for each topic and a stack bar chart similar to Figure 46 represents the percentage of positive, negative and neutral posts in each category. In addition, we present the detail tables of results for each

Figure 46: Distribution of positive/negative posts over the time.

topic in Appendix A.

4.4.1 Future

The considerable point in this category is that the amount of positive posts has increased noticeably from 2017 and in some periods, we can see the compound score of 54 percent and higher in the discussions of this category. “Cryptocurrency Adoption” has usually a high positive score which indicates a general positive perception about this topic on the forum. “Future Role of Bitcoin” has experienced a high fluctuation in score. Except for the last two or three years, the value of compound score for this topic varied in the range of 0.12 to 0.37. However, during the latest years the compound score of the posts in this topic has risen to 0.4 and 0.5. Proponent to the increase in the value of compound score, the percentage of positive posts has already increased during the latest years (around 15 percent) and the greatest change is the tendency towards having higher positive compound scores. The compound score of “Future of Bitcoin” is almost constant with a tiny fluctuation around 0.25. The information about the average compound score of each topic of this category and the distribution of positive, negative and neutral posts are depicted in Figure 48 and

Figure 47: Compound score of posts in categories over the time.

Figure 49.

4.4.2 General

We can find different polarity scores for different topics of this category. Except for “Blockchain Technology” in which the general perception is positive, we can see diverse sentiment polarity for the rest of the topics. For instance, the range of compound score in “Bitcoin Transaction Cost/Time” varies between 0.03 and 0.4 which indicates the diversity of sentiment polarity in this topic. The percentage of positive, negative and neutral posts in this category is similar to what we find about all of the posts and gradually, the number of neutral posts has decreased and the number of positive posts has increased correspondingly. The trend of changes in this category has been depicted in Figure 50 and Figure 51.

Figure 48: Compound score of topics in *Future* category over the time.

Figure 49: Distribution of positive/negative posts in *Future* category over the time.

Figure 50: Compound score of topics in *General* category over the time.

Figure 51: Distribution of positive/negative posts in *General* category over the time.

Figure 52: Compound score of topics in *Mining* category over the time.

4.4.3 Mining

In the main topic of this group which is “Mining: Transactions”, we can usually see that the compound score is lower than the majority of topics of the forum and even we can find a case with the compound score of -0.15 in this topic in 2010b. On the other hand, in the second topic of this category which is “Mining: Requirement” we can see a monotonous sentiment weight among posts and the compound scores usually varies between 0.2 to .03. This dissimilarity can also be seen in the changing trend of positive, negative and neutral posts, and “Mining: Transactions” has fewer positive posts compared to “Mining: Requirement”. The trend of changes in this category has been depicted in Figure 52 and Figure 53.

4.4.4 Monetary

As we can see in Figure 54 and Figure 55, the compound scores of posts in this category are equal or slightly higher than the overall polarity on the forum. In subcategory level, *Currency* usually includes posts with a compound score of 0.3 and only in 2018b this value has risen to 0.51 and to 0.08 in 2019a. The compound score of posts in *Financial* is usually between 0.2 and 0.3 and only in the last two years this value increased to 0.4. The value of compound score is usually around 0.3 for

Figure 53: Distribution of positive/negative posts in *Mining* category over the time.

Figure 54: Compound score of subcategories in *Monetary* category over the time.

Price.

In topic level, we can see that “Payment with Bitcoin“ usually has a positive sentiment weight and the compound score for the discussions of this topic varies between 0.29 and 0.47 (except for one case in 2013b with the value of 0.13) “Bitcoin Trading” which has been created in last 2 years has the compound score of higher than 0.4. The compound score of other topics could be found on Figure 56.

Figure 55: Distribution of positive/negative posts in *Monetary* category over the time.

Figure 56: Compound score of topics in *Monetary* category over the time.

Figure 57: Compound score of topics in *Regulations* category over the time.

Figure 58: Distribution of positive/negative posts in *Regulations* category over the time.

4.4.5 Regulations

The topics in this category usually have low compound scores, and this value is mostly lower than the overall sentiment polarity. The compound score of posts in this topic range from 0.08 to 0.28 which indicates a tendency toward posting negative posts in this category, the numbers in most cases vary around 0.1. The change trend of compound score of in this category can be found in Figure 57 and the distribution of positive, negative posts in Figure 58.

Figure 59: Compound score of subcategories in *Technical* category over the time.

4.4.6 Technical

This section has two subcategories which are *Wallet* and *Others*. As we can see in Figure 59, the compound score of posts in *Wallet* subcategory usually varies between 0.18 and 0.36, and over the recent years the compound scores in this subcategory has increased. On the other hand, the range of compound scores for *Others* subcategory is more diverse (the numbers are in the range of 0.07 and 0.38) and less than the overall average.

While the range of compound scores of posts in “Fork” topic is relatively narrow (between 0.1 and 0.4), these values vary between 0.1 and 0.4 in “Technical Issue” topic which is comparably a wide range. The trend of changes has been depicted in Figure 60 and Figure 61.

Figure 60: Compound score of topics in *Technical* category over the time.

Figure 61: Distribution of positive/negative posts in *Technical* category over the time.

Answer to RQ4:

Analysing the sentiment polarity of posts in the forum, we found that in general positive posts are more dominant than negative ones. Furthermore, over the recent years the percentage of neutral posts has been reduced which implies that there is a tendency towards the emergence and growth of sentiment polarity in posts. The compound score of different categories varies, and while some categories such as *Monetary* contain more positive topics, the average compound score of other topics such as *Regulation* and *Mining* is usually lower comparably.

4.5 RQ5: Is there any correlation between the evolution of discussion topics related to Bitcoin and the change in Bitcoin prices?

To answer this question, we evaluated the correlation of price with the parameters we had identified in previous sections. In this high level evaluation we considered two distinct prices for every period as the basis of our evaluation: 1) the average daily price over the 6 month period, and 2) the median daily price in the same period. Considering the linear nature of the correlation method and the fact that most topics were absent in one or more than one period, we evaluated the model on the category level. We implemented the model under two different circumstances: in the first state we surveyed the general relation of the number posts and the sentiment polarity with the price.

As we can see in Figure 62, the sentiment polarity of posts has a linear relation with the price of Bitcoin. But, the number of posts does not have such a linear relation with Bitcoin price. In order to make sure the Bitcoin price being independent of the number of posts, we already measured the correlation of the amount of discussions with the daily prices in the whole dataset and even under this condition, the value of

	# Post	Sentiment	AveB	MedB
# Post	1.00	(0.33)	0.11	0.04
Sentiment	(0.33)	1.00	0.61	0.60
AveB	0.11	0.61	1.00	0.99
MedB	0.04	0.60	0.99	1.00

Figure 62: Overall correlation of Bitcoin price with parameters.

	Count Future	Count General	Count Mining	Count Monetary	Count Regulations	Count Technical	Sentiment Future	Sentiment General	Sentiment Mining	Sentiment Monetary	Sentiment Regulations	Sentiment Technical	Percent Future	Percent General	Percent Mining	Percent Monetary	Percent Regulations	Percent Technical
Average Price	0.03	0.24	(0.04)	0.31	0.28	(0.09)	0.77	0.21	0.65	0.38	0.06	0.72	0.27	0.40	(0.37)	0.41	0.55	(0.52)
Median Price	0.06	0.19	(0.10)	0.24	0.23	(0.18)	0.79	0.19	0.68	0.37	0.06	0.73	0.32	0.41	(0.36)	0.37	0.57	(0.55)

Figure 63: Correlation of Bitcoin price with topic category discussion volume, sentiment and percent of discussions per topic category.

correlation was 0.19 which again confirmed our findings.

For the next stage, we evaluated the relation between Bitcoin price and the target parameters in the category level. The results of these evaluations are depicted in Figure 63.

As we can see, the highest correlation between sentiment polarity and price is found in discussions in the *Future*, *Technical* and *Mining* categories. The correlation of these three categories with median price is 0.79, 0.73 and 0.68, respectively. Furthermore, we can see that discussions about *Monetary* have a midmost correlation (around 0.37), and the discussions in the *General* category have a low correlation (around 0.20) with Bitcoin price. *Regulation* topic has almost no relation with the price of Bitcoin. Speaking of the number of posts, we can find that the correlation ratio of none of the categories with Bitcoin price is higher than 0.3 and the mentioned ratios can be mostly found in *Monetary*, *Regulation* and *General* categories which

none of them have a tight correlation with Price. However, as we can find from the percentage of posts in this figure, there could be an intermediate correlation between the number of posts and Bitcoin price. The largest correlation ratio in this part is related to *Regulation* which has a correlation ratio of 0.57 compared to median price. An important point is that *Technical* and *Mining* categories have negative correlation with price (-0.55 and -0.36 respectively), the greater the number of posts in these categories, the lower the value of Bitcoin price.

Answer to RQ5: In this work, we found that the sentiment polarity of posts is correlated to Bitcoin price and the most correlation value for this dependency is related to discussions in *Future*, *Technical* and *Mining* categories, while *Regulations* has the least relation from this respect. On the other hand, we could not find any correlation between the number of posts and Bitcoin price. However, the amount of posts in some specific categories has a slight correlation with Bitcoin price.

Chapter 5

Discussion

In this chapter, we present the results of our investigations. In Section 5.1, we review the results of this work and compare them with previous similar works. Then, in Section 5.2, we discuss the implications of our work and describe threats to validity in Section 5.3.

5.1 Findings

Our work was an empirical study of users' discussions in a specialized forum, and we tried to provide answers to the research questions stated in Section 1.3 by applying NLP and topic modelling techniques described in Section 3.2. We first review the results reported in Chapter 4 and next, we study and compare our findings with previous studies in this domain which we introduced in Section 2.3.2.

In this work, we study and analyzed all of the posts extracted from the `bitcointalk.org` forum and found 33 topics which we presented in Table 5. We then categorized the topics into six categories: *Future*, *General*, *Mining*, *Monetary*, *Regulations*, and *Technical*. In our investigations we realized that the diversity of discussions, especially in *Monetary* category, increased over the time as more topics could be found in this forum in comparison to earlier years. Moreover, we found

that the discussion topics were dynamic and varying; except for the topics such as “Mining: Transaction” or “Bitcoin Regulatory“, most topics appeared in the forum dynamically, thus, these changes should be monitored constantly and proper measures should be taken where these topics are used. In Section 4.2 and Section 4.3, we analyzed the volume of posts in the forum. Our first finding was that the number of post was varying over the time and up until now; we have found three local maximums on 2011a, 2014a and 2017b which indicate the fact that in different time periods the forum had different levels of popularity among users, and experts need to consider the effect of the popularity of forum in their analysis. In our later investigation we observed that the largest growth in the number of posts happened in “Monetary” category, and the topics which were related to price were the most important topics in the forum over the past years.

According to what we found in previous papers and the importance of sentiment analysis in Bitcoin price prediction [9,64], we evaluated the sentiment polarity of the posts in Section 4.4. Generally, we can say that the overall sentiment polarity of posts in the forum is positive with the average compound score of 0.26. Furthermore, we found that over the time the percentage of neutral posts decreased in the forum as we saw more of the posts with the positive or negative sentiment weight. In evaluation of compound score per category we found that this measure has various values in different categories. *Future*, *General* and *Monetary* categories with the average compound score of 0.30 have higher average compound scores. On the other hand, *Technical*, *Mining* and *Regulations* categories have lower compound scores. Finally, for answering the last research question we tried to measure the correlation of the number and the sentiment of posts with Bitcoin price using Pearson correlation coefficient. We did not find any relation between the number of posts and Bitcoin price. However, when considering the sentiment of posts, we found that the overall correlation of sentiment polarity of posts and Bitcoin price is more than 0.6. Moreover,

when we evaluated this correlation in each one of the categories separately, we found that sentiment weight of posts in *Future*, *Technical* and *Mining* categories has relation with Bitcoin price. On the other hand, discussions in *General* and *Regulations* do not have a considerable correlation with Bitcoin price and only a slight correlation in the *Monetary* category.

According to these results, we evaluate our findings and compare them with previous studies from three perspectives. First, we study the way previous studies adopted topics in their works. Second, we focus on the sentiment domain and the relation between the sentiment polarity of the discussions and Bitcoin price. Finally, we talk about using Bitcointalk and other datasets in research works.

In terms of **topics**, among all of the papers we surveyed, Kang et al. [7], Philip et al. [8], and Lee et al. [64] adopted topic modeling in their works. Kang et al. and Lee et al. both applied topic modeling on their corpus and identified topics in the forum and adopted the results for their further steps in their work. As we found in this study, the topics in the forums are dynamic and varying, thus, it would be challenging to identify the topics accurately with a single implementation (i.e., one model) of topic modeling. Philips et al. adopted dynamic topic modeling rightly and took into account the changes of topics. In their paper, the authors only studied a single year and did not consider the matter of creation and disappearance of topics. As we found in this research, the topics are changing over the time, and the matter of the change in topics is a parameter that should be considered in building such models.

In terms of **sentiment**, in previous works, Mai et al. [9] and Kim et al. [64] worked on sentiment analysis domain. Kim et al. presented an overall analysis of sentiment and proposed a price predictive model using sentiment analysis. Mai et al. followed the ideas of Kang et al. [7] and categorized the forum's users and compared the difference of sentiment polarity of silent majority groups versus active

Table 8: Datasets used in previous research.

Paper	Time Frame	Source
Phillips et al. [8]	Aug 2016–Aug 2017	reddit.com
Kang et al. [7]	Nov 2009–Feb 2018	bitcointalk.org
Lee et al. [6]	Dec 2013–Sep 2016	bitcointalk.org
Kim et al. [64]	Dec 2013–Feb 2016	bitcointalk.org
Mai et al. [9]	Jan 2012–Dec 2014	bitcointalk.org

users. Both works evaluated sentiment in the whole forum and did not work on the study of sentiment on topic level. On the other hand, in our study, we realized that the proportion of correlation between Bitcoin price and sentiment polarity is different for different categories. Therefore, in order to achieve more precise results, a good approach would be to work on studying the relationship between price and selected categories such as *Technical* and *Mining*.

With respect to the **dataset**, we present the papers that used Reddit or Bitcointalk in Table 5.1. As we can see in this table, except for [7], most of the works adopted data from a period of 1 to 4 years in their research and each one of these papers had their own justifications for choosing their datasets.

As Figure 20 in Section 4.3 suggests, the number of comments has decreased in this forum over the past two years, which is most probably the consequence of the emergence of some research and academic papers that recommend `reddit.com` as a forum for evaluating social media about Bitcoin [8, 101]. Although we agree that currently `reddit.com` is a better source of data, our goal was to evaluate the change trends within a wide time span of ten years, and therefore, we decided to go with `bitcointalk.org` in our work. To sum up, given the fact that every forum might have different levels of popularity and different volume of discussions in different time periods, we think that the best approach for conducting a comprehensive study is

to use a combination of different datasets to eliminate the effect of popularity or unpopularity of different sources.

5.2 Implications

A variety of stakeholders are involved in cryptocurrency communities such as traders, miners, users, developers and so on. We think that the findings of our research would be embraced by two categories of these stakeholders: 1) data scientists and designers of price analysis models, and 2) public beneficiaries on community and media level. We next describe the implications of our work for these two groups.

5.2.1 Implications for Bitcoin pricing analysts

The importance of Bitcoin price analysis has increased considerably over the past years. Only in 2020, the market value of Bitcoin has reached the price of more than 400 billion USD by the end of the year (while it used to be less than 150 billion USD in the beginning of the year). Consequently, the knowledge in this domain and the models that have the ability of predicting price have gained special attention.

First of all, the information on social networking websites are related to Bitcoin price. Similar to previous works in this domain [6–9, 64], we found the relation between price and discussions in the forum. In particular, we found a difference in the correlation of price with the sentiment of several categories. Therefore, sentiment analysis per category can be valuable for including in price analysis models.

Secondly, designers of the models need to pay attention to the dynamics of topics and their changes over the time. They are better to reconsider the assignments and distribution of topics time by time. Finally, speaking of data sources, we can say that generally `reddit.com` is a better source for real-time data. However, according to our investigations, the popularity of `bitcointalk.org` increased two times after

a period of temporal unpopularity, and this might happen again in the future. As a result, we suggest researchers to use multiple resources in their work.

5.2.2 Implications for Bitcoin community

Bitcoin, like other cryptocurrencies, is decentralized and its governance is distributed. Therefore, the opinion of each one of the stakeholders plays some role in its popularity [3,10]. In this research, we tried to take an overall look at the topics in the forum and highlight the key trends. For instance, we found that “Bitcoin adoption” topic was created in the forum which indicates a trend for Bitcoin to become a more stable cryptocurrency from the perspective of the forum’s users. As another example, we found “Bitcoin foundation” topic which is related to a period in which a NGO with the same name was established in the USA. Therefore, the results of our research provide the opportunity for the users of the forum (i.e., Bitcoin community members) to become more familiar with its potential. Additionally, several stakeholders can benefit from the results on studying the evolution of forum discussions:

- Central banks monitor different cryptocurrencies and the news related to them. We found that one of the topics of the forum is in fact “Effect of Bitcoin on Banking”. Banks can monitor the expectation of the public or their response to the cryptocurrencies.
- Governments have set several rules and developed policies for managing and monitoring the financial ecosystem of Bitcoin over the past years. Review and analysis of the discussion related to regulation can provide feedback about the response of the public to such actions. Governments also can gain insights into the use of Bitcoin in illegal activities and scams and develop new policies and legislation rules (e.g., cryptocurrency tax laws and regulations).

5.3 Threats to Validity

In this research, we identified several threats to the validity of our work, and we now describe them as well as the measures we took to curb them.

- **Data source:** we started our work with a data source which was published by Kang et al. [7] and included information up to February 2018. This dataset contains discussions about one of the subcategories of `Bitcointalk.org`. According to the goal of this work of conducting a comprehensive study, we embarked on crawling and collecting the data from October 1st 2020. We thank Kang et al. authors [7] for sharing their data sources. The question is whether `Bitcointalk.org` has an edge over `reddit.com`? We discussed this matter in Section 5.1. Due to time constraints, we only used the main subject of Bitcoin Discussions, and our work does not cover all the discussion topics in this forum.
- **Data preprocessing:** Given the fact that preprocessing could act as a double edged sword (we might lose some part of semantic information by removing or reforming the words of the corpus), we built several models with applying different options of preprocessing algorithms to make sure we have reached an reasonable precision.
- **Quality of our LDA model:** The accuracy of our topic model and its imperfection in grouping related items is one limitation in this research. For tackling this one, we trained different models with different numbers of topics as mentioned in Section 3.2.2 to make sure that we are close to the optimal distribution of contextual separation in the corpus.
- **Human error in manual topic labeling:** There is a possibility of human error in selecting the right label for each set. Also there is a challenge for creating a harmony in the labeling team for selecting the same name for the

same topic in different sets. As we explained in Section 3.2.4, we made a map of topics and used it as a reference in our work. Finally, we reviewed the labels manually to check for the accuracy of labels in different sets.

- **Correlation with price:** In this work, we had 22 different datasets and we only evaluated the correlation with the average and median price in each one of the 6-month periods. Therefore, because of the relatively long length of time periods, the results of our work might have lower accuracy in comparison with the other studies that evaluated the daily price or over short time periods.
- **Fake news/posts:** In this work, we have not try to assess the quality of discussions nor identify fake users, we took the data as is and our findings may be subject to the existence of fake users who may intentionally try to manipulate other's opinion on specific topics, aka spreading fake news.

Chapter 6

Conclusions

We conclude this thesis with the thesis statement, list of our contributions summarized in Section 6.1 and our suggestions for future directions in Section 6.2.

Thesis Statement: While discussion topics have been evolved over the past decade in `bitcointalk.org`, six key categories of discussions were prevalent during this time. Our findings demonstrate a relation between Bitcoin price and the sentiment polarity of the selected discussion categories on the forum.

6.1 Summary of Contributions

In this research we studied the evolution of Bitcoin-related topics extracted from an online forum and made the following contributions to the research community.

First, as we mentioned in Section 5.1, we performed a longitudinal study of analyzing topics extracted from the online forum for the period of 10 years; to the best of our knowledge, our work is the most comprehensive study on this topic.

Second, in our work, we extracted 31 topics related to various discussions about cryptocurrency and classified them into six categories which we labeled as Future, General, Mining, Monetary, Regulations, and Technical.

Third, we performed an analysis of the evolution of topics in the forum and identified changes in the popularity of topics in the forum and the way some topics emerged, diminished or disappeared in discussions.

Fourth, we applied a sentiment analysis on the discussions and studied the changes of sentiment over the past 10 years and presented our findings about the difference in the sentiment polarity of different topics in this work.

Fifth, we analyzed the correlation of different factors with Bitcoin price and found the relation between Bitcoin price and the sentiment polarity for some categories, this is a novel contribution. It is worth mentioning that previous studies only worked on the correlation of sentiment and Bitcoin price on the whole data set level. But in this work we performed a fine-grained analysis by considering this correlation per discussion category and we determined that only some discussions in the forum are correlated with Bitcoin price.

Finally, our *sixth* contribution of this work was creating and making publicly available our comprehensive dataset about Bitcointalks discussion for any future work or replication studies.

6.2 Future Work

During the latest stages of this work, we identified a number of directions that could be investigated in depth in future extension of this work. In this study, we identified and labeled all the posts in the forum, identified a number of topics, assigned them to posts and performed analyses. Our findings demonstrate the correlation between the sentiment polarity of some topics and Bitcoin price, therefore, one suggestion for future direction is to build a comprehensive price analysis model using our data.

Previous studies [9] and [64] have investigated the relation between the sentiment

polarity of posts and Bitcoin price. We took a deeper look at this subject and measured this relation between each one of the categories and cryptocurrency price. We believe that analyzing the sentiment polarity of selected categories can offer further insights and leave this potential for future researchers in this field.

In this research we identified topics using topic modeling. Topic modeling is an unsupervised learning method, and we spent a considerable time on manual labelling the topics. As a outcome of this labelling, we identified several topics, a list of relevant words and all of the posts which were relevant to each one of these topics. These labelled data could be utilized in supervised machine learning methods for classifying posts of this forum in different topics and building predictive models.

In this study, we used Bitcointalk as the main source of data. Generally, we could not find any comprehensive study that compares the results of using Bitcointalk and Reddit as the source of information. Given the importance of this matter in predicting Bitcoin price, comparing these two forums would be next research direction. More specifically, a comprehensive and detailed study that compares different online sources of data can provide other researchers the opportunity to gain better insights into the diversity, popularity, and quality of the online social media. We hope that greater research community continues to work on this topic and advance the collective knowledge, models and techniques in this field.

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Appendix A

Sentiment Polarity Analysis Results

Table 9: Distribution of positive/negative posts in categories/subcategories over the time.

Category/Topic	2010b	2011a	2011b	2012a	2012b	2013a	2013b	2014a	2014b	2015a	2015b	2016a	2016b	2017a	2017b	2018a	2018b	2019a	2019b	2020a	2020b	Total
Future		3361	1218	933	1350		1180	2218	1489		2256		1143	2014		2500	1582	970	889	879	1343	25325
Negative		26%	24%	19%	23%		23%	22%	23%		34%		21%	23%		12%	14%	19%	18%	16%	21%	22%
Neutral		21%	15%	15%	18%		21%	17%	18%		15%		20%	13%		10%	9%	14%	8%	8%	12%	15%
Positive		53%	61%	66%	60%		56%	61%	59%		51%		59%	63%		78%	77%	67%	74%	77%	67%	63%
General	627	4205	2417	1290	2191	4501	4448	5314	6496	3563	5454	4147	3503	7240	6343	10235	2715	4777	4520	4171	1673	89830
Negative	16%	27%	15%	12%	16%	18%	22%	25%	20%	22%	23%	29%	22%	26%	20%	26%	18%	19%	25%	26%	23%	23%
Neutral	16%	21%	21%	20%	24%	25%	18%	17%	25%	16%	15%	17%	12%	14%	12%	12%	12%	11%	12%	10%	11%	16%
Positive	68%	52%	63%	69%	61%	58%	59%	58%	55%	62%	62%	54%	66%	60%	67%	62%	70%	70%	63%	64%	66%	61%
Mining	1010	2088	1837	2245	1476	4305	2492	2987	1861	2159	4643	3791	2470	1561	6967	4633	1492	1053	1294	1807	567	52738
Negative	33%	34%	35%	26%	26%	30%	27%	36%	36%	36%	32%	26%	35%	32%	30%	29%	33%	31%	28%	33%	32%	
Neutral	17%	18%	17%	26%	21%	20%	32%	19%	17%	16%	16%	20%	15%	12%	18%	12%	10%	11%	11%	11%	9%	17%
Positive	50%	48%	48%	47%	53%	51%	41%	45%	47%	48%	48%	48%	59%	52%	49%	58%	61%	56%	58%	61%	58%	51%
Monetary	1107	7400	6992	2744	2306	4942	4726	11166	8765	10961	5210	8161	4635	6771	23635	25193	9912	6143	5336	5040	1190	162335
Negative	19%	23%	22%	17%	23%	20%	24%	25%	22%	23%	22%	23%	24%	24%	22%	24%	25%	25%	23%	27%	23%	23%
Neutral	18%	19%	17%	16%	16%	19%	20%	19%	19%	16%	16%	15%	13%	12%	13%	14%	12%	11%	11%	11%	8%	15%
Positive	63%	58%	61%	67%	61%	61%	56%	56%	59%	61%	63%	62%	63%	64%	65%	61%	63%	64%	66%	62%	69%	62%
Currency Subcategory	1107	3509	4896	2744	2306	3269	3075	7869	4856	3836	1242	4469	3141	5424	6345	10365	1354	1070	1407	1886		74170
Negative	19%	22%	21%	17%	23%	21%	25%	23%	20%	18%	25%	23%	22%	23%	20%	23%	13%	39%	23%	26%		22%
Neutral	18%	17%	17%	16%	16%	18%	21%	19%	18%	17%	16%	15%	14%	12%	13%	14%	11%	11%	10%	9%		15%
Positive	63%	61%	61%	67%	61%	61%	54%	58%	62%	65%	59%	62%	65%	65%	67%	63%	76%	50%	67%	64%		63%
Financial Subcategory	1431						1651	3297	3909	3079	3968	3692	1494			4150	6809	2798	2376	1194	835	40683
Negative		20%					21%	27%	24%	23%	21%	23%	29%			26%	25%	27%	22%	14%	23%	24%
Neutral		19%					20%	20%	21%	14%	15%	16%	12%			14%	16%	12%	10%	8%	7%	15%
Positive		61%					60%	53%	56%	62%	64%	61%	59%			60%	60%	62%	69%	78%	70%	61%
Price Subcategory		2460	2096			1673				4046				1347	13140	8019	5760	2697	2735	2319	1190	47482
Negative		27%	23%			19%				27%				27%	21%	26%	26%	22%	27%	29%	23%	24%
Neutral		22%	18%			21%				17%				13%	13%	13%	13%	12%	12%	13%	8%	14%
Positive		52%	59%			59%				55%				60%	66%	61%	61%	66%	61%	57%	69%	61%
Regulations	321	1806	4325	918	728	1706	1545	7190	2200	3957				2593	5963	5143	2438	1598	2759	2413	1634	49237
Negative	31%	36%	25%	37%	29%	37%	34%	34%	42%	35%				27%	34%	33%	27%	32%	37%	32%	40%	33%
Neutral	15%	15%	25%	12%	17%	15%	17%	23%	16%	16%				11%	13%	13%	12%	10%	9%	9%	10%	16%
Positive	54%	49%	49%	52%	54%	48%	49%	42%	42%	49%				62%	53%	54%	61%	58%	54%	59%	50%	51%
Technical	1001	6058	3775	2591	2320	2958	4550	3414	4111	4737	5649	4882	3280	6180	13267	4181	4248	2588	1608	1149	1031	83578
Negative	26%	29%	22%	24%	22%	23%	22%	24%	22%	27%	27%	27%	28%	34%	27%	25%	26%	24%	23%	24%	26%	26%
Neutral	18%	20%	21%	18%	20%	20%	20%	19%	19%	16%	18%	15%	13%	12%	13%	13%	13%	13%	11%	11%	10%	16%
Positive	56%	52%	57%	57%	58%	57%	58%	56%	59%	57%	55%	58%	59%	54%	60%	62%	60%	63%	66%	65%	65%	58%
Others Subcategory	603			638	520		1362	1899	2876	3865	2856	1872	4196	4539		2577					415	28218
Negative	27%			28%	27%		20%		21%	28%	30%	31%	34%	39%	31%		25%				22%	30%
Neutral	18%			15%	17%		19%		20%	16%	19%	15%	13%	12%	13%		13%				8%	15%
Positive	55%			57%	56%		60%		58%	56%	50%	54%	53%	49%	56%		62%				70%	55%
Wallet Subcategory	398	6058	3775	1953	1800	2958	3188	3414	2212	1861	1784	2026	1408	1984	8728	4181	1671	2588	1608	1149	616	55360
Negative	24%	29%	22%	23%	21%	23%	23%	24%	23%	27%	26%	22%	20%	22%	24%	25%	27%	24%	23%	24%	28%	24%
Neutral	18%	20%	21%	20%	20%	20%	19%	18%	16%	16%	15%	13%	12%	13%	13%	13%	15%	13%	11%	11%	11%	16%
Positive	58%	52%	57%	57%	59%	57%	57%	56%	59%	57%	64%	63%	66%	66%	63%	62%	58%	63%	66%	65%	62%	60%
Off Topic	1147	5826	6777	3315	1761	5332	4868	11347	6702	3024	4028	4271	2252	3746	7508	3021	1707	1082	2109		497	80320
Negative	15%	19%	21%	17%	26%	18%	18%	19%	20%	21%	19%	20%	21%	33%	27%	20%	30%	18%	20%		16%	21%
Neutral	20%	27%	18%	19%	16%	20%	17%	19%	17%	25%	14%	14%	11%	11%	12%	13%	12%	8%	9%		11%	17%
Positive	65%	54%	61%	64%	58%	62%	64%	62%	64%	54%	67%	65%	68%	56%	61%	67%	58%	74%	71%		72%	62%

Table 10: Distribution of positive/negative posts in *Future* category topics over the time.

Category/Topic	2010b	2011a	2011b	2012a	2012b	2013a	2013b	2014a	2014b	2015a	2015b	2016a	2016b	2017a	2017b	2018a	2018b	2019a	2019b	2020a	2020b	Total	
# Posts		3361	1218	933	1350		1180	2218	1489		2256		1143	2014		2500	1582	970	889	879	1343	25325	
Cryptocurrency Adoption																		970	889		440	2299	
Negative																		19%	18%		19%	18%	
Neutral																		14%	8%		9%	11%	
Positive																		67%	74%		72%	71%	
Future of Bitcoin		1676			706		1180							952							355	4869	
Negative		24%			26%		23%							26%							30%	25%	
Neutral		25%			16%		21%							16%							12%	20%	
Positive		51%			58%		56%							58%								59%	55%
Future Role of Bitcoin		1685	1218	933	644			2218	1489		2256		1143	1062		2500	1582			879	548	18157	
Negative		28%	24%	19%	20%			22%	23%		34%		21%	21%		12%	14%			16%	17%	21%	
Neutral		17%	15%	15%	19%			17%	18%		15%		20%	11%		10%	9%			8%	14%	14%	
Positive		55%	61%	66%	61%			61%	59%		51%		59%	68%		78%	77%			77%	69%	64%	

Table 11: Distribution of positive/negative posts in *General* category topics over the time.

Category/Topic	2010b	2011a	2011b	2012a	2012b	2013a	2013b	2014a	2014b	2015a	2015b	2016a	2016b	2017a	2017b	2018a	2018b	2019a	2019b	2020a	2020b	Total
# Posts	627	4205	2417	1290	2191	4501	4448	5314	6496	3563	5454	4147	3503	7240	6343	10235	2715	4777	4520	4171	1673	89830
Bitcoin Transaction						1131			1842	1723		1433	1347	1940		2867	1157	774	1122	910		16246
Negative						24%			26%	30%		25%	29%	24%		29%	25%	15%	28%	16%		26%
Neutral						19%			23%	18%		18%	13%	14%		14%	14%	8%	10%	9%		15%
Positive						57%			51%	52%		57%	59%	62%		57%	61%	76%	62%	74%		59%
Bitcoin Foundation						1340		2147	1737													5224
Negative						18%		18%	17%													17%
Neutral						16%		16%	17%													16%
Positive						66%		67%	66%													66%
Bitcoin Transaction Cost/Time	277	1690					1545							2881				1050		1070	670	9183
Negative	19%	40%					23%							37%				26%		20%	27%	31%
Neutral	15%	18%					16%							14%				13%		10%	13%	14%
Positive	65%	42%					61%							49%				61%		69%	61%	55%
Bitcoin User Experience						2030																2030
Negative						14%																14%
Neutral						33%																33%
Positive						53%																53%
Blockchain Technology											1599		972		3318	3399	1558	1262	895		518	13521
Negative											19%		23%		14%	13%	12%	12%	20%		13%	15%
Neutral											14%		11%		10%	11%	11%	11%	10%		7%	11%
Positive											67%		66%		76%	76%	76%	77%	71%		80%	74%
Effects of Covid on Bitcoin																				847		847
Negative																				30%		30%
Neutral																				10%		10%
Positive																				60%		60%
General Bitcoin Discussion					655		996		2917	1840	1796	1281			3025			1691	1338	1344	485	17368
Negative					20%		26%		18%	14%	27%	35%			27%			23%	29%	35%	28%	25%
Neutral					17%		18%		30%	15%	18%	18%			15%			10%	13%	10%	14%	17%
Positive					63%		56%		52%	71%	55%	47%			58%			67%	58%	55%	57%	58%
Project Development	350	2515	2417	1290	1536		1907	3167				2059	1433	1184	2419		3969			1165		25411
Negative	14%	18%	15%	12%	14%		20%	30%				23%	27%	15%	14%		35%			22%		22%
Neutral	16%	24%	21%	20%	26%		20%	17%				13%	15%	11%	13%		12%			13%		17%
Positive	70%	58%	63%	69%	59%		60%	52%				64%	58%	74%	73%		53%			65%		61%

Table 12: Distribution of positive/negative posts in *Mining* category topics over the time.

Category/Topic	2010b	2011a	2011b	2012a	2012b	2013a	2013b	2014a	2014b	2015a	2015b	2016a	2016b	2017a	2017b	2018a	2018b	2019a	2019b	2020a	2020b	Total
# Posts	1010	2088	1837	2245	1476	4305	2492	2987	1861	2159	4643	3791	2470	1561	6967	4633	1492	1053	1294	1807	567	52738
Mining : Transactions	341		1837	1393	843	1701	2492	2987	1861	2159	2192	2606	1134	1561	6967	4633				734	567	36008
Negative	52%		35%	28%	27%	38%	27%	36%	36%	36%	44%	36%	31%	35%	32%	30%				22%	33%	33%
Neutral	14%		17%	31%	21%	17%	32%	19%	17%	16%	15%	21%	16%	12%	18%	12%				14%	9%	18%
Positive	34%		48%	41%	52%	46%	41%	45%	47%	48%	41%	42%	54%	52%	49%	58%				63%	58%	48%
Mining: Requirement	669	2088		852	633	2604					2451	1185	1336				1492	1053	1294	1073		16730
Negative	23%	34%		24%	24%	24%					28%	24%	21%				29%	33%	31%	32%		28%
Neutral	18%	18%		19%	21%	22%					18%	15%	14%				10%	11%	11%	8%		16%
Positive	58%	48%		57%	55%	54%					55%	61%	65%				61%	56%	58%	59%		56%

Table 13: Distribution of positive/negative posts in *Monetary* category topics over the time.

Category/Topic	2010b	2011a	2011b	2012a	2012b	2013a	2013b	2014a	2014b	2015a	2015b	2016a	2016b	2017a	2017b	2018a	2018b	2019a	2019b	2020a	2020b	Total
# Posts	1107	7400	6992	2744	2306	4942	4726	11166	8765	10961	5210	8161	4635	6771	23635	25193	9912	6143	5336	5040	1190	162335
Currency Subcategory	1107	3509	4896	2744	2306	3269	3075	7869	4856	3836	1242	4469	3141	5424	6345	10365	1354	1070	1407	1886	0	74170
Bitcoin Alternatives	287							2104					1882	3068	2732	3321		1070		859		15323
Negative	26%							27%					26%	25%	20%	29%		39%		27%		26%
Neutral	18%							24%					14%	12%	12%	13%		11%		11%		14%
Positive	56%							49%					60%	63%	68%	59%		50%		61%		60%
Bitcoin Exchange Rate	444	1786	1511	964	887	1615	1580	2720	2385		1242	2343				3613	3288	1354		1407	1027	28166
Negative	16%	24%	18%	16%	24%	21%	20%	28%	25%		25%	29%				20%	20%	13%		23%	26%	22%
Neutral	27%	16%	17%	16%	15%	19%	21%	16%	19%		16%	15%				14%	13%	11%		10%	8%	15%
Positive	57%	60%	65%	68%	61%	60%	59%	55%	56%		59%	56%				65%	67%	76%		67%	67%	62%
Payment with Bitcoin	376	1723	3385	1780	1419	1654	1495	3045	2471	3836		2126	1259	2356		3756						30681
Negative	16%	20%	23%	18%	22%	20%	31%	17%	15%	18%		16%	16%	20%		20%						19%
Neutral	9%	18%	17%	16%	16%	17%	20%	17%	16%	17%		15%	13%	12%		17%						16%
Positive	75%	62%	60%	66%	62%	62%	49%	67%	68%	65%		69%	71%	68%		63%						64%
Financial Subcategory		1431					1651	3297	3909	3079	3968	3692	1494		4150	6809	2798	2376	1194	835		40683
Bitcoin Trading																		1148	1194	835		3177
Negative																		19%	14%	23%		18%
Neutral																		8%	8%	7%		8%
Positive																		73%	78%	70%		74%
Effect of Bitcoin on Banking									1767	1464	1950	1748	1494			2983	1355	1228				13989
Negative									29%	28%	18%	22%	29%			28%	26%	24%				25%
Neutral									18%	14%	15%	16%	12%			15%	13%	11%				14%
Positive									53%	59%	67%	62%	59%			57%	61%	65%				60%
Financial Return		1431					1651	3297	2142	1615	2018	1944			4150	3826	1443					23517
Negative		20%					21%	27%	20%	20%	23%	23%			26%	22%	27%					24%
Neutral		19%					20%	20%	23%	15%	16%	16%			14%	16%	10%					17%
Positive		61%					60%	53%	57%	65%	60%	60%			60%	62%	62%					60%
Price Subcategory		2460	2096			1673				4046				1347	13140	8019	5760	2697	2735	2319	1190	47482
Bitcoin Future Price Discussion										1592				1347	3619	2665	1259	822	757	734	454	13249
Negative										24%				27%	16%	22%	22%	18%	29%	26%	22%	22%
Neutral										20%				13%	11%	14%	16%	13%	12%	16%	6%	14%
Positive										56%				60%	73%	63%	62%	69%	59%	58%	72%	65%
Bitcoin Price Discussion		2460	2096			1673				2454					9521	5354	4501	1875	1978	1585		33497
Negative		27%	23%			19%				20%					23%	27%	28%	24%	27%	31%		26%
Neutral		22%	18%			21%				16%					14%	13%	12%	11%	12%	13%		15%
Positive		52%	59%			59%				55%					63%	60%	60%	65%	61%	57%		60%
Bitcoin Price Discussion (Covid)																					736	736
Negative																					24%	24%
Neutral																					9%	9%
Positive																					67%	67%

Table 14: Distribution of positive/negative posts in *Regulations* category topics over the time.

Category/Topic	2010b	2011a	2011b	2012a	2012b	2013a	2013b	2014a	2014b	2015a	2015b	2016a	2016b	2017a	2017b	2018a	2018b	2019a	2019b	2020a	2020b	Total
# Posts	321	1806	4325	918	728	1706	1545	7190	2200	3957				2593	5963	5143	2438	1598	2759	2413	1634	49237
Bitcoin in Illegal Activity			1693					4397		2339											407	8836
Negative			29%					35%		37%											43%	35%
Neutral			19%					28%		16%											9%	22%
Positive			52%					37%		48%											48%	43%
Bitcoin Regulatory	321	1806	2632	918	728	1706	1545	2793	2200	1618				2593	5963	5143	2438	1598	1630	1177	606	37415
Negative	31%	36%	23%	37%	29%	37%	34%	34%	42%	33%				27%	34%	33%	27%	32%	32%	32%	28%	32%
Neutral	15%	15%	29%	12%	17%	15%	17%	16%	16%	16%				11%	13%	13%	12%	10%	9%	10%	9%	14%
Positive	54%	49%	47%	52%	54%	48%	49%	50%	42%	51%				62%	53%	54%	61%	58%	59%	58%	63%	53%
Bitcoin Scam																			1129	1236	621	2986
Negative																			43%	32%	49%	40%
Neutral																			9%	9%	12%	10%
Positive																			47%	59%	38%	50%

Table 15: Distribution of positive/negative posts in *Technical* category topics over the time.

Category/Topic	2010b	2011a	2011b	2012a	2012b	2013a	2013b	2014a	2014b	2015a	2015b	2016a	2016b	2017a	2017b	2018a	2018b	2019a	2019b	2020a	2020b	Total
# Posts	1001	6058	3775	2591	2320	2958	4550	3414	4111	4737	5649	4882	3280	6180	13267	4181	4248	2588	1608	1149	1031	83578
Others Subcategory	603			638	520		1362		1899	2876	3865	2856	1872	4196	4539		2577				415	28218
Fork										1549	2542	1521	1872	4196	4539		1418					17637
Negative										32%	28%	29%	34%	39%	31%		29%					33%
Neutral										15%	21%	16%	13%	12%	13%		12%					14%
Positive										53%	51%	55%	53%	49%	56%		58%					53%
General Network Discussion							1362			1327												2689
Negative							20%			23%												21%
Neutral							19%			17%												18%
Positive							60%			60%												60%
Network Security	292				520																	812
Negative	27%				27%																	27%
Neutral	23%				17%																	19%
Positive	50%				56%																	53%
Technical Issue	311			638					1899		1323	1335					1159				415	7080
Negative	26%			28%					21%		35%	33%					21%				22%	27%
Neutral	14%			15%					20%		16%	14%					13%				8%	16%
Positive	60%			57%					58%		49%	53%					66%				70%	57%
Wallet Subcategory	398	6058	3775	1953	1800	2958	3188	3414	2212	1861	1784	2026	1408	1984	8728	4181	1671	2588	1608	1149	616	55360
User Security	398	3661	2042	853	1800	2958	1807	3414	2212	1861	1784	2026	1408	1984	4781	4181	1671	1161	1608	1149		42759
Negative	24%	25%	22%	24%	21%	23%	20%	24%	23%	27%	20%	22%	20%	22%	23%	25%	27%	22%	23%	24%		23%
Neutral	18%	18%	21%	18%	20%	20%	17%	19%	18%	16%	16%	15%	13%	12%	12%	13%	15%	13%	11%	11%		16%
Positive	58%	57%	57%	58%	59%	57%	62%	56%	59%	57%	64%	63%	66%	66%	65%	62%	58%	65%	66%	65%		61%
Wallet Apps		2397	1733	1100			1381								3947		1427				616	12601
Negative		34%	22%	23%			26%								26%			25%			28%	27%
Neutral		22%	21%	21%			23%								14%			13%			11%	18%
Positive		44%	58%	57%			51%								60%			62%			62%	56%