MODELLING CRYPTOCURRENCY ACTIVITIES' REPORTAGE USING CORRELATED TOPIC MODEL

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Abstract

This study aimed at unveiling the connections amidst cryptocurrency activities by users and how traders read these activities online to aid their trading capabilities. Therefore, it examined the daily actions of Bitcoin traders who may have learned about the market from news items. The study employed the latent Dirichlet Allocation (LDA) model and its version, and the Correlated Topic Model (CTM) to examine news stories that were scraped from the market section website of CNBC. Using this machine learning process, topics with their terminology and words that were hidden in the documents and articles were found. The Document-Term-matrix was used to create coherence and perplexity graphs, which were then used to determine the number of Topics (K) to prevent the CTM from being overfitted or underfitted. The topics were determined by estimating the proportions for each document, and the CTM was used to perform correlation tests between the themes that were found. Similarly, document-word proportions and topic-word proportions were also measured. The posterior covariance matrix produced by the CTM was used to create a dense topic graph, which was then fed straight into a network analysis model to show positive, negative, and no relationships between the topics. Additionally, papers were searched using the "Hellinger distance" approach to determine the relationship between two or more documents/articles. The outcome demonstrates that there were more positive correlations between the topics that were found and between the different documents and topics that might have included the collective knowledge underlying the cryptocurrency traders' actions.

Keywords: Topic modeling, Latent Dirichlet Allocation, Correlated Topic Model, Consumer News and Business Channel's market section website

1. INTRODUCTION

As early as 2200 BC, payments were made using several kinds of money before the invention of cryptocurrency. But since its inception, money has undergone constant transformation, taking on new forms while still performing the same essential functions. When money initially started to circulate, it was usually in the form of commodities, or goods with intrinsic value that were exchanged between people, such as produce or seeds. Some academics claim that the earliest money was made of cowry shells (Sehra *et al*, 2018).

As civilization developed, various forms of money, such as gold and silver, were produced and eventually took the role of barter as a medium of exchange.

Our perception of money started to change with the introduction of the World Wide Web, which eventually led to the development of credit cards, smartphones that could access bank accounts, and other financial advancements. Simultaneously, technological improvements were also impacting other facets of our existence.

Because of the cryptocurrencies' recent development and increase in market capitalization, more people are opting to invest in platforms like Litecoin, Ethereum, Ripple, and Bitcoin. The price and policy uncertainty in the cryptocurrency market have an impact on the daily return pattern of the market (Sehra *et al*, 2018). One should be aware of the considerable danger that the decentralized nature of cryptocurrencies brings before making an investment or dealing with them. The uncertainty indices for investors and many users estimate the degree of unpredictability for the future direction of the financial market, spanning from numerous themes, the market factors (internal & external), and the trade friction among all the digital currencies.

We have decided to focus our analysis on Bitcoin out of all the various cryptocurrencies. According to a website (coindesk.com), the current price of one bitcoin is more than 42,978.125 US dollars or 30,480,937.80 million naira.

The legalization of Bitcoin in countries like Australia and Japan has significantly increased demand for the cryptocurrency and positively impacted the market. More countries throughout the world are gradually accepting Bitcoin. As per "The Africa Report," an online publication, the use of cryptocurrencies in Africa surged by 120% between July 2000 and June 2021. The behavior of individuals who possess a significant quantity of Bitcoins, together with societal opinions, political beliefs, and emotional states, all influence the price of Bitcoin.

News articles are a good source of knowledge on the previously stated components because they often provide the public with first-hand information. Through several mobile applications, people who are interested in Bitcoin transactions can access the most recent news, price movements, and their causes at any time and from any location. They could utilize this knowledge to help them decide whether to buy or sell. In this study, we investigated the influence of daily news on the price of bitcoin. The investigation shows that crowd wisdom is a powerful predictor of key events affecting cryptocurrency that investors and users use and can connect to data from news articles.

By evaluating and assigning a numerical value to these resources (textual data), we attempt to make use of the result of the investigation carried out. The most useful type of information is probably the textual information seen in news items, which is the views of traders and investors. It plays several significant roles. Text (in natural language form) is the most natural way to store and encode human information. Text is the most expressive form of information since it can explain other media kinds like images and videos. For example, to identify images that match a user's textual input keyword query, the Google image search engine often matches a set of text of photos. (Zhai and Massung, 2016).

A substantial portion of the public gets at least some information via websites, applications, or social networking sites, according to several surveys. The web channel is currently the second most important source of information behind television among those who prefer reading news articles over watching or listening to the news. (Kaya and Karsligil, 2010). Given the exponential growth of digital text data, there is a great demand for methods and tools for handling and leveraging big text data in this environment. Text data is largely created by humans for communication, and as such, it is usually rich in semantic content and contains significant knowledge, opinions, and preferences. These factors all contribute to the demand for text data. However, most machine learning algorithms cannot deal with raw texts directly. News articles in plain text are converted into numerical features that can be processed by machine learning systems. The field of natural language processing (NLP) has made some text analysis algorithms and techniques easily accessible. Among the numerous text representation methods are distributional semantics, N-grams, Bag of Words, One-Hot Encoding, Vector Semantics (tf-idf), etc. The recommended approach made use of the Latent Dirichlet Allocation (LDA) and its version correlated Topic Model (CTM) which are part of the Topic model family.

Topic models that learn a limited range of topics, such as Latent Dirichlet Allocation (LDA), are said to be able to capture the co-occurrence of terms in discrete count data. (Blei and Jordan, 2003). Given themes, any article can be represented as a distribution over topics, and any downstream supervised job can then use the weights of this distribution as input. Topic models reduce the complexity of the data, which improves the interpretability of forecasts, particularly when the topics are interpretable. This renders topic models valuable in domains like criminal justice (Da *et al,* 2017) and health care (Michael *et al,* 2017) where interpretability is a need for downstream validation. Since it makes it simpler to evaluate this massive volume of textual data to learn about various information and preferences, including how much news affects the Bitcoin market, text/opinion mining has become quite popular (Zhai and Massung, 2016). Sources of textual data include both independently developed and corporately produced materials. Sources generated by the company, such as quarterly and annual reports, can provide a rich language structure that, when carefully examined, can forecast the company's future performance (Kloptchenko *et al,* 2004). Topic models are generative models with a probabilistic basis that are utilized in natural language processing and machine learning (Liu *et al,* 2016). "Topics" describes the undefined, hazy connections between words in a vocabulary and how they are used in writing. A document is conceptualized as an assortment of topics.

Topic models unearth the hidden themes in the collection and annotate the papers according to those themes. It is believed that each word comes from one of those topics. Lastly, a distribution of document coverage of topics is generated, providing a new way to analyze the topics' viewpoints data.

Blei and Jordan (2003) introduced the LDA, which is an even more extensive probabilistic generative model (unsupervised machine learning) that builds upon Probability latent semantic allocation (PLSA). Since the introduction of LDA (Blei and Jordan, 2003), the methodology has served as a foundation for several topic models. Although the LDA might be most appropriate for learning static or fixed set themes in a corpus, it can also be customized in some ways to learn dynamic topics. For example, to determine the links between topics in a corpus, Bollen *et al*, (2010) developed the Correlated Topic Model (CTM), which is based on LDA. The more adaptable Logistic Normal distribution was adopted by the CTM in place of the Dirichlet distribution for the latent variable that represents the percentage of each topic in a document. This allows for an examination of the covariance/correlation structure of the model's component elements. These provide a model where the existence of one latent topic may be related to another, and they more faithfully capture the latent topical structure of the data. The primary computational hurdle for Topic modeling using the LDA and its variants is approximating posterior distribution, and many of these problems are unsolvable. Numerous approximation strategies have been proposed, primarily categorized into two approaches: Variational Inference and Markov Chain Monte Carlo (MCMC). The MCMC approximation approach (Griffiths *et al,* 2004) uses collapse Gibbs sampling, while the variational inference approximation (Blei and Lafferty, 2006) uses mean field variational inference (Griffiths *et al,* 2004) collapse variational inference (Teh *et al,* 2006), and expectation propagation.

Stenqvist and L¨onn¨o, (2017), collected 2.27 million messages regarding Bitcoin from Twitter and utilized the dataset to infer the short-term price change. At intervals of four minutes to four hours, aggregated sentiment changes were performed, and values were advanced one to four times to correspond to corresponding price changes. The testing results show that their ideal parameters yield a 79% accuracy. Because their research is based on data from a single month, it is not representative.

400 distinct kinds of chain-lets were extracted from the Bitcoin blockchain by Akcora *et al*, (2018), who then used cosine similarity to cluster them. A random forest model was employed to predict the price of Bitcoin, and Granger Causality was utilized to show the dataset's predictive power. Certain forms of chain lets were shown to have the largest predictive

influence on both investment risk and the price of Bitcoin when they examined the Granger predictive causality of chain lets.

McNally *et al,* (2018) predicted the price of Bitcoin using mining difficulty, hash rate, and historical pricing data using a machine learning algorithm. They achieved the best classification accuracy of 52% and RMSE of 8% for price data, mining difficulty, and hash rate with the use of machine learning. Their RMSE of 8% and classification accuracy score of 52% were the best.

The research by Yao *et al,* (2019) is closely related to ours; in this study, the researchers investigated if news stories have an impact on the price of bitcoin by applying machine learning and the Senti-Graph. Sentiment analysis is used by Senti-Graph to turn a news article into a graph. In comparison to previous feature extraction strategies, their trial findings indicate that the strategy had a good forecast accuracy, which also illustrates the impact of news items on the price of bitcoin.

Bollen *et al,* (2010), attempted to predict the stock market. From daily tweets, Opinion Finder and GPOMS gathered seven features. Before training self-organizing fuzzy neural networks, these traits were investigated via Granger causality. They only use news articles in their scenarios, which are different from instant communications. The news contains more thorough information and is relatively longer. The length of the tweets utilized in their research was limited to 140 characters, whereas the news does not have this restriction.

Nagar and Hahsler, (2012), searched the news and eliminated articles of specific stock categories. Articles, sentences, paragraphs, and titles are a few examples. The number of variances between positive and negative words indicates the polarity of an event. The percentage of positive polarity incidences in a corpus determines its score. They found a strong relationship between the corpora scores and the firm price.

Mueller and Rauh, (2016), provided an innovative method for topic-modelling newspaper text summaries (LDA). They predicted the beginning of the bloody fight one or two years in advance. When making their prediction, they distinguished between the possibility of violence between nations and the occurrence of conflict within each nation at a given time. Their analysis shows that the within-country variation, or their generated news data, has a comparative advantage in wartime prediction. They proposed that this is a particularly useful addition since it incorporates textual data into the most often used conflict predictors in the study.

Geletta *et al,* (2020), used natural language processing (NLP) and machine learning (ML) techniques to identify recurring patterns in narrative research materials to distinguish between successful and failed studies. Their goal was to identify the factors that led to unsuccessful research endeavours.

Colianni *et al,* (2015), looked into whether supervised machine learning algorithms may be used to develop profitable bitcoin trading techniques utilizing cryptocurrency-related Twitter data. They provided an overview of many machine-learning techniques for identifying changes in the Bitcoin market. The well-known alternative currency that is examined in this study is called Bitcoin (BTC). To ensure that exact inputs were used across the entire model, a thorough error analysis was conducted. Their analysis produced an accuracy gain of 25% on average.

Blei and Lafferty, (2006), developed the correlated topic model (CTM), which displays the correlation between topic proportions using the logistic normal distribution. They created an approximation posterior inference method based on mean-field variational inference for this model. Their analysis revealed that CTM yields a better match than LDA when applied to a batch of OCRed articles from the journal Science. They also showed how the CTM may be used to intuitively view and analyze this and other unstructured data sets.

Utilizing an interpolated multi-model approach, Wolk, (2020), examined the impact of social media on cryptocurrency prices. They illustrated how the extremely speculative valuations of cryptocurrencies were substantially impacted by the mental and behavioral attitudes of the general public.

Parekh *et al,* (2022), proposed DL-Gues, a robust and hybrid framework that considered both market sentiment and the interdependence of each coin for predicting cryptocurrency prices. They considered the Dash price projection, which was calculated for various validation loss functions based on price history and tweets from Dash, Litecoin, and Bitcoin. To evaluate the applicability of DL-Gues on other cryptocurrencies, they also analyzed the price history and tweets of Bitcoin-Cash, Litecoin, and Bitcoin to deduce findings for price prediction of Bitcoin-Cash.

Card *et al,* (2017), provided a broad neural framework based on topic models and built upon recent advancements in variational inference techniques to enable the flexible and rapid insertion of metadata and the study of alternative models. Their approach yielded good results with a fair trade-off between ambiguity, coherence, and sparsity. Finally, to demonstrate the potential of their method, they looked at a corpus of papers about immigration to the US.

Valencia *et al,* (2019), proposed predicting fluctuations in the price of Litecoin, Ethereum, Bitcoin, and Ripple cryptocurrency marketplaces by utilizing publicly accessible social media data and conventional machine learning techniques. They compared the use of neural networks (NN), support vector machines (SVM), and random forests (RF) using components from Twitter and market data as input features. The results showed that NN outperformed the other models, that machine learning and sentiment analysis may be used to predict cryptocurrency prices, and that some cryptocurrencies may be extrapolated just from Twitter data.

Previous studies like Yao *et al,* (2019) and Wolk, (2020), have shown that the impact of investor opinion on Bitcoin returns can be measured using unstructured language, such as sentiments on Twitter, which may or may not include meaningful and sufficient information. Our study will use structured textual data to examine how the sentiment of Bitcoin users affects Bitcoin returns. The goal of our suggested text-feature extraction of unsupervised Latent Dirichlet Allocation, or the CTM, is to raise traders' awareness when they rely on news items for trade expertise.

2 MATERIALS AND METHOD

The study population focused on news stories about cryptocurrency-related activity published in foreign media between 2016 and 2022. The Consumer News and Business Channel (CNBC) is the source of these news pieces, and Appendix IV has hyperlinks to each document. Because of the widespread use of Bitcoin among other cryptocurrencies, it is used in this study.

Every one of the more than 6,000 news pieces published between 2016 and 2022 was written in English. With a custom Python script called "beautiful Soap" created with the Jupyter Notebook, the text data was quickly scraped from the source mentioned above together with the accompanying meta-data. The query ‘Daily Bitcoin reports was used. The pages were stored in a comma-separated (CSV) format with the following meta-data:

i. Article Headline
ii. Article section
iii. Article link
iv. Article date
v. Article summary
vi. Article body
vii. Opening Price
viii. Closing Price

2.1 Specifications and Estimation of the CTM

To overcome a limitation, the Correlated Topic Model (CTM) introduces a more flexible distribution that permits investigating the covariance structure across components (Blei and Lafferty, 2006). This was accomplished by replacing the Dirichlet distribution with the Logistic Normal distribution (Aitchison and Shen, 2019), which is conjugated to the topic assignments and so more computationally convenient. The CTM yields a more accurate and realistic fit of the latent topical structure by using the logistic normal distribution in its hierarchical model to describe the hidden composition of topics linked with each document (Aitchison, 2019, Blei and Lafferty, 2006).

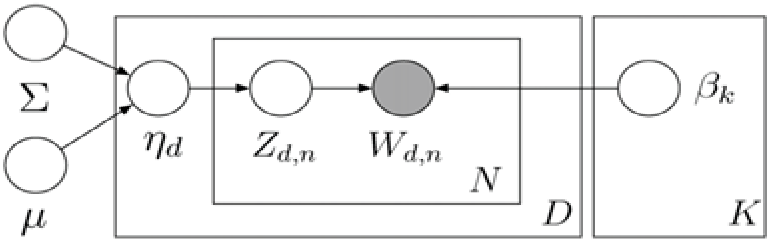

Figure 2.1: **The CTM model**

CTM assumes the following generative process and produces *N-word* documents.

1. For each topic $k \in$ {1,…,K}
   a. Draw a distribution over words $\beta_k \sim D\text{ir}\ (\emptyset)$
2. For each document $d \in$ {1,…,D},
   a. Draw $\eta_d | (\mu, \Sigma)$ ~N $(\mu, \Sigma\ )$
   b. Obtain a topic distribution $\theta_d = (\theta_{d1},\ldots,\theta_{dK})$as $\theta_{dk} = f(\eta_d)$
   c. Let η_d be the word in document d, $\forall n \in$ {1,….,N_d }
      i. Draw topic assignment $z_{d,n}|\eta$ ~ Mult(f (ηd))
      ii. Draw word $w_{d,n}|\ (z_{d,n}, \beta_{1:K})$~ Mult($\beta_{z_{d,n}}$)

where $f(\eta_d)$ is a function that maps the real vector natural parameter, η to the simplex

$$\theta = f(\eta) = \frac{\exp(\eta_i)}{\Sigma_j \exp(\eta_i)}$$

The full joint distribution is as follows:

$$p(w, z, \beta, \eta|\emptyset, \mu, \Sigma) = p(\beta|\emptyset)p(\eta|\mu, \Sigma)p(z|\eta)\ p(w|\beta, z)$$

$$= \prod_k \frac{\Gamma(\Sigma_v \emptyset_v}{\prod_v \Gamma(\emptyset_v)} \beta_{kv}^{\emptyset_w - 1} . \prod_d \frac{1}{2\pi^{\frac{k}{2}} |\Sigma|^{\frac{1}{2}}} \exp\{-\frac{1}{2}(\eta_d - \mu)^T \Sigma^{-1} (\eta_d - \mu)\} . \prod_d \prod_n \frac{\exp(\eta_{dz_{dj}})}{\Sigma_k exp(\eta_{dk})} \beta_{z_{dn} w_{dn}} \quad (1)$$

Given a collection of topics and distribution over topic proportions $\{\beta_{1:K}, \mu, \Sigma\}$, for a document w_d, the posterior distribution of the latent variables conditioned on the words of a document is;

$$p(\eta, z|w, \beta_{1:K}, \mu, \Sigma) = \frac{p(\eta|\mu,\Sigma)\prod_{n=1}^{N} p(Z_n|\eta)p(W_n|Z_n, \beta_{1:K})}{\int p(\eta|\mu,\Sigma)\prod_{n=1}^{N} \Sigma_{z_n}^{k} p(Z_n|\eta)p(W_n|Z_n, \beta_{1:K})d\eta} \quad (2)$$

We estimated the CTM parameters using variational expectation maximization and given a collection of documents by attempting to maximize the likelihood of the corpus as a function of the topic $\beta_{1:K}$ and the multivariate Gaussian (μ, Σ).

In the E-step, we will use variational inference to maximize the (coordinate ascent) objective function constrained concerning the variational parameters for each document.

$$L(\mu, \Sigma, \beta_{1:K}|w_{1:D}) \geq \sum_{d=1}^{D} \mathbb{E}_q[\ln p(\eta_d z_d w_d| \mu, \Sigma, \beta_{1:K})] + H(q_d) \quad (3)$$

We maximized the bound concerning the model parameters in the M-step. This included a maximum likelihood estimate of the themes and multivariate Gaussian using assumed adequate statistics, with the expectation being taken about the variational distributions derived in the E-step.

$$\hat{\beta}_i \ \alpha \ \sum_d \tau_{d,i} n_d \quad (4)$$

$$\hat{\mu} = \frac{1}{D}\sum_d \lambda_d \quad (5)$$

$$\hat{\Sigma} = \frac{1}{D}\sum I v_d^2 + (\lambda_d - \hat{\mu})(\lambda_d - \hat{\mu})^{\tau} \quad (6)$$

where n_d is the vector of word counts for document *d*.

2.2 Fitting the Model

The variational expectation-maximization (VEM) approach is employed to fit the models. Parameters like the "Document-Term matrix," "K" (the number of topics), and "control" (the correlated Topic Model (CTM)-VEM) were used to fit the correlated Topic Model. The algorithm's rate of convergence was modified by varying the settings of the "control" (CTM-VEM). The convergence tolerance for the variance and E-M algorithms was established using the parameters. Additionally, one of the settings for the conjugate gradient algorithm which alternates between the E-step and M-step to optimize the likelihood of the corpus sets the maximum number of iterations that may be performed.

In the M-step, the technique determines the maximum bound for the model parameters (the topics and the multivariate normal parameters), and in the E-step, it determines the maximum bound for the latent variables (the topic proportions and the topic assignments Z). Variational inference was applied until the relative change in the probability was less than 10^{-6}, and variational EM was applied until the relative change in the likelihood bound was less than

10^{-4}. The iterations on a 2.7GHz core i7 HP laptop with 8 GB RAM reached convergence in precisely 6 hours and 45 minutes.

3 RESULTS AND DISCUSSION

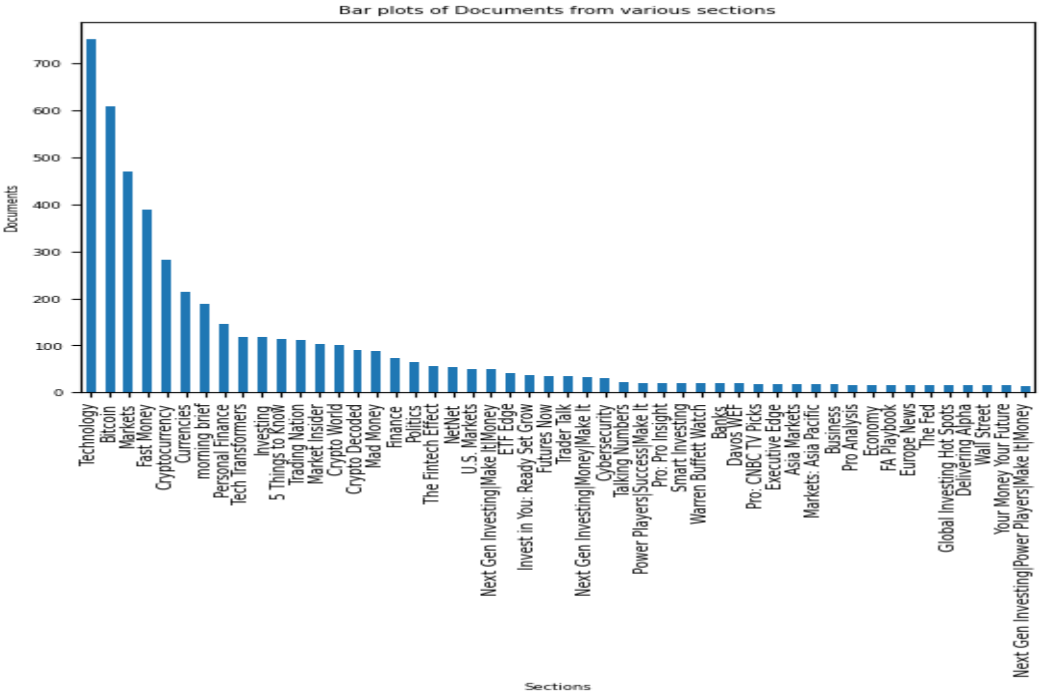

Figure 3.1: Bar plot of documents from various sections on the CNBC website.

Figure 3.1 shows that most of the documents out of the 5819 documents, came from the technology section. This simply means that cryptocurrency activities are driven by technology.

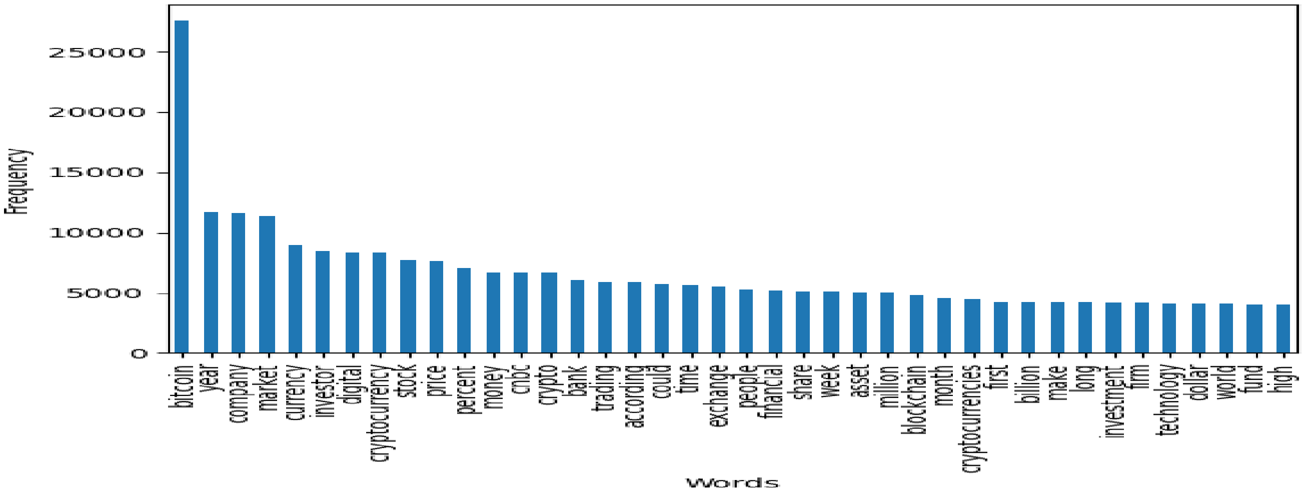

Figure 3.2: Bar plot of the top 40 words in the corpus

The top 40 words according to Figure 3.2 above show words like “bitcoin”, “year”, “company”, and “market”, e.t.c has a high frequency of occurrence in the corpus.

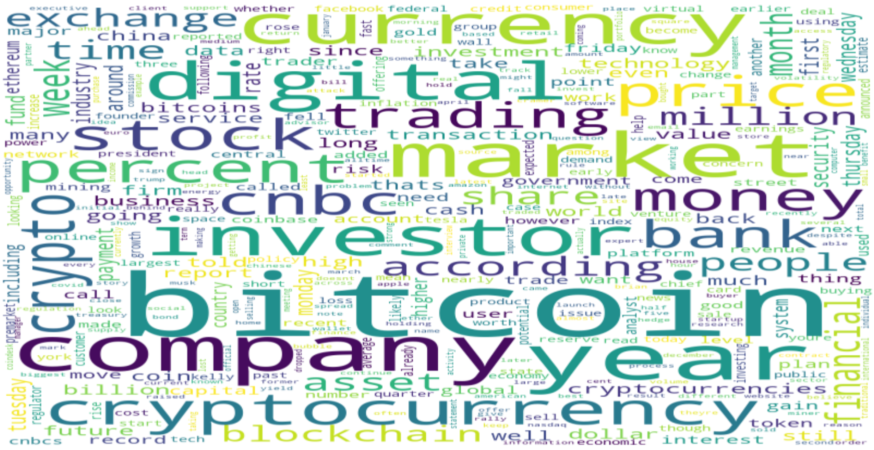

Figure 3.3: Wordcloud of the first 400 words in the corpus

Regarding Figure 3.3, the word cloud is a broader view of word occurrence frequencies when compared with the barplot in Figure 3.2 above. The bigger the word, the higher the frequencies.

Table 3.1: Tabular Summary of the corpus

Number of documents	Total word count	Total number of unique words
5,819	1,119,023	17,616

Table 3.1 shows a summary of the entire corpus, given that we analyzed 5,819 articles with a total word count of 1,119,023 and unique terms totaling 17,616.

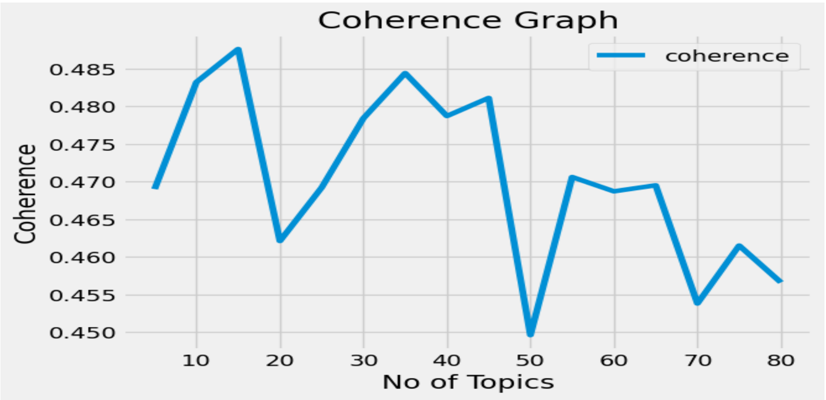

Figure 3.2: Graph of coherence scores for the corpus

We used the elbow approach to examine the graph in Figure 3.2 and determine which number of topics is the most correct. When taking the coherence score into account, the elbow with the highest frequency (k = 13) has the optimal number of topics. We chose the second elbow with the highest frequency, k = 35, to prevent the model from being under-fitted. This seems to be a good way to represent the corpus without going overboard.

Table 3.2: Table showing the first Seven (7) Topics with Ten (10) words/terms from the CTM output

Topic 1	**Topic 2**	**Topic 3**	**Topic 4**	**Topic 5**	**Topic 6**	**Topic 7**
tokenize	playing	first	developer	staid	polling	buildup
honig	netherlands	tripled	fond	mediumsized	interfax	affirmed
imply	feel	thankful	tape	firstout	piloted	superrich
maxim	marked	regret	doug	costing	crow	iaccino
Aaound	sloan	stifel	chip	oncepopular	accrued	nonaccredited
Cryptic	bashed	supervision	perjury	sample	distributor	premature
incorporates	faceless	export	takeover	wikipedia	becky	mood
safety	supplychain	celebrate	screenshot	overexuberance	bancorp	faint
supplydemand	permissioned	vaynerchuk	natixis	iaccino	private	mile
cybercrime	devastating	gear	chosen	silver	buzzy	threat

From the above table, Topic 1 talks about the News articles' safety measures, when considering adding bitcoin and other cryptocurrencies to one's retirement savings. Topic 2 exposes the News article's concern about the losses made in the bitcoin market, the sharp tumbling of bitcoin price, and its recovery trend. Awareness of scammers' activities in the Bitcoin and cryptocurrency market, education on safety guilds against falling victim, and the proportion of Bitcoin investors adopting artificial intelligence while trading were all captured in Topic 3. Topic 4 captures how Investors fled risk assets after the Federal Reserve of the US affirmed its commitment to an aggressive tightening path. Also, a measure of the activity of bitcoin miners' possibilities of giving investors a clue as to where the digital currency is headed next is captured in this Topic. Topic 5 encapsulates how Bitcoin could be having a "watershed" moment, as the cryptocurrency continued to rally off of lows. Sports trading card activities, fetching record prices in the millions, and collectors lining up online to buy virtual basketball "moments" that use blockchain were also captured in Topic 5. Activities as to how the crypto market was hit by several factors, ranging from the collapse of stable-coin terra-USD to questions of solvency at crypto lender Celsius are explained by Topic 6.

The activities of Draper, an early backer of Bitcoin and its underlying blockchain technology, participating in a so-called "initial coin offering" of Tezos was revealed by Topic 7. The Abu

Dhabi Financial Services Regulatory Authority's declaration on bitcoin having the same status as "commodities", is also captured in this same topic. The dollar falling to two-week lows on choppy trading, led by losses against the yen and euro, was recorded to be at risk sentiment improved in the afternoon session amid stock market gains and as U.S. Treasury yields rose. However, this led bitcoin price surging overnight, which is captured in Topic 8.

There are other 22 topics uncovered by the CTM, which can be seen in Appendix (i).

Table 3.4 shows the CTM Per Topic-word proportion output.

				TERMS/WORDS			
		according	**affirmed**	**aggressive**	**algorithmic**	**alltime**	**analyst**
	1	5.34E-05	5.37E-05	9.16E-05	9.83E-05	3.78E-05	5.79E-05
	2	8.25E-05	1.87E-05	8.29E-05	3.18E-05	6.71E-05	9.18E-05
TOPICS	3	3.45E-05	3.68E-05	0.00011	9.49E-05	9.66E-05	4.39E-05
	4	2.24E-05	6.25E-05	7.63E-05	4.18E-06	6.52E-05	9.3E-05
	5	3.97E-05	2.97E-05	6.81E-05	3.14E-05	8.86E-05	0.000101
	6	9.11E-05	0.000102	1.15E-05	6.1E-05	6.82E-05	7.19E-05
	7	1.63E-05	0.000112	5.11E-05	9.27E-05	4.96E-05	5.38E-05
	8	9.5E-05	6.33E-05	6.01E-05	9.87E-05	7.13E-05	2.7E-05
	9	9.83E-05	2.99E-05	0.000105	2.02E-05	6.14E-05	7.46E-05
	10	8.85E-05	7.42E-05	5.7E-05	2.11E-05	8.64E-05	2.94E-05

Table 3.4 above, shows the proportions or percentages of terms/words in each of the 35 Topics unveiled by the CTM. Ten (10) Topics and Six (6) words/terms were randomly selected and displayed in the table above while the full information can be seen in the appendix. The result reveals that 0.00534% of Topic 1 is formed by the word/term "according", 0.00825% of Topic 2 is formed by the word/term "according", 0.00345% of Topic 3 is formed by the word/term "according" and Same theory applies to other Topics and words/terms.

Table 3.5 shows the CTM Per Document-Topic proportion output.

	Topic 1	**Topic 2**	**Topic 3**	**Topic 4**	**Topic 5**	**Topic 6**	**Topic 7**
document 0	0.014426	0.011609	0.017581	0.591978	0.012079	0.012051	0.011941
document 1	0.0066	0.007897	0.008036	0.313197	0.012198	0.229338	0.007285
document 2	0.011883	0.010888	0.030879	0.015107	0.012577	0.220742	0.009185
document 3	0.009424	0.013925	0.011353	0.361039	0.010979	0.013062	0.008897
document 4	0.006524	0.007213	0.007856	0.009461	0.007212	0.007661	0.006423
document 5	0.010468	0.019943	0.01357	0.017734	0.015375	0.011094	0.010197
document 6	0.013044	0.017754	0.01755	0.022268	0.018448	0.016679	0.015714
document 7	0.015493	0.021778	0.02131	0.042051	0.024368	0.022564	0.015066
document 8	0.010995	0.011721	0.01078	0.301849	0.012202	0.009947	0.011227

According to Table 3.5 above, there is a 5819(row) by 35(column) matrix which shows that the proportions of terms/words in the documents/articles, came from the CTM Topics. However, because of the volume of this result and for clarity's sake, just the eight (8) documents/articles were selected and displayed in the table above why the full information can be seen in the appendix. The result reveals that 1.4% of the words in Document 0 are from Topic 1, 0.66% of the words in Document 1 are from Topic 1, 1.18% of the words in Document 2 are from Topic 1 and this goes on till the 35th topic and 5819th documents are exhausted.

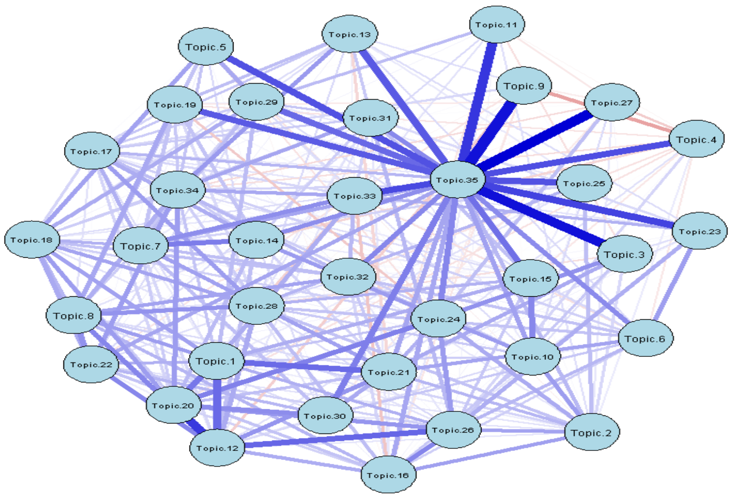

Figure 3.3: Topic Correlation graph

Visualizing the clear correlative relationship between the identified Topics using the Network analysis. [10], which relied on the edges (relationships) and the centrality of the Nodes (Topics) to determine the correlative measure of the Network Analysis graph. It is evident from Figure 3.3 above that the connecting lines, or edges, vary in thickness, distance, and color. The stronger the correlation, the more ticker the edges are; the blue and red colors indicate positive and negative correlations, respectively, between the Topics. The graph's density allows it to be successful in capturing the intricate correlation between the Topics. The hierarchy of Topic relevance is indicated by the nodes' (Topics') centrality.

Topic 35 occupies a central position in the graph, with thicker edges indicating a few Topics that are highly and positively connected with it. This only indicates that Topic 35, Topic 1, Topic 12, and Topic 21 have strong centrality and are hence highly predictive of traders.

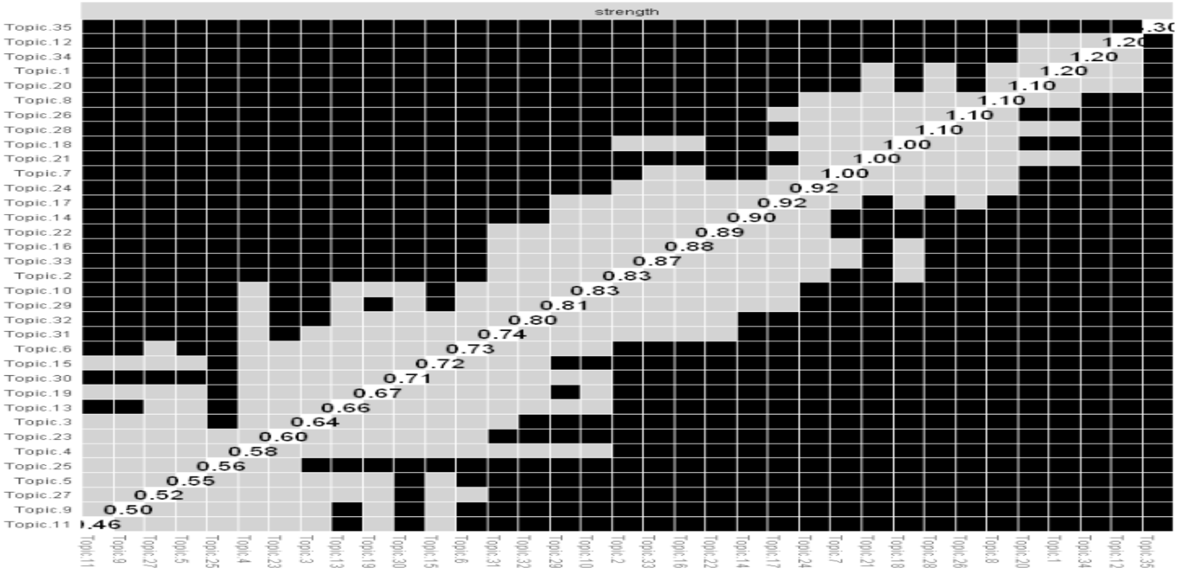

Figure 3.4: Topics' strength centrality correlation

Figure 3.4 provides further information on the graph in Figure 3.3, which illustrates the relationship between the subjects. The subjects are arranged in ascending order based on their significance and strength; correlations are shown by the black squares, whereas none are shown by the grey squares. Upon closely examining the subjects presented in Table 3.2, Subject 1 is related to subjects 21, 28, 8, 12, 34, 1, and 20. The topics 31, 32, 29, 10, 2, 33, 16, 22, 14, 17, 24, and 18 are linked to topic 2. There is a relationship between subjects 11,9,27,5,4,23,3,13,19,30,15,6,31 and topic 3. Topics 11, 9,27,5,25,4,23,3,13,19,30,15,6,31,32,29, and 10 are linked to subject 4. Correlates with subjects 11, 9, 27, 25, 4, 23, 3, 13, and 19 are topic 5. For the sake of concision, the degree of correlation between the correlated topics is displayed in Figure 3.3's dense sparse graph. Topic 1 is one instance of this, as it has favorable relationships with subjects 21, 28, 8, 12, 34, 1, and 20. The sparse graphs, however, indicate that it has a strong correlation with subject 12 initially, followed by topic 21 and then topic 20.

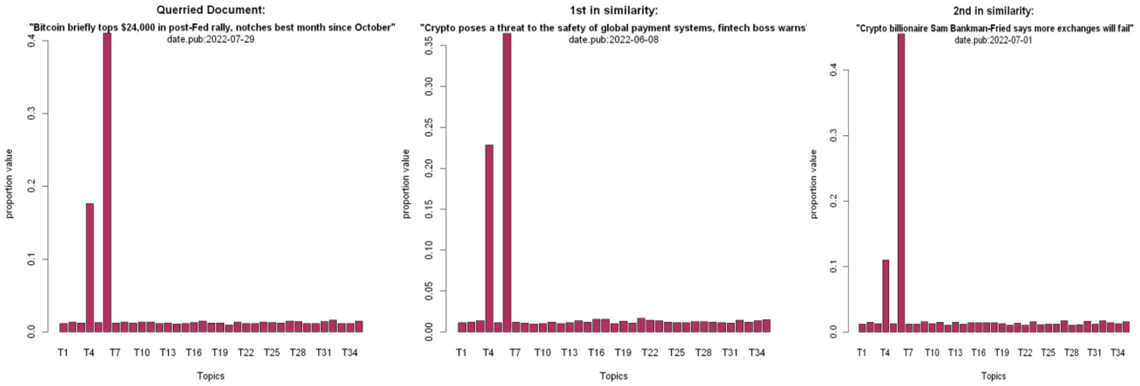

Figure 3.5: Similarity of a queried document and closest documents

One randomly chosen document was queried using the Hellinger distance approach to determine which two documents were closest to the requested document. The graphs below illustrate how the approach calculates the distances between the two nearest documents and the document being queried, accordingly. The graphs in Figure 3.5 above show that, among the two nearest documents and the questioned document, Topics 4 and 6 have the largest proportions. Every topic follows a similar pattern of appearance.

4. CONCLUSION

The significance and application of LDA and its version, the CTM, in textual data mining and analysis have been investigated to uncover latent themes, inferred topics, and topics' associations among documents. Relationships between the Hidden Topics in our textual data were also disclosed. Similarly, the relationships between the papers, Topic, and Word/terms were also disclosed. linkages between things like "safe investment plans by traders," "retirement saving incentives," "security of investors brokerage," "cryptocurrency theft," "enthusiasm among investors and traders," "excitement and interest of traders," "crypto mining and the US health care system," etc. are examples of these linkages. Lastly, the relationship between the documents was revealed thanks in large part to the "Hellinger distance."

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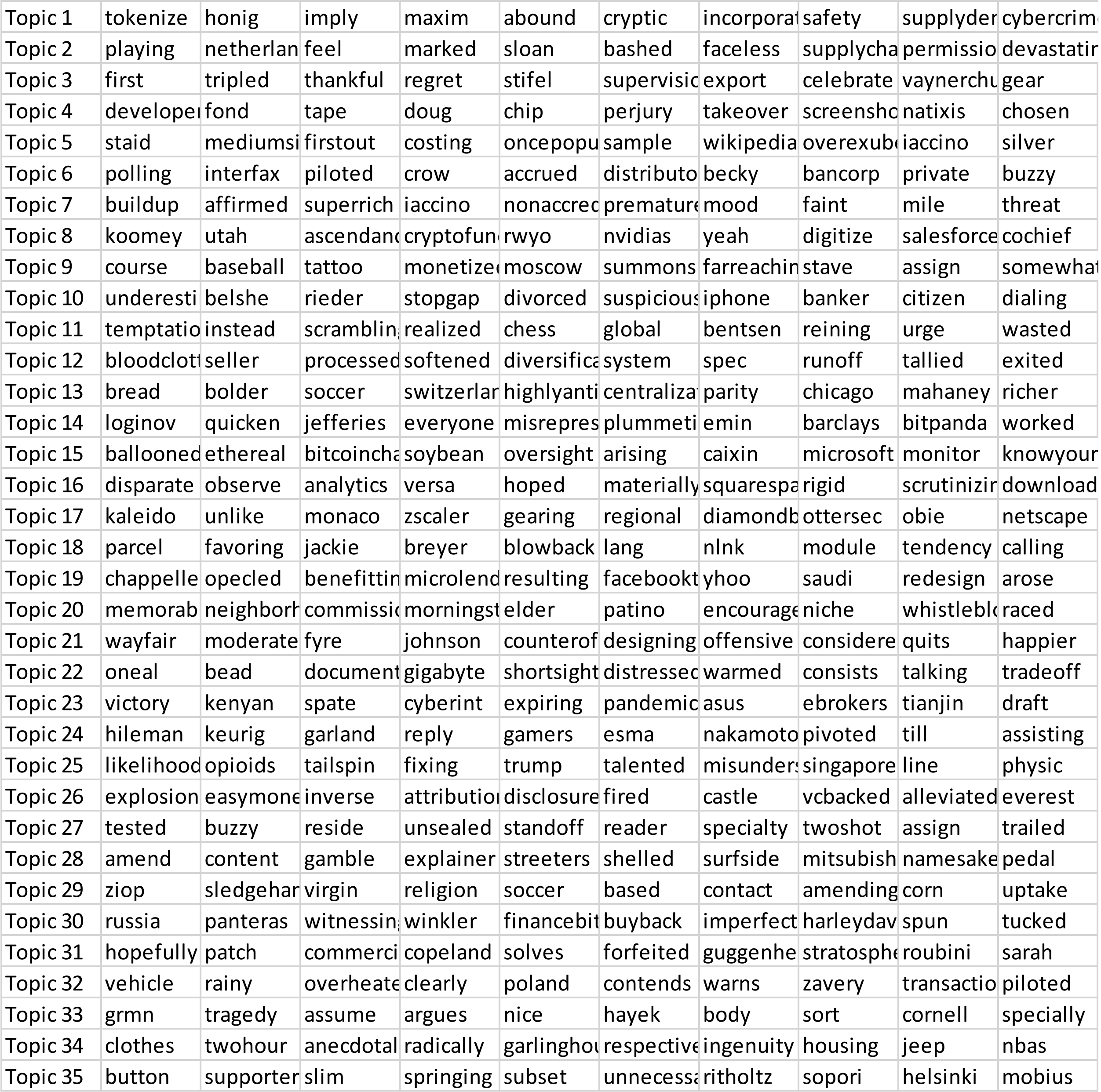
APPENDICES

(I)

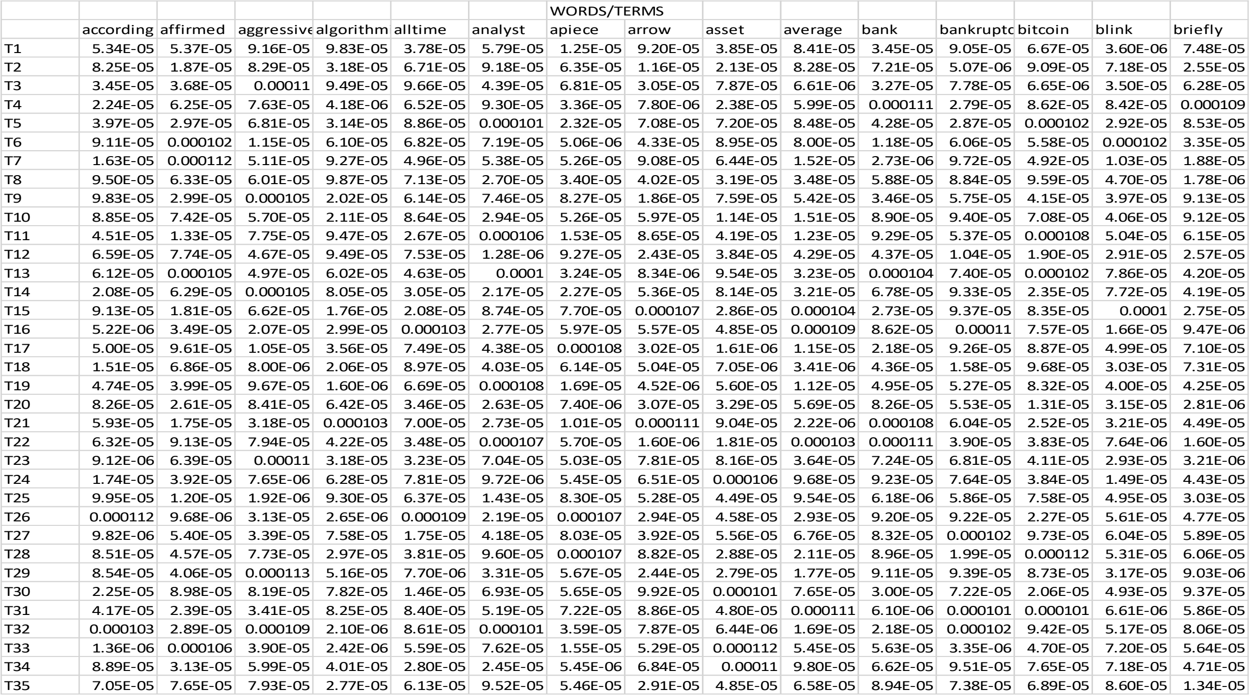
Table showing the thirty-five (35) Topics with Ten (10) words/terms from the CTM output



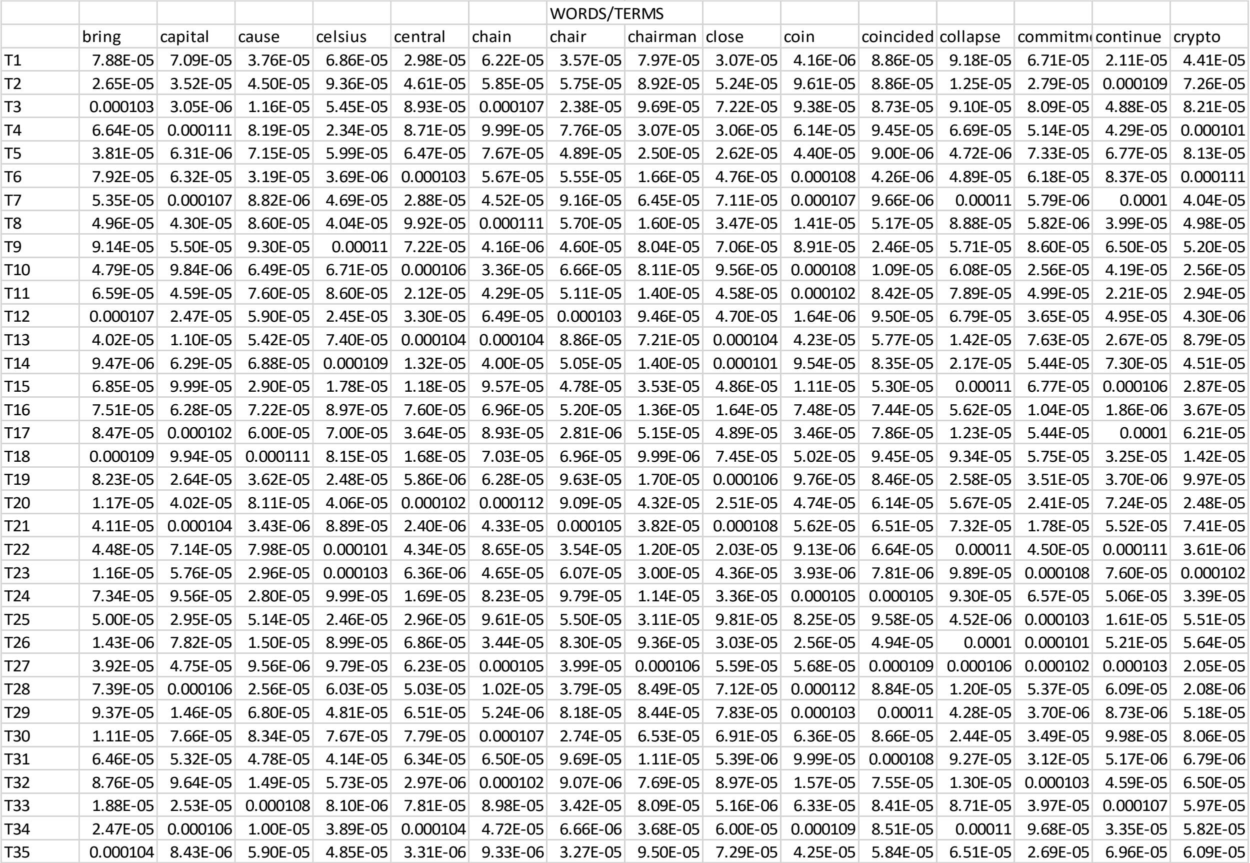
Topic 1	tokenize	honig	imply	maxim	abound	cryptic	incorporat	safety	supplyder	cybercrim
Topic 2	playing	netherlan	feel	marked	sloan	bashed	faceless	supplycha	permissio	devastatir
Topic 3	first	tripled	thankful	regret	stifel	supervisio	export	celebrate	vaynerchu	gear
Topic 4	developer	fond	tape	doug	chip	perjury	takeover	screensho	natixis	chosen
Topic 5	staid	mediumsi	firstout	costing	oncepopu	sample	wikipedia	overexube	iaccino	silver
Topic 6	polling	interfax	piloted	crow	accrued	distributo	becky	bancorp	private	buzzy
Topic 7	buildup	affirmed	superrich	iaccino	nonaccred	premature	mood	faint	mile	threat
Topic 8	koomey	utah	ascendanc	cryptofun	rwyo	nvidias	yeah	digitize	salesforce	cochief
Topic 9	course	baseball	tattoo	monetize	moscow	summons	farreachin	stave	assign	somewhat
Topic 10	underesti	belshe	rieder	stopgap	divorced	suspicious	iphone	banker	citizen	dialing
Topic 11	temptatio	instead	scramblin	realized	chess	global	bentsen	reining	urge	wasted
Topic 12	bloodclott	seller	processed	softened	diversifica	system	spec	runoff	tallied	exited
Topic 13	bread	bolder	soccer	switzerlar	highlyanti	centraliza	parity	chicago	mahaney	richer
Topic 14	loginov	quicken	jefferies	everyone	misrepres	plummeti	emin	barclays	bitpanda	worked
Topic 15	ballooned	ethereal	bitcoincha	soybean	oversight	arising	caixin	microsoft	monitor	knowyour
Topic 16	disparate	observe	analytics	versa	hoped	materially	squarespa	rigid	scrutinizir	download
Topic 17	kaleido	unlike	monaco	zscaler	gearing	regional	diamondb	ottersec	obie	netscape
Topic 18	parcel	favoring	jackie	breyer	blowback	lang	nlnk	module	tendency	calling
Topic 19	chappelle	opecled	benefittin	microlend	resulting	facebookt	yhoo	saudi	redesign	arose
Topic 20	memorab	neighborh	commissio	morningst	elder	patino	encourage	niche	whistleblo	raced
Topic 21	wayfair	moderate	fyre	johnson	counterof	designing	offensive	considere	quits	happier
Topic 22	oneal	bead	document	gigabyte	shortsight	distressed	warmed	consists	talking	tradeoff
Topic 23	victory	kenyan	spate	cyberint	expiring	pandemic	asus	ebrokers	tianjin	draft
Topic 24	hileman	keurig	garland	reply	gamers	esma	nakamoto	pivoted	till	assisting
Topic 25	likelihood	opioids	tailspin	fixing	trump	talented	misunders	singapore	line	physic
Topic 26	explosion	easymone	inverse	attributio	disclosure	fired	castle	vcbacked	alleviated	everest
Topic 27	tested	buzzy	reside	unsealed	standoff	reader	specialty	twoshot	assign	trailed
Topic 28	amend	content	gamble	explainer	streeters	shelled	surfside	mitsubish	namesake	pedal
Topic 29	ziop	sledgehar	virgin	religion	soccer	based	contact	amending	corn	uptake
Topic 30	russia	panteras	witnessing	winkler	financebit	buyback	imperfect	harleydav	spun	tucked
Topic 31	hopefully	patch	commerci	copeland	solves	forfeited	guggenhe	stratosphe	roubini	sarah
Topic 32	vehicle	rainy	overheate	clearly	poland	contends	warns	zavery	transactio	piloted
Topic 33	grmn	tragedy	assume	argues	nice	hayek	body	sort	cornell	specially
Topic 34	clothes	twohour	anecdotal	radically	garlinghou	respective	ingenuity	housing	jeep	nbas
Topic 35	button	supporter	slim	springing	subset	unnecessa	ritholtz	sopori	helsinki	mobius

(II)

Tables showing the CTM Per Topic-word proportion output (not all).



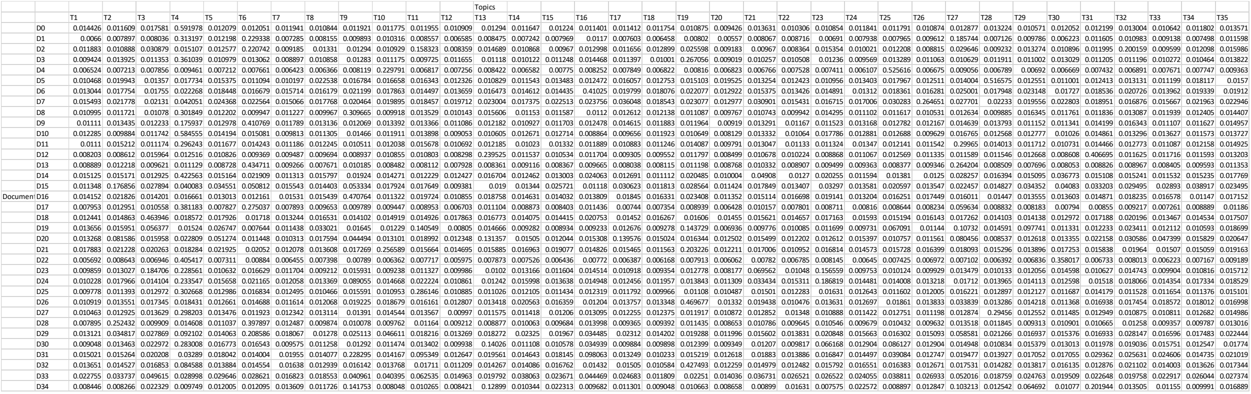
							WORDS/TERMS								
	according	affirmed	aggressive	algorithm	alltime	analyst	apiece	arrow	asset	average	bank	bankruptc	bitcoin	blink	briefly
T1	5.34E-05	5.37E-05	9.16E-05	9.83E-05	3.78E-05	5.79E-05	1.25E-05	9.20E-05	3.85E-05	8.41E-05	3.45E-05	9.05E-05	6.67E-05	3.60E-06	7.48E-05
T2	8.25E-05	1.87E-05	8.29E-05	3.18E-05	6.71E-05	9.18E-05	6.35E-05	1.16E-05	2.13E-05	8.28E-05	7.21E-05	5.07E-06	9.09E-05	7.18E-05	2.55E-05
T3	3.45E-05	3.68E-05	0.00011	9.49E-05	9.66E-05	4.39E-05	6.81E-05	3.05E-05	7.87E-05	6.61E-06	3.27E-05	7.78E-05	6.65E-06	3.50E-05	6.28E-05
T4	2.24E-05	6.25E-05	7.63E-05	4.18E-06	6.52E-05	9.30E-05	3.36E-05	7.80E-06	2.38E-05	5.99E-05	0.000111	2.79E-05	8.62E-05	8.42E-05	0.000109
T5	3.97E-05	2.97E-05	6.81E-05	3.14E-05	8.86E-05	0.000101	2.32E-05	7.08E-05	7.20E-05	8.48E-05	4.28E-05	2.87E-05	0.000102	2.92E-05	8.53E-05
T6	9.11E-05	0.000102	1.15E-05	6.10E-05	6.82E-05	7.19E-05	5.06E-06	4.33E-05	8.95E-05	8.00E-05	1.18E-05	6.06E-05	5.58E-05	0.000102	3.35E-05
T7	1.63E-05	0.000112	5.11E-05	9.27E-05	4.96E-05	5.38E-05	5.26E-05	9.08E-05	6.44E-05	1.52E-05	2.73E-06	9.72E-05	4.92E-05	1.03E-05	1.88E-05
T8	9.50E-05	6.33E-05	6.01E-05	9.87E-05	7.13E-05	2.70E-05	3.40E-05	4.02E-05	3.19E-05	3.48E-05	5.88E-05	8.84E-05	9.59E-05	4.70E-05	1.78E-06
T9	9.83E-05	2.99E-05	0.000105	2.02E-05	6.14E-05	7.46E-05	8.27E-05	1.86E-05	7.59E-05	5.42E-05	3.46E-05	5.75E-05	4.15E-05	3.97E-05	9.13E-05
T10	8.85E-05	7.42E-05	5.70E-05	2.11E-05	8.64E-05	2.94E-05	5.26E-05	5.97E-05	1.14E-05	1.51E-05	8.90E-05	9.40E-05	7.08E-05	4.06E-05	9.12E-05
T11	4.51E-05	1.33E-05	7.75E-05	9.47E-05	2.67E-05	0.000106	1.53E-05	8.65E-05	4.19E-05	1.23E-05	9.29E-05	5.37E-05	0.000108	5.04E-05	6.15E-05
T12	6.59E-05	7.74E-05	4.67E-05	9.49E-05	7.53E-05	1.28E-06	9.27E-05	2.43E-05	3.84E-05	4.29E-05	4.37E-05	1.04E-05	1.90E-05	2.91E-05	2.57E-05
T13	6.12E-05	0.000105	4.97E-05	6.02E-05	4.63E-05	0.0001	3.24E-05	8.34E-06	9.54E-05	3.23E-05	0.000104	7.40E-05	0.000102	7.86E-05	4.20E-05
T14	2.08E-05	6.29E-05	0.000105	8.05E-05	3.05E-05	2.17E-05	2.27E-05	5.36E-05	8.14E-05	3.21E-05	6.78E-05	9.33E-05	2.35E-05	7.72E-05	4.19E-05
T15	9.13E-05	1.81E-05	6.62E-05	1.76E-05	2.08E-05	8.74E-05	7.70E-05	0.000107	2.86E-05	0.000104	2.73E-05	9.37E-05	8.35E-05	0.0001	2.75E-05
T16	5.22E-06	3.49E-05	2.07E-05	2.99E-05	0.000103	2.77E-05	5.97E-05	5.57E-05	4.85E-05	0.000109	8.62E-05	0.00011	7.57E-05	1.66E-05	9.47E-06
T17	5.00E-05	9.61E-05	1.05E-05	3.56E-05	7.49E-05	4.38E-05	0.000108	3.02E-05	1.61E-06	1.15E-05	2.18E-05	9.26E-05	8.87E-05	4.99E-05	7.10E-05
T18	1.51E-05	6.86E-05	8.00E-06	2.06E-05	8.97E-05	4.03E-05	6.14E-05	5.04E-05	7.05E-06	3.41E-06	4.36E-05	1.58E-05	9.68E-05	3.03E-05	7.31E-05
T19	4.74E-05	3.99E-05	9.67E-05	1.60E-06	6.69E-05	0.000108	1.69E-05	4.52E-06	5.60E-05	1.12E-05	4.95E-05	5.27E-05	8.32E-05	4.00E-05	4.25E-05
T20	8.26E-05	2.61E-05	8.41E-05	6.42E-05	3.46E-05	2.63E-05	7.40E-06	3.07E-05	3.29E-05	5.69E-05	8.26E-05	5.53E-05	1.31E-05	3.15E-05	2.81E-06
T21	5.93E-05	1.75E-05	3.18E-05	0.000103	7.00E-05	2.73E-05	1.01E-05	0.000111	9.04E-05	2.22E-06	0.000108	6.04E-05	2.52E-05	3.21E-05	4.49E-05
T22	6.32E-05	9.13E-05	7.94E-05	4.22E-05	3.48E-05	0.000107	5.70E-05	1.60E-06	1.81E-05	0.000103	0.000111	3.90E-05	3.83E-05	7.64E-06	1.60E-05
T23	9.12E-06	6.39E-05	0.00011	3.18E-05	3.23E-05	7.04E-05	5.03E-05	7.81E-05	8.16E-05	3.64E-05	7.24E-05	6.81E-05	4.11E-05	2.93E-05	3.21E-06
T24	1.74E-05	3.92E-05	7.65E-06	6.28E-05	7.81E-05	9.72E-06	5.45E-05	6.51E-05	0.000106	9.68E-05	9.23E-05	7.64E-05	3.84E-05	1.49E-05	4.43E-05
T25	9.95E-05	1.20E-05	1.92E-06	9.30E-05	6.37E-05	1.43E-05	8.30E-05	5.28E-05	4.49E-05	9.54E-05	6.18E-06	5.86E-05	7.58E-05	4.95E-05	3.03E-05
T26	0.000112	9.68E-06	3.13E-05	2.65E-06	0.000109	2.19E-05	0.000107	2.94E-05	4.58E-05	2.93E-05	9.20E-05	9.22E-05	2.27E-05	5.61E-05	4.77E-05
T27	9.82E-06	5.40E-05	3.39E-05	7.58E-05	1.75E-05	4.18E-05	8.03E-05	3.92E-05	5.56E-05	6.76E-05	8.32E-05	0.000102	9.73E-05	6.04E-05	5.89E-05
T28	8.51E-05	4.57E-05	7.73E-05	2.97E-05	3.81E-05	9.60E-05	0.000107	8.82E-05	2.88E-05	2.11E-05	8.96E-05	1.99E-05	0.000112	5.31E-05	6.06E-05
T29	8.54E-05	4.06E-05	0.000113	5.16E-05	7.70E-06	3.31E-05	5.67E-05	2.44E-05	2.79E-05	1.77E-05	9.11E-05	9.39E-05	8.73E-05	3.17E-05	9.03E-06
T30	2.25E-05	8.98E-05	8.19E-05	7.82E-05	1.46E-05	6.93E-05	5.65E-05	9.92E-05	0.000101	7.65E-05	3.00E-05	7.22E-05	2.06E-05	4.93E-05	9.37E-05
T31	4.17E-05	2.39E-05	3.41E-05	8.25E-05	8.40E-05	5.19E-05	7.22E-05	8.86E-05	4.80E-05	0.000111	6.10E-06	0.000101	0.000101	6.61E-06	5.86E-05
T32	0.000103	2.89E-05	0.000109	2.10E-06	8.61E-05	0.000101	3.59E-05	7.87E-05	6.44E-06	1.69E-05	2.18E-05	0.000102	9.42E-05	5.17E-05	8.06E-05
T33	1.36E-06	0.000106	3.90E-05	2.42E-06	5.59E-05	7.62E-05	1.55E-05	5.29E-05	0.000112	5.45E-05	5.63E-05	3.35E-06	4.70E-05	7.20E-05	5.64E-05
T34	8.89E-05	3.13E-05	5.99E-05	4.01E-05	2.80E-05	2.45E-05	5.45E-06	6.84E-05	0.00011	9.80E-05	6.62E-05	9.51E-05	7.65E-05	7.18E-05	4.71E-05
T35	7.05E-05	7.65E-05	7.93E-05	2.77E-05	6.13E-05	9.52E-05	5.46E-05	2.91E-05	4.85E-05	6.58E-05	8.94E-05	7.38E-05	6.89E-05	8.60E-05	1.34E-05



							WORDS/TERMS								
	bring	capital	cause	celsius	central	chain	chair	chairman	close	coin	coincided	collapse	commitm	continue	crypto
T1	7.88E-05	7.09E-05	3.76E-05	6.86E-05	2.98E-05	6.22E-05	3.57E-05	7.97E-05	3.07E-05	4.16E-06	8.86E-05	9.18E-05	6.71E-05	2.11E-05	4.41E-05
T2	2.65E-05	3.52E-05	4.50E-05	9.36E-05	4.61E-05	5.85E-05	5.75E-05	8.92E-05	5.24E-05	9.61E-05	8.86E-05	1.25E-05	2.79E-05	0.000109	7.26E-05
T3	0.000103	3.05E-06	1.16E-05	5.45E-05	8.93E-05	0.000107	2.38E-05	9.69E-05	7.22E-05	9.38E-05	8.73E-05	9.10E-05	8.09E-05	4.88E-05	8.21E-05
T4	6.64E-05	0.000111	8.19E-05	2.34E-05	8.71E-05	9.99E-05	7.76E-05	3.07E-05	3.06E-05	6.14E-05	9.45E-05	6.69E-05	5.14E-05	4.29E-05	0.000101
T5	3.81E-05	6.31E-06	7.15E-05	5.99E-05	6.47E-05	7.67E-05	4.89E-05	2.50E-05	2.62E-05	4.40E-05	9.00E-06	4.72E-06	7.33E-05	6.77E-05	8.13E-05
T6	7.92E-05	6.32E-05	3.19E-05	3.69E-06	0.000103	5.67E-05	5.55E-05	1.66E-05	4.76E-05	0.000108	4.26E-06	4.89E-05	6.18E-05	8.37E-05	0.000111
T7	5.35E-05	0.000107	8.82E-06	4.69E-05	2.88E-05	4.52E-05	9.16E-05	6.45E-05	7.11E-05	0.000107	9.66E-06	0.00011	5.79E-06	0.0001	4.04E-05
T8	4.96E-05	4.30E-05	8.60E-05	4.04E-05	9.92E-05	0.000111	5.70E-05	1.60E-05	3.47E-05	1.41E-05	5.17E-05	8.88E-05	5.82E-06	3.99E-05	4.98E-05
T9	9.14E-05	5.50E-05	9.30E-05	0.00011	7.22E-05	4.16E-06	4.60E-05	8.04E-05	7.06E-05	8.91E-05	2.46E-05	5.71E-05	8.60E-05	6.50E-05	5.20E-05
T10	4.79E-05	9.84E-06	6.49E-05	6.71E-05	0.000106	3.36E-05	6.66E-05	8.11E-05	9.56E-05	0.000108	1.09E-05	6.08E-05	2.56E-05	4.19E-05	2.56E-05
T11	6.59E-05	4.59E-05	7.60E-05	8.60E-05	2.12E-05	4.29E-05	5.11E-05	1.40E-05	4.58E-05	0.000102	8.42E-05	7.89E-05	4.99E-05	2.21E-05	2.94E-05
T12	0.000107	2.47E-05	5.90E-05	2.45E-05	3.30E-05	6.49E-05	0.000103	9.46E-05	4.70E-05	1.64E-06	9.50E-05	6.79E-05	3.65E-05	4.95E-05	4.30E-06
T13	4.02E-05	1.10E-05	5.42E-05	7.40E-05	0.000104	0.000104	8.86E-05	7.21E-05	0.000104	4.23E-05	5.77E-05	1.42E-05	7.63E-05	2.67E-05	8.79E-05
T14	9.47E-06	6.29E-05	6.88E-05	0.000109	1.32E-05	4.00E-05	5.05E-05	1.40E-05	0.000101	9.54E-05	8.35E-05	2.17E-05	5.44E-05	7.30E-05	4.51E-05
T15	6.85E-05	9.99E-05	2.90E-05	1.78E-05	1.18E-05	9.57E-05	4.78E-05	3.53E-05	4.86E-05	1.11E-05	5.30E-05	0.00011	6.77E-05	0.000106	2.87E-05
T16	7.51E-05	6.28E-05	7.22E-05	8.97E-05	7.60E-05	6.96E-05	5.20E-05	1.36E-05	1.64E-05	7.48E-05	7.44E-05	5.62E-05	1.04E-05	1.86E-06	3.67E-05
T17	8.47E-05	0.000102	6.00E-05	7.00E-05	3.64E-05	8.93E-05	2.81E-06	5.15E-05	4.89E-05	3.46E-05	7.86E-05	1.23E-05	5.44E-05	0.0001	6.21E-05
T18	0.000109	9.94E-05	0.000111	8.15E-05	1.68E-05	7.03E-05	6.96E-05	9.99E-06	7.45E-05	5.02E-05	9.45E-05	9.34E-05	5.75E-05	3.25E-05	1.42E-05
T19	8.23E-05	2.64E-05	3.62E-05	2.48E-05	5.86E-06	6.28E-05	9.63E-05	1.70E-05	0.000106	9.76E-05	8.46E-05	2.58E-05	3.51E-05	3.70E-06	9.97E-05
T20	1.17E-05	4.02E-05	8.11E-05	4.06E-05	0.000102	0.000112	9.09E-05	4.32E-05	2.51E-05	4.74E-05	6.14E-05	5.67E-05	2.41E-05	7.24E-05	2.48E-05
T21	4.11E-05	0.000104	3.43E-06	8.89E-05	2.40E-06	4.33E-05	0.000105	3.82E-05	0.000108	5.62E-05	6.51E-05	7.32E-05	1.78E-05	5.52E-05	7.41E-05
T22	4.48E-05	7.14E-05	7.98E-05	0.000101	4.34E-05	8.65E-05	3.54E-05	1.20E-05	2.03E-05	9.13E-06	6.64E-05	0.00011	4.50E-05	0.000111	3.61E-06
T23	1.16E-05	5.76E-05	2.96E-05	0.000103	6.36E-06	4.65E-05	6.07E-05	3.00E-05	4.36E-05	3.93E-06	7.81E-06	9.89E-05	0.000108	7.60E-05	0.000102
T24	7.34E-05	9.56E-05	2.80E-05	9.99E-05	1.69E-05	8.23E-05	9.79E-05	1.14E-05	3.36E-05	0.000105	0.000105	9.30E-05	6.57E-05	5.06E-05	3.39E-05
T25	5.00E-05	2.95E-05	5.14E-05	2.46E-05	2.96E-05	9.61E-05	5.50E-05	3.11E-05	9.81E-05	8.25E-05	9.58E-05	4.52E-06	0.000103	1.61E-05	5.51E-05
T26	1.43E-06	7.82E-05	1.50E-05	8.99E-05	6.86E-05	3.44E-05	8.30E-05	9.36E-05	3.03E-05	2.56E-05	4.94E-05	0.0001	0.000101	5.21E-05	5.64E-05
T27	3.92E-05	4.75E-05	9.56E-06	9.79E-05	6.23E-05	0.000105	3.99E-05	0.000106	5.59E-05	5.68E-05	0.000109	0.000106	0.000102	0.000103	2.05E-05
T28	7.39E-05	0.000106	2.56E-05	6.03E-05	5.03E-05	1.02E-05	3.79E-05	8.49E-05	7.12E-05	0.000112	8.84E-05	1.20E-05	5.37E-05	6.09E-05	2.08E-06
T29	9.37E-05	1.46E-05	6.80E-05	4.81E-05	6.51E-05	5.24E-06	8.18E-05	8.44E-05	7.83E-05	0.000103	0.00011	4.28E-05	3.70E-06	8.73E-06	5.18E-05
T30	1.11E-05	7.66E-05	8.34E-05	7.67E-05	7.79E-05	0.000107	2.74E-05	6.53E-05	6.91E-05	6.36E-05	8.66E-05	2.44E-05	3.49E-05	9.98E-05	8.06E-05
T31	6.46E-05	5.32E-05	4.78E-05	4.14E-05	6.34E-05	6.50E-05	9.69E-05	1.11E-05	5.39E-06	9.99E-05	0.000108	9.27E-05	3.12E-05	5.17E-06	6.79E-06
T32	8.76E-05	9.64E-05	1.49E-05	5.73E-05	2.97E-06	0.000102	9.07E-06	7.69E-05	8.97E-05	1.57E-05	7.55E-05	1.30E-05	0.000103	4.59E-05	6.50E-05
T33	1.88E-05	2.53E-05	0.000108	8.10E-06	7.81E-05	8.98E-05	3.42E-05	8.09E-05	5.16E-06	6.33E-05	8.41E-05	8.71E-05	3.97E-05	0.000107	5.97E-05
T34	2.47E-05	0.000106	1.00E-05	3.89E-05	0.000104	4.72E-05	6.66E-06	3.68E-05	6.00E-05	0.000109	8.51E-05	0.00011	9.68E-05	3.35E-05	5.82E-05
T35	0.000104	8.43E-06	5.90E-05	4.85E-05	3.31E-06	9.33E-06	3.27E-05	9.50E-05	7.29E-05	4.25E-05	5.84E-05	6.51E-05	2.69E-05	6.96E-05	6.09E-05

(III)

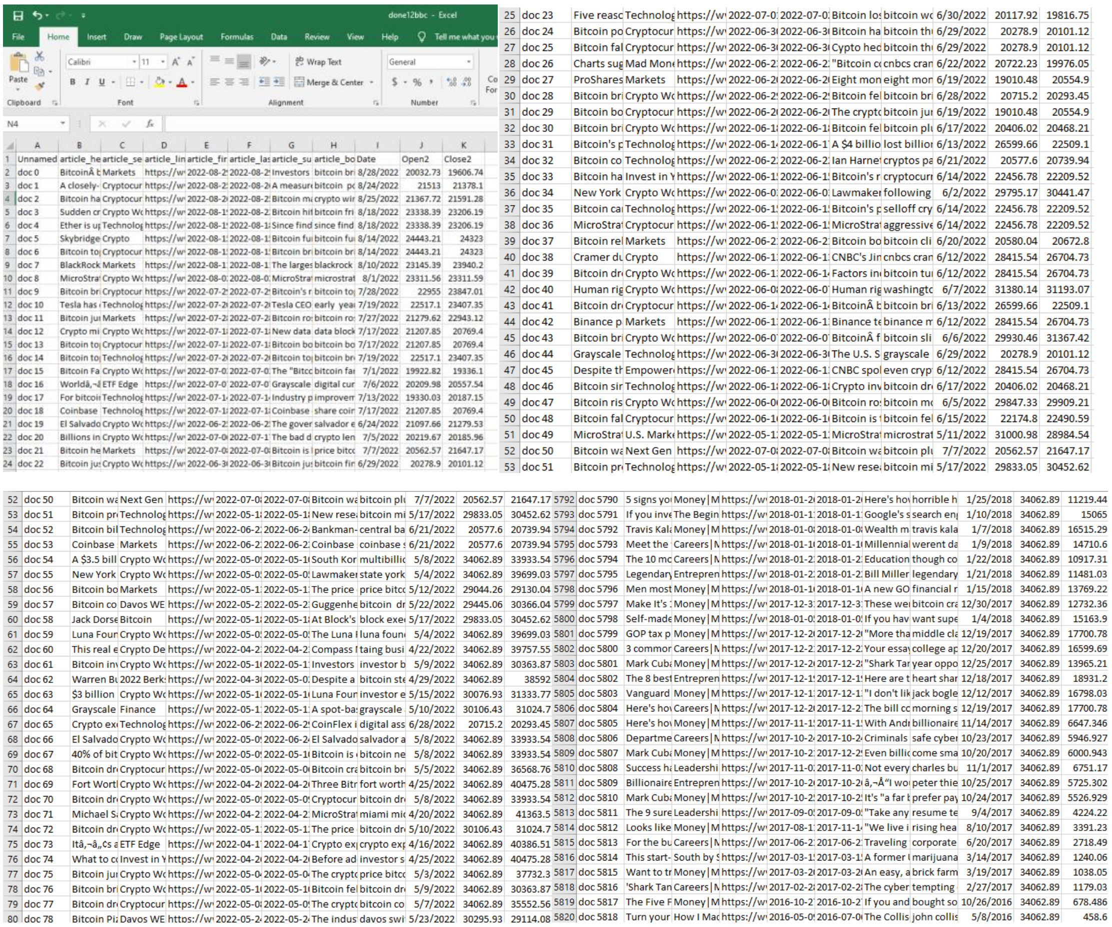
Table showing the CTM Per Document-Topic proportion output, For 34 documents out of 5819 documents.



		T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18	T19	T20	T21	T22	T23	T24	T25	T26	T27	T28	T29	T30	T31	T32	T33	T34	T35
														Topics																						
	D0	0.014426	0.011609	0.017581	0.591978	0.012079	0.012051	0.011941	0.010844	0.011921	0.011775	0.011955	0.010909	0.01294	0.011647	0.01224	0.011401	0.011412	0.011754	0.010875	0.009426	0.013631	0.010306	0.010854	0.011841	0.011791	0.010874	0.012877	0.013224	0.010571	0.012052	0.012199	0.013004	0.010642	0.011802	0.013571
	D1	0.0066	0.007897	0.008036	0.313197	0.012198	0.229338	0.007285	0.008155	0.009893	0.010316	0.008557	0.006585	0.008475	0.007242	0.007969	0.0117	0.007603	0.006458	0.00802	0.00557	0.008067	0.008716	0.00691	0.007938	0.007965	0.009612	0.185744	0.007126	0.009786	0.006223	0.011605	0.010983	0.009138	0.007498	0.011598
	D2	0.011883	0.010888	0.030879	0.015107	0.012577	0.220742	0.009185	0.01331	0.01294	0.010929	0.158323	0.008359	0.014689	0.010868	0.00967	0.012998	0.011656	0.012899	0.025598	0.009183	0.00967	0.008364	0.015354	0.010021	0.012208	0.008815	0.029646	0.009232	0.013274	0.010896	0.011995	0.200159	0.009599	0.012098	0.015986
	D3	0.009424	0.013925	0.011353	0.361039	0.010979	0.013062	0.008897	0.010858	0.01283	0.011175	0.009725	0.011655	0.01118	0.010122	0.011248	0.014468	0.011397	0.01001	0.267056	0.009019	0.010257	0.010508	0.01236	0.009569	0.013289	0.011063	0.010629	0.011911	0.011002	0.013029	0.011205	0.011196	0.010272	0.010464	0.013822
	D4	0.006524	0.007213	0.007856	0.009461	0.007212	0.007661	0.006423	0.006366	0.008119	0.229791	0.006817	0.007256	0.008422	0.006582	0.00775	0.008252	0.007849	0.006822	0.00816	0.006823	0.006766	0.007528	0.007411	0.006107	0.525616	0.006675	0.009056	0.006789	0.00692	0.006669	0.007432	0.006891	0.007671	0.007747	0.009363
	D5	0.010468	0.019943	0.01357	0.017734	0.015375	0.011094	0.010197	0.022538	0.016784	0.016658	0.016343	0.012326	0.010829	0.011543	0.013483	0.012472	0.016057	0.012753	0.015103	0.019525	0.013254	0.012423	0.010956	0.013403	0.017967	0.012511	0.014004	0.516575	0.012551	0.011001	0.012413	0.013131	0.011199	0.018117	0.0157
	D6	0.013044	0.017754	0.01755	0.022268	0.018448	0.016679	0.015714	0.016179	0.021199	0.017863	0.014497	0.013659	0.016473	0.014612	0.014435	0.41025	0.019799	0.018076	0.022077	0.012922	0.015375	0.013426	0.014891	0.01312	0.018361	0.016281	0.025001	0.017948	0.023148	0.01727	0.018536	0.020726	0.013962	0.019339	0.01912
	D7	0.015493	0.021778	0.02131	0.042051	0.024368	0.022564	0.015066	0.017768	0.020464	0.019895	0.018457	0.019712	0.023004	0.017375	0.022513	0.023756	0.036048	0.018543	0.023077	0.012977	0.030901	0.015431	0.016715	0.017006	0.030283	0.264651	0.027701	0.02233	0.019556	0.022803	0.018951	0.016876	0.015667	0.021963	0.022946
	D8	0.010995	0.011721	0.01078	0.301849	0.012202	0.009947	0.011227	0.009967	0.309665	0.009918	0.013529	0.010143	0.015606	0.01153	0.011587	0.0112	0.012612	0.012138	0.011087	0.009767	0.010743	0.009942	0.014295	0.011102	0.011617	0.010531	0.012634	0.009885	0.016345	0.011761	0.011836	0.013087	0.011939	0.012405	0.014407
	D9	0.01111	0.013435	0.012233	0.175937	0.012978	0.410769	0.011789	0.013136	0.012069	0.013392	0.013366	0.011086	0.012182	0.010927	0.011703	0.012478	0.014615	0.011883	0.011964	0.00919	0.013291	0.01167	0.011523	0.013168	0.012782	0.012167	0.014639	0.013793	0.011152	0.011341	0.014199	0.016343	0.011107	0.011627	0.014957
	D10	0.012285	0.009884	0.011742	0.584555	0.014194	0.015081	0.009813	0.011305	0.01466	0.011911	0.013898	0.009053	0.010605	0.012671	0.012714	0.008864	0.009656	0.011923	0.010649	0.008129	0.013332	0.01064	0.017786	0.012881	0.012688	0.009629	0.016765	0.012568	0.012777	0.01026	0.014861	0.013296	0.013627	0.011573	0.013727
	D11	0.0111	0.015212	0.011174	0.296243	0.011677	0.014243	0.011186	0.012245	0.010511	0.012038	0.015678	0.010692	0.012185	0.01023	0.01332	0.011889	0.010883	0.011246	0.014087	0.009791	0.013047	0.01133	0.011324	0.01347	0.012141	0.011542	0.29965	0.014013	0.011712	0.010731	0.014466	0.012773	0.011087	0.012158	0.014925
	D12	0.008203	0.008612	0.015964	0.012516	0.010826	0.009369	0.009487	0.009694	0.008937	0.010855	0.010803	0.008298	0.239525	0.011537	0.010534	0.011704	0.009305	0.009552	0.011797	0.008499	0.010678	0.010224	0.008868	0.011067	0.012569	0.011335	0.011589	0.011546	0.012668	0.008608	0.406695	0.011625	0.011716	0.011593	0.013203
	D13	0.008889	0.012218	0.009621	0.011129	0.008728	0.434711	0.009266	0.007671	0.010185	0.008482	0.008112	0.007928	0.008361	0.009116	0.008367	0.009665	0.008038	0.008115	0.011198	0.008768	0.010332	0.008907	0.009499	0.009363	0.008377	0.009346	0.264204	0.008509	0.007696	0.008053	0.008826	0.008967	0.008405	0.009593	0.011353
	D14	0.015125	0.015171	0.012925	0.422563	0.015164	0.021909	0.011313	0.015797	0.01924	0.014271	0.012229	0.012427	0.016704	0.012462	0.013003	0.024063	0.012691	0.011112	0.020485	0.010004	0.04908	0.0127	0.020255	0.011594	0.01381	0.0125	0.028257	0.016394	0.015095	0.036773	0.015108	0.015241	0.011532	0.015235	0.017769
	D15	0.011348	0.176856	0.027894	0.040083	0.034551	0.050812	0.015543	0.014403	0.053334	0.017924	0.017649	0.009381	0.019	0.01344	0.025721	0.01118	0.030623	0.011813	0.028564	0.011424	0.017849	0.013407	0.03297	0.013581	0.020597	0.013547	0.022457	0.014827	0.034352	0.04083	0.033203	0.029495	0.02893	0.038917	0.023495
Document	D16	0.014152	0.021826	0.014201	0.016661	0.013013	0.012161	0.01531	0.015439	0.470764	0.011322	0.019724	0.010855	0.018758	0.014631	0.014032	0.013809	0.01845	0.016331	0.023408	0.011352	0.015114	0.016698	0.019141	0.013204	0.016251	0.017449	0.016011	0.01447	0.013555	0.013603	0.014871	0.018235	0.016578	0.01147	0.017152
	D17	0.007953	0.012951	0.010558	0.381183	0.007827	0.275037	0.007893	0.009653	0.009789	0.009447	0.008953	0.006703	0.011104	0.008873	0.008403	0.011436	0.00744	0.007354	0.008939	0.006428	0.010157	0.007801	0.008711	0.00816	0.008644	0.008234	0.059634	0.008832	0.008183	0.00794	0.00855	0.009217	0.007261	0.008889	0.01186
	D18	0.012441	0.014863	0.463946	0.018572	0.017926	0.01718	0.013244	0.016531	0.014102	0.014919	0.014926	0.017863	0.016773	0.014075	0.014415	0.020753	0.01452	0.016267	0.01606	0.01455	0.015621	0.014657	0.017163	0.01593	0.015194	0.016143	0.017262	0.014103	0.014138	0.012972	0.017188	0.020196	0.013467	0.014534	0.017507
	D19	0.013656	0.015951	0.056377	0.01524	0.026747	0.007644	0.011438	0.033021	0.01645	0.01229	0.140549	0.00805	0.014666	0.009282	0.008934	0.009233	0.012676	0.009278	0.143729	0.006936	0.009776	0.010085	0.011699	0.009731	0.067091	0.01144	0.10732	0.014591	0.097741	0.011331	0.012233	0.023411	0.012112	0.010593	0.018699
	D20	0.013268	0.081586	0.015958	0.022809	0.051274	0.011448	0.010313	0.017594	0.044494	0.013101	0.018992	0.012348	0.131357	0.01505	0.012044	0.015308	0.139576	0.015024	0.016344	0.012502	0.015499	0.012202	0.012612	0.015397	0.010757	0.011561	0.080456	0.008537	0.012618	0.013355	0.022158	0.030586	0.047399	0.015829	0.020647
	D21	0.017883	0.021228	0.020263	0.018284	0.021925	0.02052	0.012078	0.013608	0.017269	0.256589	0.015664	0.014695	0.015885	0.016963	0.019077	0.014826	0.015465	0.011563	0.203226	0.012211	0.017006	0.010952	0.016814	0.014573	0.015728	0.016399	0.018093	0.015296	0.013896	0.017253	0.015838	0.01964	0.01507	0.015059	0.019163
	D22	0.005692	0.008643	0.006946	0.405417	0.007311	0.00884	0.006455	0.007398	0.00789	0.006362	0.007717	0.005975	0.007873	0.007526	0.006436	0.00772	0.006387	0.006168	0.007913	0.006062	0.00782	0.006785	0.008145	0.00645	0.007425	0.006972	0.007102	0.006392	0.006836	0.358017	0.006733	0.008013	0.006223	0.007167	0.009189
	D23	0.009859	0.013027	0.184706	0.228561	0.010632	0.016629	0.011704	0.009212	0.015931	0.009238	0.011327	0.009986	0.0102	0.013166	0.011604	0.014514	0.010918	0.009354	0.012778	0.008177	0.069562	0.01048	0.156559	0.009753	0.010124	0.009929	0.013479	0.010133	0.012056	0.014598	0.010627	0.014743	0.009904	0.010816	0.015712
	D24	0.010228	0.017966	0.014104	0.233547	0.015658	0.021165	0.012058	0.013369	0.089055	0.014668	0.022224	0.010861	0.01242	0.015998	0.013638	0.014948	0.012456	0.011957	0.013843	0.011309	0.033434	0.015311	0.186819	0.014481	0.014008	0.013218	0.01712	0.013965	0.014113	0.012598	0.01518	0.018066	0.014354	0.017334	0.018529
	D25	0.009778	0.011393	0.012972	0.302668	0.012986	0.016834	0.012495	0.010466	0.015591	0.010953	0.286146	0.010885	0.011026	0.012105	0.011434	0.012319	0.011792	0.009966	0.01108	0.010487	0.01501	0.012283	0.01631	0.012643	0.011602	0.012005	0.016221	0.012897	0.012127	0.011687	0.014179	0.011528	0.011654	0.011376	0.015101
	D26	0.010919	0.013551	0.017345	0.018431	0.012661	0.014688	0.011614	0.012068	0.019225	0.018679	0.016161	0.012807	0.013418	0.020563	0.016359	0.01204	0.013757	0.013348	0.469677	0.01332	0.019438	0.010476	0.013631	0.012697	0.01861	0.013833	0.033839	0.013286	0.014218	0.011368	0.016938	0.017454	0.018572	0.018012	0.016998
	D27	0.010463	0.012925	0.013629	0.298203	0.013476	0.011923	0.012342	0.013114	0.01391	0.014544	0.013567	0.00997	0.011575	0.011418	0.01206	0.013095	0.012255	0.012375	0.011917	0.010872	0.012852	0.01348	0.010888	0.011422	0.012751	0.011198	0.012874	0.29456	0.012552	0.011485	0.012949	0.010875	0.010811	0.012682	0.014986
	D28	0.007895	0.252432	0.009909	0.014608	0.011037	0.397897	0.012487	0.009874	0.010078	0.009762	0.01164	0.009212	0.008877	0.010063	0.009684	0.013998	0.009365	0.009392	0.011435	0.008653	0.010786	0.009645	0.010546	0.009679	0.010432	0.009632	0.013518	0.011845	0.009313	0.010901	0.010665	0.01258	0.009357	0.009787	0.013016
	D29	0.013121	0.034817	0.027869	0.092102	0.014063	0.208586	0.018067	0.01278	0.025113	0.046611	0.018216	0.013269	0.018272	0.02325	0.01967	0.034485	0.02312	0.014202	0.019288	0.011996	0.015602	0.013831	0.020848	0.015663	0.016302	0.015093	0.058581	0.021266	0.016937	0.015376	0.016933	0.028147	0.016596	0.017483	0.022444
	D30	0.009048	0.013463	0.022972	0.283008	0.016773	0.016543	0.009575	0.011258	0.01292	0.011474	0.013402	0.009938	0.14026	0.011108	0.010578	0.034939	0.009884	0.009898	0.012399	0.009349	0.01207	0.009817	0.066168	0.012904	0.086127	0.012904	0.014948	0.010834	0.015379	0.013013	0.011978	0.019036	0.015751	0.012547	0.01774
	D31	0.015021	0.015264	0.020208	0.03289	0.018042	0.014004	0.01955	0.014077	0.228295	0.014167	0.095349	0.012647	0.019561	0.014643	0.018145	0.098063	0.013249	0.010233	0.015219	0.012618	0.01883	0.013886	0.016847	0.014497	0.039084	0.012747	0.019477	0.013927	0.017052	0.017055	0.029362	0.025631	0.024606	0.014735	0.021019
	D32	0.013651	0.014527	0.016853	0.084588	0.013884	0.014554	0.01638	0.012939	0.016142	0.013768	0.01711	0.011209	0.014267	0.014086	0.016762	0.01432	0.01505	0.010584	0.427493	0.012259	0.014979	0.012482	0.015792	0.016551	0.016383	0.012671	0.017531	0.014282	0.013817	0.016135	0.012876	0.021102	0.014003	0.013626	0.017344
	D33	0.022755	0.033737	0.049615	0.028998	0.029646	0.028621	0.016823	0.018553	0.040961	0.040395	0.062535	0.014963	0.019792	0.038063	0.023671	0.044469	0.024683	0.011809	0.02251	0.014036	0.036731	0.026521	0.026522	0.024055	0.038811	0.026933	0.052016	0.018759	0.024763	0.019509	0.022648	0.019758	0.022917	0.026044	0.027374
	D34	0.008446	0.008266	0.022329	0.009749	0.012005	0.012095	0.013609	0.011726	0.141753	0.008048	0.010265	0.008421	0.12899	0.010344	0.022313	0.009682	0.011301	0.009048	0.010663	0.008658	0.00899	0.01631	0.007575	0.022572	0.008897	0.012847	0.103213	0.012542	0.064692	0.01077	0.201944	0.013505	0.01155	0.009991	0.016889

(IV)

Table showing Preprocessed data randomly attached from Document 0 to Document 5818.



	A	B	C	D	E	F	G	H	I	J	K
1	Unnamed	article_he	article_se	article_lin	article_fir	article_las	article_su	article_bo	Date	Open2	Close2
2	doc 0	BitcoinÂ b	Markets	https://w	2022-08-2	2022-08-2	Investors	bitcoin bri	8/28/2022	20032.73	19606.74
3	doc 1	A closely-	Cryptocur	https://w	2022-08-2	2022-08-2	A measur	bitcoin pc	8/24/2022	21513	21378.1
4	doc 2	Bitcoin ha	Cryptocur	https://w	2022-08-2	2022-08-2	Bitcoin m	crypto wir	8/25/2022	21367.72	21591.28
5	doc 3	Sudden cr	Crypto W	https://w	2022-08-1	2022-08-2	Bitcoin hi	bitcoin fri	8/18/2022	23338.39	23206.19
6	doc 4	Ether is up	Technolog	https://w	2022-08-1	2022-08-1	Since find	since find	8/18/2022	23338.39	23206.19
7	doc 5	Skybridge	Crypto	https://w	2022-08-1	2022-08-1	Bitcoin fu	bitcoin fu	8/14/2022	24443.21	24323
8	doc 6	Bitcoin to	Cryptocur	https://w	2022-08-1	2022-08-1	Bitcoin br	bitcoin bri	8/14/2022	24443.21	24323
9	doc 7	BlackRock	Markets	https://w	2022-08-1	2022-08-1	The larges	blackrock	8/10/2022	23145.39	23940.2
10	doc 8	MicroStrat	Crypto W	https://w	2022-08-0	2022-08-0	MicroStrat	microstrat	8/1/2022	23311.56	23311.59
11	doc 9	Bitcoin bri	Cryptocur	https://w	2022-07-2	2022-07-2	Bitcoin's r	bitcoin to	7/28/2022	22955	23847.01
12	doc 10	Tesla has	Technolog	https://w	2022-07-2	2022-07-2	Tesla CEO	early yea	7/19/2022	22517.1	23407.35
13	doc 11	Bitcoin jui	Markets	https://w	2022-07-2	2022-07-2	Bitcoin ro	bitcoin ro	7/27/2022	21279.62	22943.12
14	doc 12	Crypto mi	Crypto W	https://w	2022-07-1	2022-07-1	New data	data block	7/17/2022	21207.85	20769.4
15	doc 13	Bitcoin to	Cryptocur	https://w	2022-07-1	2022-07-1	Bitcoin bo	bitcoin bo	7/17/2022	21207.85	20769.4
16	doc 14	Bitcoin to	Technolog	https://w	2022-07-2	2022-07-2	Bitcoin to	bitcoin br	7/19/2022	22517.1	23407.35
17	doc 15	Bitcoin Fa	Crypto W	https://w	2022-07-0	2022-07-0	The "Bitco	bitcoin fa	7/1/2022	19922.82	19336.1
18	doc 16	Worldâ,¬â	ETF Edge	https://w	2022-07-0	2022-07-0	Grayscale	digital cur	7/6/2022	20209.98	20557.54
19	doc 17	For bitcoi	Technolog	https://w	2022-07-1	2022-07-1	Industry p	improvem	7/13/2022	19330.03	20187.15
20	doc 18	Coinbase	Technolog	https://w	2022-07-1	2022-07-1	Coinbase	share coir	7/17/2022	21207.85	20769.4
21	doc 19	El Salvado	Crypto W	https://w	2022-06-2	2022-06-2	The gover	salvador e	6/24/2022	21097.66	21279.53
22	doc 20	Billions in	Crypto W	https://w	2022-07-0	2022-07-1	The bad d	crypto len	7/5/2022	20219.67	20185.96
23	doc 21	Bitcoin he	Markets	https://w	2022-07-0	2022-07-0	Bitcoin is	price bitc	7/7/2022	20562.57	21647.17
24	doc 22	Bitcoin ju	Crypto W	https://w	2022-06-3	2022-06-3	Bitcoin ju	bitcoin fir	6/29/2022	20278.9	20101.12
25	doc 23	Five reasc	Technolog	https://w	2022-07-0	2022-07-0	Bitcoin los	bitcoin wc	6/30/2022	20117.92	19816.75
26	doc 24	Bitcoin po	Cryptocur	https://w	2022-06-3	2022-06-3	Bitcoin ha	bitcoin th	6/29/2022	20278.9	20101.12
27	doc 25	Bitcoin fal	Cryptocur	https://w	2022-06-3	2022-06-3	Cypto hec	bitcoin th	6/29/2022	20278.9	20101.12
28	doc 26	Charts sug	Mad Mone	https://w	2022-06-2	2022-06-2	"Bitcoin c	cnbcs cran	6/22/2022	20722.23	19976.05
29	doc 27	ProShares	Markets	https://w	2022-06-2	2022-06-2	Eight mon	eight mon	6/19/2022	19010.48	20554.9
30	doc 28	Bitcoin bri	Crypto W	https://w	2022-06-2	2022-06-2	Bitcoin fel	bitcoin bri	6/28/2022	20715.2	20293.45
31	doc 29	Bitcoin bo	Cryptocur	https://w	2022-06-2	2022-06-2	The crypto	bitcoin jur	6/19/2022	19010.48	20554.9
32	doc 30	Bitcoin bri	Crypto W	https://w	2022-06-1	2022-06-1	Bitcoin fel	bitcoin plu	6/17/2022	20406.02	20468.21
33	doc 31	Bitcoin's p	Technolog	https://w	2022-06-1	2022-06-1	A $4 billio	lost billior	6/13/2022	26599.66	22509.1
34	doc 32	Bitcoin co	Technolog	https://w	2022-06-2	2022-06-2	Ian Harnet	cryptos pa	6/21/2022	20577.6	20739.94
35	doc 33	Bitcoin ha	Invest in Y	https://w	2022-06-1	2022-06-1	Bitcoin's r	cryptocurr	6/14/2022	22456.78	22209.52
36	doc 34	New York	Crypto W	https://w	2022-06-0	2022-06-0	Lawmaker	following	6/2/2022	29795.17	30441.47
37	doc 35	Bitcoin ca	Technolog	https://w	2022-06-1	2022-06-1	Bitcoin's p	selloff cry	6/14/2022	22456.78	22209.52
38	doc 36	MicroStrat	Cryptocur	https://w	2022-06-1	2022-06-1	MicroStrat	aggressive	6/14/2022	22456.78	22209.52
39	doc 37	Bitcoin rel	Markets	https://w	2022-06-2	2022-06-2	Bitcoin bo	bitcoin cli	6/20/2022	20580.04	20672.8
40	doc 38	Cramer du	Crypto	https://w	2022-06-1	2022-06-1	CNBC's Jin	cnbcs cran	6/12/2022	28415.54	26704.73
41	doc 39	Bitcoin dr	Crypto W	https://w	2022-06-1	2022-06-1	Factors in	bitcoin tu	6/12/2022	28415.54	26704.73
42	doc 40	Human rig	Crypto W	https://w	2022-06-0	2022-06-0	Human rig	washingto	6/7/2022	31380.14	31193.07
43	doc 41	Bitcoin dr	Cryptocur	https://w	2022-06-1	2022-06-1	BitcoinÂ b	bitcoin bri	6/13/2022	26599.66	22509.1
44	doc 42	Binance p	Markets	https://w	2022-06-1	2022-06-1	Binance te	binance m	6/12/2022	28415.54	26704.73
45	doc 43	Bitcoin bri	Crypto W	https://w	2022-06-0	2022-06-0	BitcoinÂ f	bitcoin sli	6/6/2022	29930.46	31367.42
46	doc 44	Grayscale	Technolog	https://w	2022-06-3	2022-06-3	The U.S. S	grayscale	6/29/2022	20278.9	20101.12
47	doc 45	Despite th	Empower	https://w	2022-06-1	2022-06-1	CNBC spol	even cryp	6/12/2022	28415.54	26704.73
48	doc 46	Bitcoin sir	Technolog	https://w	2022-06-1	2022-06-1	Crypto inv	bitcoin dr	6/17/2022	20406.02	20468.21
49	doc 47	Bitcoin ris	Crypto W	https://w	2022-06-0	2022-06-0	Bitcoin ro	bitcoin m	6/5/2022	29847.33	29909.21
50	doc 48	Bitcoin fal	Cryptocur	https://w	2022-06-1	2022-06-1	Bitcoin is	bitcoin fel	6/15/2022	22174.8	22490.59
51	doc 49	MicroStrat	U.S. Mark	https://w	2022-05-1	2022-05-1	MicroStrat	microstrat	5/11/2022	31000.98	28984.54
52	doc 50	Bitcoin wa	Next Gen	https://w	2022-07-0	2022-07-0	Bitcoin wa	bitcoin plu	7/7/2022	20562.57	21647.17
53	doc 51	Bitcoin pr	Technolog	https://w	2022-05-1	2022-05-1	New resea	bitcoin mi	5/17/2022	29833.05	30452.62
52	doc 50	Bitcoin wa	Next Gen	https://w	2022-07-0	2022-07-0	Bitcoin wa	bitcoin plu	7/7/2022	20562.57	21647.17
53	doc 51	Bitcoin pr	Technolog	https://w	2022-05-1	2022-05-1	New resea	bitcoin mi	5/17/2022	29833.05	30452.62
54	doc 52	Bitcoin bil	Technolog	https://w	2022-06-2	2022-06-2	Bankman-	central ba	6/21/2022	20577.6	20739.94
55	doc 53	Coinbase	Markets	https://w	2022-06-2	2022-06-2	Coinbase	coinbase s	6/21/2022	20577.6	20739.94
56	doc 54	A $3.5 bill	Crypto W	https://w	2022-05-0	2022-05-1	South Kor	multibillic	5/8/2022	34062.89	33933.54
57	doc 55	New York	Crypto W	https://w	2022-05-0	2022-05-0	Lawmaker	state york	5/4/2022	34062.89	39699.03
58	doc 56	Bitcoin bo	Markets	https://w	2022-05-1	2022-05-1	The price	price bitc	5/12/2022	29044.26	29130.04
59	doc 57	Bitcoin co	Davos WE	https://w	2022-05-2	2022-05-2	Guggenhe	bitcoin dr	5/22/2022	29445.06	30366.04
60	doc 58	Jack Dorse	Bitcoin	https://w	2022-05-1	2022-05-1	At Block's	block exe	5/17/2022	29833.05	30452.62
61	doc 59	Luna Foun	Crypto W	https://w	2022-05-0	2022-05-0	The Luna I	luna foun	5/4/2022	34062.89	39699.03
62	doc 60	This real e	Crypto De	https://w	2022-04-2	2022-04-2	Compass I	taing busi	4/22/2022	34062.89	39757.55
63	doc 61	Bitcoin in	Crypto W	https://w	2022-05-1	2022-05-1	Investors	investor b	5/9/2022	34062.89	30363.87
64	doc 62	Warren Bu	2022 Berk	https://w	2022-04-3	2022-05-0	Despite a	bitcoin ste	4/29/2022	34062.89	38592
65	doc 63	$3 billion	Crypto W	https://w	2022-05-1	2022-05-1	Luna Four	investor e	5/15/2022	30076.93	31333.77
66	doc 64	Grayscale	Finance	https://w	2022-05-1	2022-05-1	A spot-ba	grayscale	5/10/2022	30106.43	31024.7
67	doc 65	Crypto ex	Technolog	https://w	2022-06-2	2022-06-2	CoinFlex i	digital ass	6/28/2022	20715.2	20293.45
68	doc 66	El Salvado	Crypto W	https://w	2022-05-0	2022-06-2	El Salvado	salvador a	5/8/2022	34062.89	33933.54
69	doc 67	40% of bit	Crypto W	https://w	2022-05-0	2022-05-1	Bitcoin is	bitcoin ne	5/8/2022	34062.89	33933.54
70	doc 68	Bitcoin dr	Cryptocur	https://w	2022-05-0	2022-05-0	Bitcoin cra	bitcoin br	5/5/2022	34062.89	36568.76
71	doc 69	Fort Wort	Crypto W	https://w	2022-04-2	2022-04-2	Three Bitr	fort worth	4/25/2022	34062.89	40475.28
72	doc 70	Bitcoin dr	Crypto W	https://w	2022-05-0	2022-05-0	Cryptocur	bitcoin dr	5/8/2022	34062.89	33933.54
73	doc 71	Michael S	Crypto W	https://w	2022-04-2	2022-04-2	MicroStrat	miami mic	4/20/2022	34062.89	41363.5
74	doc 72	Bitcoin dr	Crypto W	https://w	2022-05-1	2022-05-1	The price	bitcoin dr	5/10/2022	30106.43	31024.7
75	doc 73	Itâ,¬â„¢s a	ETF Edge	https://w	2022-04-1	2022-04-1	Crypto ex	crypto exp	4/16/2022	34062.89	40386.51
76	doc 74	What to c	Invest in Y	https://w	2022-04-2	2022-04-2	Before ad	investor s	4/25/2022	34062.89	40475.28
77	doc 75	Bitcoin jur	Crypto W	https://w	2022-05-0	2022-05-0	The crypto	price bitc	5/3/2022	34062.89	37732.3
78	doc 76	Bitcoin bri	Crypto W	https://w	2022-05-1	2022-05-1	Bitcoin fel	bitcoin dr	5/9/2022	34062.89	30363.87
79	doc 77	Bitcoin dr	Cryptocur	https://w	2022-05-0	2022-05-0	The crypto	bitcoin co	5/7/2022	34062.89	35552.56
80	doc 78	Bitcoin Pi	Davos WE	https://w	2022-05-2	2022-05-2	The indus	davos swi	5/23/2022	30295.93	29114.08
5792	doc 5790	5 signs yo	Money|M	https://w	2018-01-2	2018-01-2	Here's ho	horrible h	1/25/2018	34062.89	11219.44
5793	doc 5791	If you inve	The Begin	https://w	2018-01-1	2018-01-1	Google's s	search en	1/10/2018	34062.89	15065
5794	doc 5792	Travis Kal	Money|M	https://w	2018-01-0	2018-01-0	Wealth m	travis kala	1/7/2018	34062.89	16515.29
5795	doc 5793	Meet the	Careers|M	https://w	2018-01-1	2018-01-1	Millennial	werent da	1/9/2018	34062.89	14710.6
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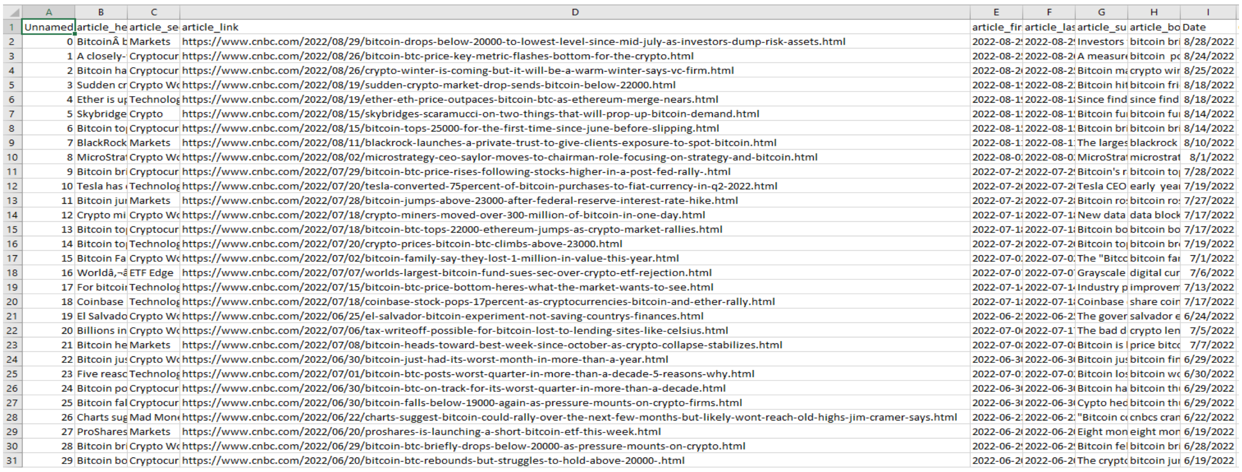

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