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Modelling procedure while assessing the impact of news articles on cryptocurrency (Bitcoin) market movement

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Abstract

Background: Cryptocurrencies have a variety of unique qualities, from cutting-edge technology to highly secure architecture. Additionally, the ability to invest in cryptocurrency, as an asset or a function of its prosperity has made crypto-currencies attractive to venture capitalists, computer scientists, and statisticians.
Aims: In this study, we concentrated on a collection of documents web-scrapped from the market section of CNBC, where each document is associated with a response variable.
Methodology: These documents contain preprocessed words/terms of day-to-day reportage on cryptocurrency (Bitcoin). The corresponding response variables are the daily opening and closing price of Bitcoin prices. The Supervised Latent Dirichlet Allocation(sLDA), a statistical model of labeled documents, was used to analyze the textual data alongside their corresponding response variables, since our study aims to predict the response variable for unlabeled new documents.
Results: Hidden Topics with their unique terms from the preprocessed articles were exposed through a Natural language processor. Mean absolute error (MAE), Mean absolute percentage error (MAPE), and Root mean square error (RMSE) graphs were constructed for the sLDA models with 'k = 3,10,20,30,50,75,100 and 200 Topics' values where the model with the best evaluation metric, was selected for prediction purpose.
Conclusion: It was discovered that the sLDA model with k = 20. A posterior covariance matrix which shows the proportion of terms from the documents, making up a Topic. Coefficient values were generated in other to graphically visualize how important the discovered topics are and how they affect the market trend. Finally, the prediction of new labels (numeric-decoded closing prices) for the unlabeled documents was done and comparisons were made; the predicted labels follow a similar pattern to that of the time series closing price trend.

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1. Introduction

Cryptocurrencies have a variety of unique qualities, from cutting-edge technology to highly secure architecture. Additionally, the ability to invest in cryptocurrency, as an asset or a function of its prosperity has made crypto-currencies attractive to venture capitalists, computer scientists, and statisticians. Aside from all these aspects, there are other troubling issues such as the absence of financial institution regulation (Buchholz et al., 2012). Therefore, sentiments and ideologies have an impact on the movement of Bitcoin's price. The way that large-scale Bitcoin owners behave, as well as society norms, political beliefs, and emotional states, all influence the price of Bitcoin. Financial analysts and scholars have become increasingly interested in digital currency because of its widespread acceptance. Financial analysts and researchers enjoy the challenge of market price extrapolation, but the developing cryptocurrency marketplaces lack in-depth study (Yao et al., 2019).

The lack of this in-depth study prompted us to investigate other hidden factors contributing to the market price trend. In clear terms, we identified a factor which is textual crowd-trading-knowledge. Textual crowd-trading-knowledge is believed to have a strong root in articles, especially News articles. Through several mobile applications, those interested in Bitcoin transactions can obtain the latest information about price movements, causes, and news at any time and location. They could use this knowledge to decide whether to buy or sell. It has been shown by numerous studies that a significant portion of the public uses' websites, applications, or social networking sites to receive information in some capacity. According to Kaya and Karsligil (2010), web channels are now the second most important source of information for people who prefer reading news articles over watching or listening to the news. Television is the most important source of information.

The above resource is what we have taken advantage of to analyze and give it a meaning numerically. The way Bitcoin market price trend gets affected by the daily News articles on traders' activities was investigated. Eklund & Bejerholm (2004) postulated that sources of textual data include both independently developed and corporately produced materials. Sources generated by the organization, such as quarterly and yearly reports, can provide a rich language structure; when carefully examined, can forecast future performance.

Our chosen model in analyzing this phenomenon is a supervised Topic model known as the Supervised Latent Dirichlet Allocation (sLDA), simply because, our target is prediction. According to Blei et al. (2017), the sLDA is a variant of the Latent Dirichlet Allocation (LDA).

A supervised topic model is required for document collections that contain response variables where the objective is to predict the response variable given the document in the collection. The Supervised Latent

Dirichlet Allocation (sLDA), created by Blei et al. (2017), aims to infer latent themes that predict the response variable. First, they used a publicly available dataset of newspaper movie reviews introduced by Pang & Lee (2008), which contains movie reviews paired with a certain number of stars (ratings). The analysis was treated as a regression problem rather than a classification task. Next, they applied the sLDA to the analysis of two real-world tasks. The second application was to study amendment texts from the 109th and 110th U.S. senates. The discriminating parameters from an ideal-point analysis based on voting history which is utilized in quantitative political science in this case to map senators to a real-valued point on a political spectrum, make up the response variables (Clinton et al., 2004). The authors observed that the sLDA offered a better prediction on all datasets when compared to the results of linear regression and the Least Absolute Shrinkage and Selection Operator (LASSO) regression of the unsupervised LDA model.

Zang and Kjellström (2014) researched on the ways to supervise a topic model. The research suggested two factorized supervised topic models that factorize the topics into signal and noise. They also offered a detailed analysis of the behaviour of supervised topic models using Supervised Latent Dirichlet Allocation (SLDA). The findings of experiments conducted on synthetic and real-world data for computer vision tasks indicate that factorized topic models can improve performance and that increased supervision is necessary for optimal outcomes.

Survival-supervised latent Dirichlet allocation models were developed by Dawson and Kendziorski (2012) for the genomic study of time-to-event outcomes. With the use of their approach, groups of clinical and genomic characteristics that are common to patient subgroups can be efficiently identified, and each patient is then uniquely defined by these qualities. A useful patient subgroup was discovered by applying survLDA to The Cancer Genome At-las (TCGA) ovarian research. These patient subgroups are distinguished by varying propensities to display aberrant mRNA expression and methylations, which correlate to varying rates of survival from first therapy. The study demonstrates how technological developments such as supervised topic modeling continue to improve the ease and precision of measuring the genome and phenome; as a result, genomic-based studies of the disease frequently involve the collection of a wide variety of data types from large patient populations.

Wilcox et al. (2021) researched on Supervised Latent Dirichlet Allocation with Covariates which is a Bayesian Structural and Measurement Model of Text and Covariates. They proposed a novel statistical model, supervised latent Dirichlet allocation with covariates (SLDAX) that jointly incorporates a latent variable measurement model of text and a structural regression model to allow the latent topics and

other manifest variables to serve as predictors of an outcome. Using a simulation study with data characteristics consistent with psychological text data, they found that SLDAX estimates were generally more accurate and more efficient. To illustrate the application of SLDAX and a two-stage approach, they provided an empirical clinical application to compare the application of both the two-stage and SLDAX approaches.

Perotte et al. (2011) presented a model for hierarchically and multiple labeled bag-of-word data called hierarchically supervised latent Dirichlet allocation (HSLDA). Their work focused mostly on out-of-sample label prediction, but it was also interesting to see better lower-dimensional representations of the bag-of-word data. Using large-scale data from retail product classification and healthcare document labeling tasks, they showcased HSLDA. They demonstrated that, as compared to models that do not use the structure from hierarchical labels, out-of-sample label prediction is much improved.

Mohan et al. (2019) gathered a significant quantity of time series data and used deep learning models to analyze it in connection to linked news stories, improving the accuracy of stock price predictions. The study shows that there is difficulty in forecasting stock values due to their extremely volatile character, which is influenced by a wide range of political and economic issues, shifts in leadership, investor attitude, and numerous other factors. The study was able to reveal a high association between the movement of stock prices and the release of news stories with the use of topic modeling. The quantity of training data supplied determined how accurate deep learning algorithms were. However, by compiling a sizable amount of time series data and applying deep learning models to analyze it for relevant news stories, they were able to increase the accuracy of stock price predictions.

Yap et al. (2012) used computer methods to forecast stock values using financial data. They relied on intricate mathematical models and historical market data, which was limited to evaluating data that was available to them. Because of this flaw, they were unable to respond to unforeseen circumstances that deviated from previous patterns. Weighted terms were assigned to a new piece by the study's prediction to ascertain its expected direction of movement. To their credit, these more straightforward techniques have demonstrated a limited but significant ability to forecast price direction but not actual price. The popularity of Quantitative funds, or Quants, has grown in the last few years. Quants automatically sort through financial data using numbers and select stocks. These systems vary in the degree of trading control they possess, from basic stock recommenders to transaction executors, despite being built on proprietary technology.

Sharma (2020) compared stock price prediction models using news articles, using global indices, exchange rates, historical stock prices, global news, and technical indicators. They utilized an ensemble of Long Short-Term Memory (LSTM) models. To compare the results,

their investigation was also expanded to include some benchmark categorization models. According to their results, an ensemble of three LSTM models predicted growing and falling trends equally well and steadily, yielding an accuracy of 60% with the best recall and true negative score.

Sahut et al. (2024) evaluated five models based on cutting-edge machine-learning techniques. These models were picked from the literature on crude oil forecasting to evaluate the impact of news-based sentiment on crude oil price prediction. The COVID-19 pandemic era and the years from 1990 to the start of the pandemic were included in the results for each approach. This made it possible for them to investigate how news-based mood functions in various stages of economic growth and disaster. Compared to other eras, such as the 2008–2009 financial crisis, a notable impact of news-based sentiment was seen on the forecasting performance of machine learning techniques during the Covid-19 period.

Loughran et al. (2019) investigated if investors respond to news stories about oil that disclose supply and demand information in a timely and logical manner. To facilitate investors' and researchers' assessment of the information value of oil tales, their study generated a unique keyword list of 130 terms and modifiers connected to the oil industry. They discovered a notable overreaction in the short run to the news stories on oil connected to the Dow Jones. Lower oil prices the next trading day were linked to phrases in delayed news items like output cut, production reduced, scarcity, and demand rising. The data supports the theory that oil traders exaggerate their reactions to news articles that are extensively read.

The major challenge of using structured textual data to predict traders' interest is because of its extremely volatile character of such data, which is influenced by a wide range of political and economic issues, shifts in leadership, investor attitude, and numerous other factors (Mohan et al., 2019; Fataliyev et al., 2021).

The baseline models for textual data are social media content, News content, official company announcements, traditional textual representation techniques, deep learning based advanced NLP techniques, statistical models, machine learning techniques and deep learning models (Frank et al., 2017; Li et al., 2018; Shah et al., 2019; Kumar et al., 2020; Thakkar & Chaudhari, 2021; Fataliyev et al., 2021).

Hence, our suggested text-feature extraction of the sLDA a supervised Latent Dirichlet Allocation aims to predict traders' interest in cryptocurrency and raise traders' awareness when they rely on news stories for trading information.

This paper contributes to existing literatures on the potentials and capabilities of sLDA (supervised Latent Dirichlet Allocation) to predict traders' interest in cryptocurrency.

2. Materials and Method

News articles on cryptocurrency-related activities published in foreign media between 2016 and 2022 were the research population's focus. The Consumer News and Business Channel is where these news stories are found (CNBC). Because Bitcoin is so popular compared to other cryptocurrencies, it will be the only cryptocurrency sampled in this study.

As secondary data, the corpus of news items serves as the data set for this study. From 2016 until 2022, every one of the more than 6,000 news pieces or articles was written in English. Leveraging a custom Python script called "Beautiful Soap" created with the Jupyter Notebook, quick scrapping of the text data was accomplished by leveraging relevant meta-data from the previously mentioned source. The following meta-data was included in the pages, which were kept in a comma-separated (CSV) format: (i) article summary, (ii) article section, (iii) article link, (iv) article date, (v) article summary, (vi) article body, (vii) opening price, (viii) closing price.

We used the query "Daily Bitcoin reports". Furthermore, we made use of the articles' corresponding closing prices as our response variable.

The bag-of-words document representation is assumed by topic models (Blei et al., 2017). Each document is represented here as a bag of its terms/words, with no respect for word order or grammar. Many Natural Language Processing and Information Retrieval algorithms use this simplified model. The NLP stage consisted primarily of four broad steps: (1) loading the input data (News articles), (2) pre-processing the data, (3) transforming texts into bag-of-words vectors, and (4) training the sLDA models (Mckinney, 2010).

The news items (which will now be referred to as documents) cannot be simply fed into the model as raw data or free-text but must instead be transformed into a suitable form for the modeling framework. Normalization, tokenization, stemming/lemmatization, and stop-word removal are common text data pre-processing techniques. Following the collection and collation of articles, the text will be pre-processed in Python using the SpaCy, Gensim, and Pandas modules (Mckinney, 2010). Pre-processing is required before performing NLP on the text. The texts of the articles were subsequently normalized by making them lowercase. Then, word elongations and foreign characters that weren't words, such as punctuation and other non-ASCII characters, were eliminated. Next, non-informative stop-words that regularly occur, such as "the", "is", "I", and "did" were eliminated (using stop-words provided in the genism module of Python). Following that, token words were lemmatized in Python using the genism module. Lemmatization is a type of text normalization that involves grouping inflected forms of words into their base or dictionary root terms, known as lemma. For example, lemmatizing the terms 'trouble', 'troubling', and 'troubled'

yields the lemma 'trouble'. The traditional stemming of tokens will be avoided, based on Schofield et al. (2017)'s recommendation that topic coherence is rarely enhanced between the pre-stemming and post-steaming Topic models. Finally, whitespaces were removed to make the document more compact. Documents containing fewer than 50 words were eliminated. Words that appeared in less than 70% of the corpus were pruned as well.

2.1. Specifications and Estimation of the sLDA

For response-document pairs, the supervised latent Dirichlet allocation model (sLDA) shows better strength in executing such a plan.

Distributions over document collections are known as topic models, in which each document is represented by a set of discrete random variables, $W_{1:\,n}$, which are its words. The words in a document are treated as emerging from a set of latent themes in topic models, which are a set of unknown distributions over the vocabulary. Each document in a corpus uses a mixture of subjects with topic proportions that are specific to it, but all documents in the corpus share the same K topics. Different from traditional document mixing models, which link every document to a single, unidentified topic, topic models isolate each document. Erosheva et al. (2004) describe them as mixed-membership models. Each document has a corresponding response as covariates which are jointly modelled for prediction when determining labels for unlabeled new documents. By allowing a response to be associated with each document and jointly modeling the response variable and the corpus of documents, the LDA model is extended to a supervised learning environment using Supervised Latent Dirichlet Allocation (sLDA). According to Blei et al. (2017), this enables it to identify the latent topics that are most predictive of the response variables in the training set and even to make predictions about future unlabeled documents. Following the LDA model's notation, let y represent a response variable from a generalized linear model with parameters η and δ. Should we consider the subsequent fixed;$\beta_{1:K}$: the k topics with each β_k a vector of term probability, η and δ and the Dirichlet hyperparameter for the per-document topic proportion θ. For every document and response variable, the generative process assumed by the sLDA is as follows:

1. Draw topic proportion, $\theta|\ \alpha \sim Di(\alpha)$;
2. for each word,
   a) Draw a topic assignment $Z_n \mid \theta \sim Mult(\theta)$
   b) Draw word $w_n \mid Z_n, \beta_{1:K} \sim Mult(\beta_{z_n})$;
3. Draw a response variable $y|\ z_{1:N}, \eta, \delta \sim$GLM $(\overline{z}, \eta, \delta)$, where $\overline{z} = \frac{1}{N}\sum_{n=1}^{N} z_n$.

For sLDA, the Dirichlet distribution (Di) is used as a prior for the topic distributions. Each document is assumed to have a distribution

over topics drawn from a Dirichlet distribution. This helps in capturing the variability in topic proportions across different documents. Each topic is represented by a multinomial distribution over the vocabulary, indicating the probability of each word appearing in that topic. This allows the model to not only discover Topics but also predict the response variable based on the document's topic distribution.

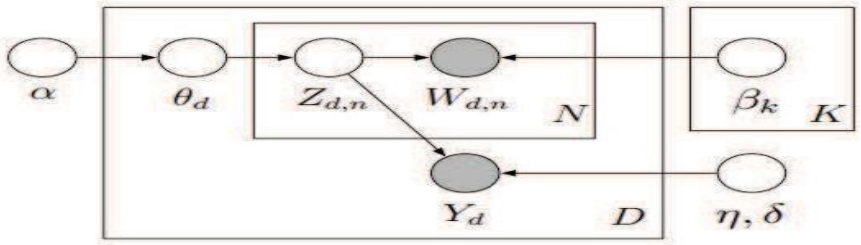

Figure 1. Graphical Model representation of Supervised Latent Dirichlet Allocation (sLDA)

2.2. Fitting the model

The method used for fitting the model is the variational expectation-maximization (VEM) algorithm. The sLDA model was equipped with parameters such as the "Document-Term matrix", "K" (the number of topics), "vocab" (vocabulary words associated with word indices used in documents), "e.iteration", "m.iteration", "alpha", "eta", "var" (variance of the response variable), "annotation" (response variable) and various parameters was used to adjust the speed of convergence of the algorithm. Though there are no standards for the choice of parameters the parameters were used to set the convergence tolerance for the variance and E-M algorithms, respectively. Also, the maximum number of iterations for the conjugate gradient algorithm was set by one of the parameters which iterates between the E-step and M-step in a bid to maximize the likelihood of the corpus. The procedure finds the maximum bound about the latent variables (the topic proportions and the topic assignments Z) in the E-step, and the M-step, finds the maximum bound for the model parameters (the topics and the multivariate normal parameters).

Application of variational EM was done until the relative change in the likelihood bound was achieved. The iterations convergence ranged between 1hr to 6hrs 45minutes on a core i7 HP laptop of 2.7GHz with 8 GB RAM for each of the K values.

A data split was done on the 5000 plus preprocessed documents/articles in the proportion of 70% training data and 30% test data. The training data set was used to train our sLDA model while the test data set was used as a test for prediction of our response variable. The response variable is the Timeseries closing price of Bitcoin corresponding to the documents. Additionally, we categorized our response variable into a numeric classification of "low= 1", "fairly

low= 2", "fairly high= 3" and "high= 4" with a threshold of "less than or equal to 10000", "less than or equal to 20000", "less than or equal to 40000" and "less than or equal to 60000", respectively.

Using the subsequent initializations: η to a grid on [-1, 1] with increments of $1/K$, and β_k to randomly perturbed uniform topics. Different sLDA models with varying numbers of topics as 3, 10, 20, 30, 50, 75,100 and 200 were trained so that the variational EM method was executed for the per-document ELBO at the E-steps as well as until a relative change in the corpus-like likelihood bound was less than 0.021% (Blei et al., 2017).

3. Result and Discussion

The experiment below was conducted to assess the quality of prediction using the sLDA model. We carried out a sensitivity analysis juxtaposing a latent Dirichlet allocation (LDA) with a regression model with our proposed Supervised latent Dirichlet allocation (sLDA) model. This experiment was carried out using two datasets of an equal number of documents. One dataset was from the CNBC market section (as stated in section 2), and the other was from the Bitcoinist website. Both datasets went through the same preprocessing stages (as seen in section 2). We will refer to the CNBC dataset as 'Dataset(1)' and the Bitcoinist dataset as 'Dataset(2)'.

We compared the behaviors of sLDA and LDA + Regression models while trying to investigate the extrapolative strengths of the two models on the two different datasets. The LDA on its own cannot predict the Bitcoin price category. The usual practice when LDA is to be used for prediction has always been joint modeling of the LDA with a regression model (Clinton et al., 2004; Blei et al., 2017). To better understand the experiment, Figures 2 and 3 show some metric evaluations used to adjudge the better model in the topic range of 3 to 200. This explains how our proposed model (sLDA) for prediction purposes behaved against the conventional model (LDA+ regression) for prediction. In a quest for the optimal model between the LDA and the sLDA models, model evaluation metrics were employed to pick an optimal model that best fits the prediction task. The choice of our model evaluation was born out of the type of classification we used, i.e. the multinomial classification techniques. The evaluation metrics are Mean absolute Error (MAE), Mean absolute percentage Error (MAPE) Root mean squared Error (RSME), and the coefficient of Determination (R^2).

As seen in Figure 2, the sLDA model across the 'K' values, performed better with K=20 and K= 30 from Figure 3. Likewise, from Figure 2, the LDA + regression model across the 'K' values, performed better with K= 75 and K=100. Figure 3 shows that the sLDA model with K=20 has the lowest MAE, MAPE, and RSME values but has the highest R^2 value when compared with the LDA model. Also, the sLDA model with K=30 has the lowest MAE, MAPE, and RSME values and

the highest R^2 value when compared with the LDA model. The result in Figure 2 shows that LDA at K=75 has an R^2 value of 0.3246 while sLDA at K= 20 has an R^2 value of 0.6262. The sLDA model performance has an improvement of 90% when we consider the R^2 values for both models. From Figure 3, LDA at k =100 has an R^2 value of 0.4462 while sLDA at K= 30 has an R^2 value of 0.736. The sLDA model performance also had an improvement of 64%. According to Zang and Kjellström (2014), the improvement in classification results is always significant through different noise levels when the number of topics is small.

The subsequent subsections show the practical application of the above experiment using 'Dataset(1)'.

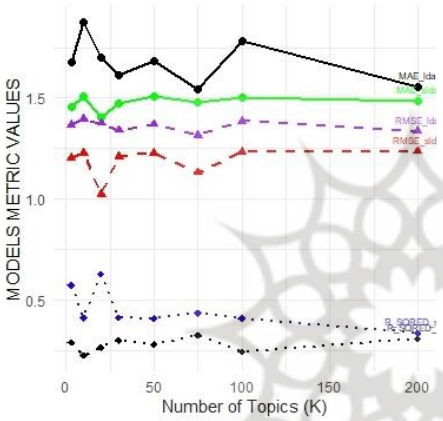

Figure 2. sLDA vs LDA behaviour with Dataset(1)

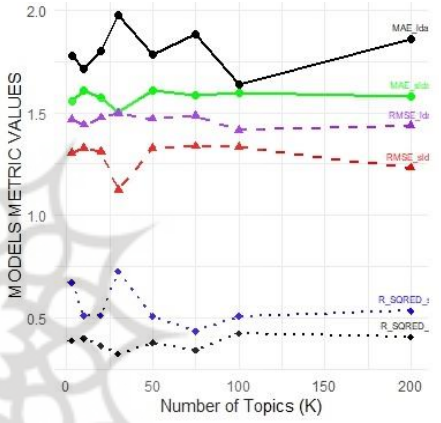

Figure 3. sLDA vs LDA behaviour with Dataset(2)

Table 1. Tabular summary of the split corpus

Number of documents	Total word count	Total number of unique words
4073(training data)	1,151,424	17,330
1746(testing data)	494,535	15,591

3.1. sLDA model evaluation

In a quest for the optimal sLDA model, model evaluation metrics were employed to pick an optimal model that best fits our prediction task on the first dataset. The evaluation metrics are Mean absolute error, mean absolute percentage error, and root mean squared error.

Table 2 shows the sLDA model with its numeric evaluation values was picked. A good look across the table shows that the sLDA model with K= 3 has the lowest numeric values across the three metrics but choosing that of K= 3 may lead to underfitting our model. We settled for the sLDA model with the next lowest numeric value, which is the K= 20 sLDA model, as the optimal model.

Exploring Figure 4, gives an insight into the topics that are predictive of the reported News from each of the documents. Our Topics ranges

from Minner's investment, Crypto ransom, Economic policies, Scandals, exchange rates etc. We will briefly discuss the first four Topics. Topic 1 depicts simply, talked about the community of bitcoin miners in Texas who thinks that investing in the energy sector can aid in resolving the state's (Texas) power grid issues. This news was heavily reported by the media and appeared in some of the web scraped documents at different dates (Figure 4).

Table 2. Table showing numeric values of three sLDA model evaluation metric

K	MAE	RMSE	MAPE
3	1.05841	1.202434	0.6576
10	1.11	1.228	0.72566
20	1.070072	1.223507	0.639
30	1.076113	1.220401	0.6587
50	1.11068	1.227168	0.7296
75	1.073	1.231	0.645
100	1.11445	1.2332	0.7268
200	1.082776	1.235816	0.6508

Topic 1	mining	bitcoin	miner	power	energy	mine	state	electricity	cost	texas
Topic 2	attack	account	hacker	security	data	wallet	computer	criminal	informatic	ransomwa
Topic 3	crypto	cryptocurr	token	musk	digital	dogecoin	ether	asset	market	tesla
Topic 4	china	country	chinese	governme	bank	south	korea	yuan	world	north
Topic 5	stock	percent	market	year	growth	price	investor	average	analyst	equity
Topic 6	blockchair	technolog	network	transactio	token	ripple	ledger	project	applicatio	coin
Topic 7	card	credit	account	income	gain	cash	inflation	youre	return	rate
Topic 8	president	trump	house	russia	bill	senate	russian	governme	state	federal
Topic 9	exchange	security	company	million	commissio	offering	agency	comment	customer	statement
Topic 10	dollar	rate	inflation	bank	market	index	week	high	yield	reserve
Topic 11	bank	currency	digital	financial	central	cryptocurr	payment	regulator	regulatior	libra
Topic 12	investor	fund	asset	investmer	bitcoin	investing	market	invest	financial	advisor
Topic 13	people	money	student	home	life	woman	family	inflation	school	university
Topic 14	long	trader	kelly	brian	short	fast	call	buyer	spread	adami
Topic 15	bitcoin	currency	bitcoins	gold	value	digital	transactio	price	read	virtual
Topic 16	bitcoin	price	cryptocurr	percent	trading	exchange	digital	currency	market	according
Topic 17	company	coinbase	million	square	venture	startup	billion	customer	product	business
Topic 18	inflation	going	money	cramer	really	thats	thing	want	people	know
Topic 19	share	stock	premarke	revenue	cnbc	earnings	company	quarter	tesla	estimate
Topic 20	buffett	apple	read	berkshire	warren	google	amazon	food	book	billionaire

Figure 4. The twenty probable (20) Topics with Ten (10) words/terms from the sLDA model with K= 20

Topic 2 is all about (crypto security) such as ransomware attacks posing a severe risk, thus companies in the financial services, healthcare & pharmaceuticals, and employee personally identifiable information (PII) and HR sectors need to implement strong security measures to safeguard their data and systems. The news was also reported by the media and appeared in some of the web scraped documents at different dates, either by reference to it or just a few mentions.

Topic 3 shows deep thought about Bitcoin's market competition

amidst other cryptocurrencies. That is, despite its humorous beginnings, Dogecoin has grown into an intriguing aspect of the cryptocurrency world, mostly because of Elon Musk's lighthearted engagement. Observing Musk's tweets as the market moves forward may be just as important as examining technical charts.

Topic 4 is about how some countries' economic circumstances affect the market trend of Bitcoin. All the topics had words that were either heavily mention, partially mentioned or not mentioned at all in the news encapsulated in our various published documents.

Figure 5 explains how important the topics are to the documents. Topic 3, shows a high level of importance to the documents while Topic 20, shows the lowest level of importance to the documents.

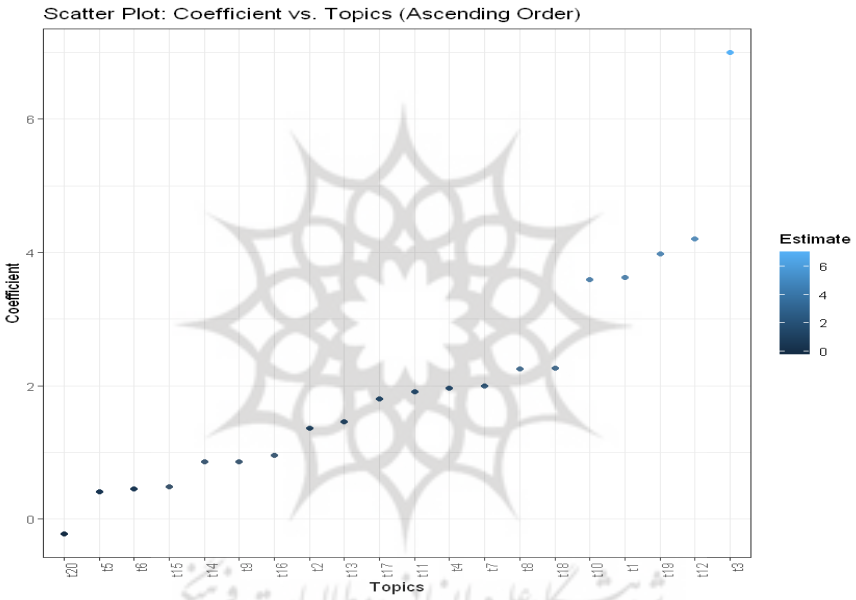

Figure 5. Graph of the coefficients of the sLDA model's probable Topics

Table 3 is a 4073 (row) by 20 (column) matrix which shows the proportions of terms/words from the documents/articles that make up the sLDA Topics. It is a posterior covariance matrix. However, because of the volume of this result and for clarity's sake, just the first eight Topics and the first Fourteen documents were selected and displayed in Table 4, while the full information can be seen in the appendix.

A critical look into the first four documents, Table 4 shows how the topic-proportion in the News known as a document and the response of the market price trend, 24 hours after publication. With reference to Table 4, Topic 1, 6, 7 and 8 from Document 0 had its impact on the market trend while Topic 2, 3, 4, 5 had their proportional impact on the market trend from Document 0. Topic 6 had no impact on the market trend from Document 1 while Topic 1, 2, 3, 4, 5, 7 and 8 had their proportional impact on the market trend from Document 1.

Table 3. The sLDA model per topic-document proportion output

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8
Doc 0	0	0.011905	0.02381	0.011905	0.154762	0	0	0
Doc 1	0.013699	0.034247	0.013699	0.136986	0.068493	0	0.006849	0.020548
Doc 2	0.008	0.054	0.002	0.02	0.022	0.286	0.018	0.008
Doc 3	0.003236	0.038835	0.074434	0.116505	0	0.223301	0.029126	0.016181
Doc 4	0	0.00463	0.125	0.023148	0.101852	0.041667	0	0.013889
Doc 5	0.048421	0.065263	0.008421	0.012632	0.176842	0.002105	0.027368	0
Doc 6	0.021277	0.035461	0.014184	0.070922	0.060284	0.049645	0.035461	0.053191
Doc 7	0	0	0.22	0	0.28	0.02	0	0
Doc 8	0.601027	0.005137	0.02226	0.119863	0.025685	0.003425	0.001712	0.035959
Doc 9	0.008086	0	0.040431	0.016173	0.040431	0.002695	0.016173	0.105121
Doc 10	0.012346	0.018519	0.074074	0.018519	0.098765	0.006173	0	0.030864
Doc 11	0	0.018127	0.003021	0.039275	0.009063	0.069486	0.012085	0.003021
Doc 12	0.002899	0.005797	0.023188	0.156522	0.034783	0.008696	0.017391	0
Doc 13	0	0.003876	0.003876	0	0.027132	0.003876	0.023256	0.027132
Doc 14	0.009479	0.009479	0	0.004739	0.530806	0.080569	0.018957	0.004739

Table 4. The price market trend for the few selected published documents (see Appendix)

Doc	Date published	open	High	Low	Close	Volume	% Change
Doc 0	28/8/2022	20032.73	20133.36	19606	19606	4.16E+10	-2.13%
Doc1	24/8/2022	21513.00	21826.33	21172.0	21378.1	5.06E+10	-0.63%
Doc 2	25/8/2022	21367.72	21773.15	21330.7	21591.28	5.04E+10	1.05%
Doc 3	18/8/2022	23338.393	23575.61	23140.4	23206.1	5.1E+10	-0.57%

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All the Topics had their proportional effects on the market trend from Document 2. Also, all the topics had their proportional effect on the market trend from document 3 except for Topic 5. The effects were either positive or negative change in the market trend. While there are many factors that can cause price fluctuations in financial markets, the function of the media, is a consistent source of information and sentiment.

Figure 6 is a graph of an in-sample forecast which we did to predict response variables for a Document; i.e., a document could be read and inferences made as to how it is going to affect the market price. This could be made useful by a would-be miner or cryptocurrency analysts. The sLDA prediction model was tested using the testing data which is assumed to be unlabeled documents/articles. The predicted classification in line with the earlier mentioned classification in section (2.2), was juxtaposed with the testing data's initial response variable (classification). For the case of our voluminous data, 200 documents of the testing data and its response variable, alongside the corresponding predicted response, were captured. The result shows that the two trends appear in a near-similar pattern.

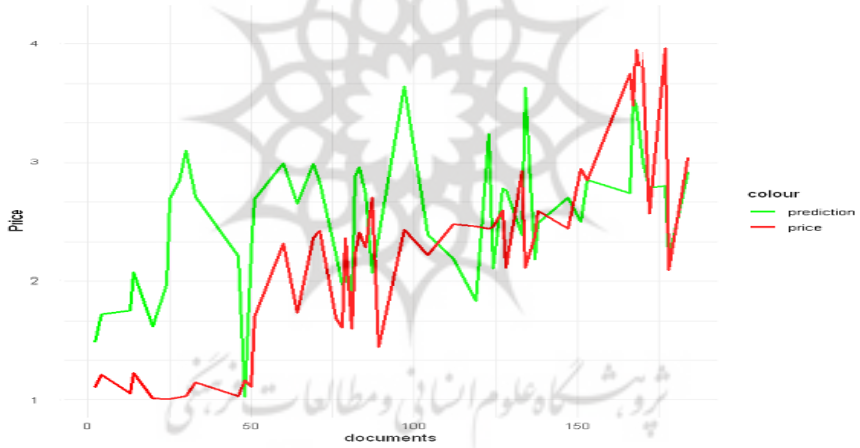

Figure 6. The initial price classification and the sLDA predicted classification

4. Conclusion

A helpful technique for examining huge text corpora is topic modeling. Topic modeling has applications outside of text mining, linguistics, and language modeling; it has been utilized in computer vision, population genetics analysis, social sciences, and humanities research.

Topic modeling, by revealing the topic structure buried in the text collection, can offer a higher-level exploration strategy to have a solid grasp of big text corpora when combined with other text-mining and machine-learning technologies. Additionally, the outputs of topic models can strengthen tasks like information retrieval, collaborative filtering, classification/categorization, and recommendation systems.

To understand how latent crowd knowledge affects the bitcoin market and to further leverage its predictive power, the research has looked at the significance and use of the sLDA-VEM and sLDA-predict for textual data mining and analysis. Hidden predictive topics used by traders in our textual data were exposed. Similarly, the links between Documents/ articles and topics were disclosed. Finally, we investigated the sLDA model's predictive power by extrapolating traders' interest or response variables for unlabeled documents.

Conflict of interest

The authors declared no conflicts of interest.

Ethical considerations

The authors have completely considered ethical issues, including informed consent, plagiarism, data fabrication, misconduct, and/or falsification, double publication and/or redundancy, submission, etc. This article was not authored by artificial intelligence.

Authors Contributions

TM, MOA and MUA: Developed the conceptual framework; TM-Source for the data and analyze the data; MOA and MUA-Supervised the work; TM-Came up with the first draft; TM, MOA and MUA- came up with the final draft; MOA and MUA- Do the editing of the workData availability.

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Appendix 1. The sLDA model Per Topic-Document proportion output (doc0-doc101

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	Topic 9	Topic 10	Topic 11	Topic 12	Topic 13	Topic 14	Topic 15	Topic 16	Topic 17	Topic 18	Topic 19	Topic 20
doc 0	0	0.011905	0.02381	0.011905	0.154762	0	0	0	0	0.095238	0	0.083333	0.035714	0	0	0.214286	0	0.130952	0.238095	0
doc 1	0.013699	0.034247	0.013699	0.136986	0.068493	0	0.006849	0.020548	0.061644	0.006849	0.041096	0.027397	0	0.041096	0.089041	0.363014	0	0.041096	0.034247	0
doc 2	0.008	0.054	0.002	0.02	0.022	0.286	0.018	0.008	0.006	0.06	0.042	0.002	0.388	0.006	0.046	0.008	0.006	0.004	0	0.014
doc 3	0.003236	0.038835	0.074434	0.116505	0	0.223301	0.029126	0.016181	0.12945	0.019417	0.110032	0.035599	0.006472	0.003236	0	0.110032	0.058252	0.022654	0	0.003236
doc 4	0	0.00463	0.125	0.023148	0.101852	0.041667	0	0.013889	0.037037	0.00463	0.00463	0.064815	0.023148	0.00463	0.074074	0.337963	0.009259	0.12037	0.00463	0.00463
doc 5	0.048421	0.065263	0.008421	0.012632	0.176842	0.002105	0.027368	0	0.002105	0	0	0.008421	0.018947	0	0.008421	0.006316	0.035789	0.416842	0.109474	0.052632
doc 6	0.021277	0.035461	0.014184	0.070922	0.060284	0.049645	0.035461	0.053191	0.028369	0.010638	0.439716	0	0	0	0.099291	0.053191	0	0.010638	0.01773	0
doc 7	0	0	0.22	0	0.28	0.02	0	0	0	0.02	0.04	0	0	0.02	0.02	0.32	0	0	0.06	0
doc 8	0.601027	0.005137	0.02226	0.119863	0.025685	0.003425	0.001712	0.035959	0	0.063356	0	0	0.035959	0.001712	0.025685	0.027397	0.001712	0.02226	0.001712	0.005137
doc 9	0.008086	0	0.040431	0.016173	0.040431	0.002695	0.016173	0.105121	0.070081	0.221024	0.013477	0.002695	0.008086	0.002695	0.002695	0.110512	0.010782	0.005391	0.312668	0.010782
doc 10	0.012346	0.018519	0.074074	0.018519	0.098765	0.006173	0	0.030864	0.006173	0	0.006173	0.006173	0.018519	0.006173	0.320988	0.074074	0	0.117284	0	0.185185
doc 11	0	0.018127	0.003021	0.039275	0.009063	0.069486	0.012085	0.003021	0.012085	0.018127	0.181269	0.015106	0.006042	0	0.084592	0.453172	0.003021	0.021148	0	0.05136
doc 12	0.002899	0.005797	0.023188	0.156522	0.034783	0.008696	0.017391	0	0.005797	0.002899	0.002899	0.055072	0	0.002899	0	0.605797	0.005797	0.06087	0.002899	0.005797
doc 13	0	0.003876	0.003876	0	0.027132	0.003876	0.023256	0.027132	0.069767	0.015504	0.042636	0.341085	0.015504	0.015504	0.104651	0.267442	0.01938	0.003876	0	0.015504
doc 14	0.009479	0.009479	0	0.004739	0.530806	0.080569	0.018957	0.004739	0	0.037915	0	0	0.004739	0	0	0.033175	0.004739	0.180095	0.052133	0.028436
doc 15	0	0.014493	0.007246	0.021739	0	0.014493	0.007246	0.188406	0	0.5	0.014493	0	0.007246	0	0.014493	0.036232	0	0.15942	0	0.014493
doc 16	0.010101	0.020202	0.020202	0.010101	0.010101	0.010101	0.050505	0.050505	0	0.010101	0.090909	0.020202	0.010101	0.020202	0.10101	0.191919	0.30303	0.070707	0	0
doc 17	0.00692	0.00346	0	0.013841	0.287197	0	0	0	0	0.256055	0.034602	0.027682	0.038062	0	0.058824	0.027682	0.017301	0.183391	0.038062	0.00692
doc 18	0	0	0.048077	0	0.019231	0.028846	0.009615	0	0.346154	0	0	0.076923	0.019231	0.009615	0.173077	0	0.105769	0.048077	0.019231	0.096154
doc 19	0.006849	0	0.205479	0	0	0	0.013699	0.020548	0.431507	0	0.020548	0.006849	0	0	0.013699	0.006849	0.006849	0.027397	0.232877	0.006849
doc 20	0.022346	0	0	0	0.072626	0.005587	0.03352	0.145251	0	0.03352	0.340782	0.027933	0.005587	0.005587	0.039106	0.122905	0.01676	0.122905	0	0.005587
doc 21	0.013889	0.023148	0.037037	0	0.00463	0.018519	0	0.00463	0.226852	0.013889	0.097222	0	0.041667	0.013889	0.027778	0.384259	0.009259	0.032407	0.037037	0.013889
doc 22	0.007117	0	0.071174	0.181495	0.003559	0.032028	0.007117	0.003559	0.010676	0	0.330961	0.071174	0	0.003559	0.014235	0.199288	0.021352	0.039146	0	0.003559
doc 23	0	0.077586	0.008621	0	0.012931	0.017241	0	0.008621	0.517241	0.017241	0.017241	0.099138	0.025862	0.00431	0.168103	0	0.00431	0.012931	0.00431	0.00431
doc 24	0.000866	0.019913	0.017316	0.049351	0.057143	0.35671	0.050216	0.001732	0.045022	0	0.117749	0.01039	0.021645	0	0.018182	0.038095	0.08658	0.104762	0.002597	0.001732
doc 25	0.022222	0.066667	0.007407	0.02716	0.019753	0.004938	0.012346	0.116049	0.083951	0.037037	0	0.002469	0	0.002469	0.017284	0.009877	0.002469	0.024691	0.516049	0.02716
doc 26	0.004082	0.008163	0	0.028571	0.004082	0.008163	0.012245	0.073469	0.004082	0.730612	0.008163	0.004082	0.008163	0.004082	0	0.004082	0	0.085714	0	0.012245
doc 27	0	0	0.002632	0.013158	0.005263	0	0.007895	0.013158	0.002632	0.036842	0.013158	0	0.010526	0.010526	0.015789	0.018421	0.039474	0.042105	0.747368	0.021053
doc 28	0.003125	0.003125	0.025	0	0.028125	0.025	0.021875	0.003125	0.225	0.034375	0.1375	0.059375	0.015625	0	0.025	0.3125	0.034375	0.040625	0.003125	0.003125
doc 29	0	0.009569	0.009569	0	0.004785	0.181818	0.033493	0	0.004785	0	0.009569	0.062201	0	0.004785	0	0.148325	0.009569	0.07177	0.028708	0.421053
doc 30	0.002188	0.015317	0.002188	0	0.013129	0	0.875274	0.013129	0.006565	0.004376	0	0.006565	0	0.010941	0.021882	0.002188	0.008753	0.015317	0	0.002188
doc 31	0.005848	0.005848	0.017544	0.023392	0.064327	0.017544	0.017544	0.011696	0.023392	0.02924	0.017544	0.005848	0	0	0.023392	0.707602	0	0.005848	0.023392	0
doc 32	0	0	0.011905	0	0	0.041667	0.136905	0	0.005952	0.071429	0.291667	0.071429	0.005952	0	0.208333	0.107143	0	0.017857	0.011905	0.017857
doc 33	0.005025	0.005025	0.01005	0.025126	0.045226	0.01005	0.085427	0	0.005025	0.015075	0	0.01005	0.030151	0.015075	0.055276	0.190955	0.39196	0.015075	0.085427	0
doc 34	0.506127	0.019608	0.001225	0.023284	0.002451	0.019608	0.007353	0.055147	0.001225	0.008578	0.003676	0.012255	0.084559	0	0.017157	0.007353	0.046569	0.126225	0.001225	0.056373
doc 35	0.041509	0.026415	0.041509	0.003774	0.241509	0	0.007547	0.003774	0	0	0.003774	0.003774	0	0.011321	0.003774	0.003774	0.071698	0.358491	0.177358	0
doc 36	0.002012	0.006036	0.199195	0.002012	0.040241	0.076459	0.014085	0.026157	0.012072	0.020121	0.01006	0.034205	0.026157	0.004024	0	0.01006	0.406439	0.100604	0.002012	0.008048
doc 37	0.815934	0	0.002747	0.021978	0.002747	0.008242	0.010989	0.019231	0	0.016484	0	0.016484	0.03022	0.008242	0.002747	0.013736	0.002747	0.019231	0.008242	0
doc 38	0.010582	0.716931	0	0.079365	0	0.002646	0.002646	0.087302	0.015873	0.02381	0.013228	0	0.002646	0	0	0.002646	0.015873	0.010582	0	0.015873
doc 39	0.017699	0.0059	0.00295	0	0.011799	0.294985	0.00295	0.00295	0.085546	0.023599	0.076696	0.053097	0	0	0.014749	0.053097	0.351032	0	0.00295	0
doc 40	0.134021	0	0.061856	0.006873	0.024055	0.151203	0.003436	0	0.013746	0.006873	0.268041	0.054983	0.006873	0	0.034364	0.072165	0.120275	0.027491	0	0.013746
doc 41	0.006849	0.020548	0.006849	0.013699	0.068493	0.013699	0	0	0.013699	0.006849	0	0.013699	0.006849	0	0.452055	0.020548	0	0.30137	0.020548	0.034247
doc 42	0	0	0.00625	0	0.075	0.025	0	0	0.025	0.05625	0.0125	0.0125	0.01875	0	0.18125	0.3	0.0375	0.20625	0.01875	0.025
doc 43	0.027435	0.001372	0.001372	0.056241	0.010974	0.001372	0.030178	0.109739	0.043896	0.010974	0.024691	0.012346	0.030178	0.004115	0.00823	0.045267	0.050754	0	0.474623	0.056241
doc 44	0	0.005386	0.005386	0.001795	0.001795	0	0.003591	0.08079	0.010772	0.057451	0.025135	0	0.016158	0.001795	0.001795	0.021544	0.043088	0.012567	0.70377	0.007181
doc 45	0.020661	0	0.082645	0	0.099174	0.061983	0.004132	0.008264	0.012397	0.016529	0.004132	0.041322	0	0.004132	0.008264	0.061983	0.347107	0.020661	0.206612	0
doc 46	0.005405	0.037838	0.07027	0.032432	0	0.005405	0.027027	0.010811	0.010811	0.081081	0.243243	0.027027	0.07027	0.005405	0.010811	0.135135	0.07027	0.118919	0.021622	0.016216
doc 47	0.003205	0.009615	0.019231	0	0.044872	0.259615	0.022436	0	0.064103	0.012821	0.102564	0.112179	0.003205	0	0	0.022436	0.13141	0.169872	0.016026	0.00641
doc 48	0.02968	0.004566	0.002283	0.027397	0.203196	0.018265	0.009132	0.086758	0	0.369863	0.006849	0	0.011416	0	0	0.027397	0.004566	0.070776	0.10274	0.025114
doc 49	0	0.032787	0	0.004098	0.008197	0.012295	0.020492	0.008197	0.028689	0.036885	0.020492	0.028689	0	0.016393	0	0.008197	0.053279	0	0.713115	0.008197
doc 50	0.020408	0	0.010204	0.010204	0.193878	0	0.020408	0	0.010204	0	0	0	0	0	0.030612	0.153061	0.173469	0.193878	0.122449	0.061224
doc 51	0	0	0	0	0	0	0	0.014493	0	0	0	0	0	0.971014	0	0	0	0	0	0.014493
doc 52	0.004202	0	0	0.063025	0	0.012605	0.033613	0	0.415966	0.016807	0.205882	0.004202	0	0	0.222689	0	0.021008	0	0	0
doc 53	0.046784	0.007797	0.007797	0.068226	0.007797	0.025341	0.005848	0.204678	0.015595	0.136452	0.003899	0	0	0	0.007797	0.02924	0.005848	0	0.413255	0.013645
doc 54	0.005848	0.002924	0.026316	0.040936	0.362573	0.005848	0.020468	0.017544	0.011696	0.377193	0.046784	0.011696	0.002924	0.002924	0	0.011696	0.011696	0.011696	0.017544	0.011696
doc 55	0.003344	0.010033	0.006689	0.036789	0.073579	0	0.013378	0.023411	0.006689	0.685619	0.020067	0.003344	0.003344	0.003344	0	0.0301	0.006689	0.056856	0.013378	0.003344
doc 56	0.003597	0.014388	0.02518	0.122302	0.003597	0.438849	0.010791	0	0.032374	0.010791	0.215827	0	0	0	0.003597	0.039568	0.064748	0.007194	0	0.003597
doc 57	0.006494	0	0	0.064935	0.019481	0.019481	0.012987	0.006494	0.181818	0	0	0	0	0	0.032468	0.603896	0.012987	0	0.038961	0
doc 58	0.004566	0	0	0.009132	0.045662	0	0.073059	0.045662	0.004566	0.525114	0.068493	0.027397	0	0	0.009132	0.150685	0.009132	0.004566	0.004566	0.018265
doc 59	0.040404	0.03367	0.060606	0	0	0.037037	0.13468	0.043771	0.003367	0.094276	0.208754	0.003367	0.013468	0.013468	0.191919	0.006734	0.003367	0.087542	0.006734	0.016835
doc 60	0.011019	0.030303	0.082645	0	0.300275	0	0.002755	0.00551	0.013774	0	0.022039	0.016529	0.030303	0.002755	0.002755	0.404959	0	0.057851	0.016529	0
doc 61	0	0.424332	0.002967	0.002967	0	0.002967	0.062315	0.020772	0.035608	0.002967	0.008902	0.005935	0.136499	0.002967	0.047478	0.008902	0	0.21365	0.008902	0.011869
doc 62	0.086207	0.034483	0.045977	0.017241	0.413793	0	0.051724	0	0.005747	0.028736	0	0	0.005747	0	0	0.137931	0	0	0.155172	0.017241
doc 63	0	0.013072	0.084967	0.078431	0.019608	0.013072	0.019608	0.03268	0.333333	0.019608	0.006536	0.006536	0	0	0	0.352941	0	0.013072	0.006536	0
doc 64	0.003861	0.011583	0.494208	0.015444	0.003861	0.084942	0.027027	0.042471	0.096525	0	0.027027	0.027027	0.011583	0	0.003861	0.003861	0.084942	0.015444	0.019305	0.027027
doc 65	0	0	0	0.019553	0.011173	0.022346	0.055866	0	0.019553	0.002793	0.365922	0.03352	0.22067	0.005587	0.086592	0.002793	0.00838	0.136872	0	0.00838
doc 66	0.004167	0	0	0	0.241667	0	0	0.004167	0	0.058333	0	0.083333	0.016667	0.008333	0.075	0.245833	0.004167	0.245833	0	0.0125
doc 67	0.015385	0.553846	0	0	0.005128	0.005128	0.020513	0.035897	0.015385	0	0.025641	0.005128	0.020513	0	0.055276	0.18282	0	0.051282	0	0.05641
doc 68	0.010256	0.005128	0.051282	0.010256	0.169231	0.066667	0.010256	0	0.117949	0.005128	0.010256	0.030769	0	0	0.082051	0.328205	0.071795	0.025641	0.005128	0
doc 69	0.046512	0.162791	0.005814	0.023256	0.087209	0	0.023256	0	0.040698	0	0.052326	0.05814	0.174419	0	0.22093	0.052326	0.011628	0.017442	0.005814	0.017442
doc 70	0.022556	0.022556	0	0.015038	0.06015	0.015038	0	0.067669	0	0.142857	0	0.090226	0	0.097744	0.090226	0.18797	0.007519	0.165414	0.015038	0
doc 71	0.007463	0.037313	0.014925	0.007463	0	0.671642	0.007463	0.022388	0.022388	0	0.029851	0.007463	0.022388	0.007463	0.007463	0.007463	0.029851	0.037313	0.052239	0.007463
doc 72	0	0.007692	0	0.007692	0	0	0.023077	0	0.023077	0.015385	0.023077	0	0.007692	0.684615	0	0	0.007692	0.030769	0.169231	0
doc 73	0.012397	0	0	0.024793	0	0.582645	0.012397	0.008264	0.028926	0	0.066116	0.012397	0.008264	0.012397	0.008264	0	0.202479	0	0.008264	0.012397
doc 74	0.021739	0.504348	0	0.017391	0	0	0.147826	0.008696	0.013043	0	0	0.008696	0.06087	0	0.004348	0	0.030435	0.13913	0.026087	0.017391
doc 75	0.027477	0.000901	0	0.011712	0.060811	0.000901	0.05045	0.118919	0.002703	0.196396	0.276577	0.015315	0.004955	0.00045	0.005405	0.001351	0.002252	0.215766	0.001802	0.005856
doc 76	0.004032	0.004032	0.028226	0.028226	0.004032	0.072581	0	0.008065	0.008065	0.028226	0.104839	0.120968	0.008065	0.004032	0.004032	0.483871	0.012097	0.028226	0.020161	0.028226
doc 77	0	0	0.013274	0.004425	0.134956	0	0	0.112832	0.017699	0.019912	0.108407	0.103982	0.024336	0.006637	0.037611	0.00885	0.002212	0.05531	0.068584	0.280973
doc 78	0	0	0.012048	0.012048	0.036145	0.048193	0	0.012048	0	0.168675	0	0	0.024096	0	0	0.60241	0.060241	0	0	0.024096
doc 79	0.092628	0.003781	0.035917	0.009452	0.037807	0.034026	0.007561	0.005671	0.00189	0.192817	0.035917	0.10775	0	0.00189	0.126654	0.277883	0	0.024575	0	0.003781
doc 80	0	0	0	0	0.006667	0	0	0	0	0	0	0	0	0.993333	0	0	0	0	0	0
doc 81	0.006452	0.002151	0.215054	0.036559	0.187097	0.017204	0.017204	0.002151	0.025806	0.019355	0.062366	0.053763	0	0	0.021505	0.24086	0.015054	0.006452	0.066667	0.004301
doc 82	0.008889	0.022222	0.017778	0.044444	0.008889	0.004444	0.017778	0.022222	0.004444	0.751111	0.004444	0.004444	0.017778	0.004444	0	0.048889	0	0.013333	0.004444	0
doc 83	0.015326	0.030651	0.005747	0.074713	0.019157	0.011494	0.070881	0.266284	0.007663	0.009579	0.01341	0.02682	0.02682	0.001916	0.009579	0.003831	0.068966	0.005747	0.241379	0.090038
doc 84	0.012397	0.008264	0.014463	0.016529	0	0	0	0.086777	0.030992	0.144628	0.012397	0.002066	0.018595	0	0.008264	0.070248	0.028926	0.004132	0.485537	0.055785
doc 85	0.008547	0.031339	0.005698	0.02849	0.011396	0.407407	0.005698	0.002849	0.008547	0.031339	0.088319	0.019943	0.011396	0	0.005698	0.011396	0.202279	0.091168	0.025641	0.002849
doc 86	0.038194	0	0.013889	0.003472	0.402778	0.003472	0.006944	0.010417	0.010417	0.076389	0.034722	0.052083	0.003472	0.006944	0.065972	0.006944	0.0625	0.152778	0.006944	0.041667
doc 87	0.009346	0	0.261682	0	0	0	0.014019	0.014019	0	0	0.004673	0.065421	0.116822	0.004673	0.228972	0	0.051402	0.182243	0.023364	0.023364
doc 88	0.020101	0.040201	0.180905	0	0.110553	0.005025	0.01005	0.040201	0.005025	0.060302	0.030151	0.221106	0	0.020101	0.040201	0.005025	0	0.030151	0.055276	0.125628
doc 89	0	0	0.040541	0	0.351351	0	0.013514	0	0	0.22973	0.040541	0.121622	0	0	0.013514	0.148649	0	0.013514	0.013514	0.013514
doc 90	0.006329	0.006329	0.018987	0	0.06962	0.012658	0	0.050633	0.006329	0.018987	0.012658	0.037975	0.012658	0.664557	0	0.044304	0.006329	0.006329	0.012658	0.012658
doc 91	0.007463	0	0	0	0.007463	0	0	0	0	0	0	0	0	0.977612	0.007463	0	0	0	0	0
doc 92	0.053977	0.011364	0.002841	0.025568	0.073864	0.005682	0.059659	0.099432	0.153409	0.005682	0.022727	0.215909	0.017045	0.008523	0	0.014205	0.139205	0.068182	0.005682	0.017045
doc 93	0.005814	0	0.087209	0.011628	0.241279	0.011628	0	0.052326	0.005814	0.177326	0	0.011628	0.002907	0.002907	0.020349	0.252907	0	0.046512	0.063953	0.005814
doc 94	0	0	0.035398	0	0.353982	0	0	0	0	0.079646	0	0.061947	0	0.053097	0.141593	0.070796	0.053097	0.150442	0	0
doc 95	0	0	0	0	0	0	0	0	0	0	0	0.032787	0	0.942623	0.008197	0	0	0.008197	0	0.008197
doc 96	0.004049	0.016194	0.218623	0.004049	0.076923	0.008097	0.012146	0	0.012146	0.036437	0.012146	0.109312	0.036437	0.004049	0.080972	0	0.060729	0.105263	0.008097	0.194332
doc 97	0	0.003891	0.163424	0.019455	0.003891	0.003891	0	0.011673	0	0.058366	0.587549	0.042802	0	0	0.023346	0.023346	0.011673	0.038911	0	0.007782
doc 98	0.009524	0	0.019048	0.009524	0.228571	0.07619	0	0.019048	0.114286	0.009524	0	0.047619	0	0.038095	0.038095	0.266667	0.057143	0	0.066667	0
doc 99	0.026667	0.02	0	0.026667	0.18	0.013333	0.04	0.033333	0.006667	0.046667	0.006667	0.22	0.073333	0.04	0.006667	0.04	0.026667	0.18	0.013333	0
doc 100	0.011696	0.555556	0	0.005848	0	0.02924	0.035088	0.233918	0.005848	0	0.05848	0	0	0.005848	0	0.011696	0	0.017544	0.017544	0.011696
doc 101	0	0.163743	0.239766	0	0.011696	0.005848	0.035088	0.023392	0.134503	0.052632	0	0	0.005848	0.005848	0.087719	0	0	0.152047	0.035088	0.046784

Appendix 2. The sLDA model Per Topic-Document proportion output (doc3970-doc4072)

doc 3970	0.015584	0.711688	0.015584	0.083117	0.012987	0.005195	0.018182	0.012987	0.012987	0.012987	0.018182	0	0.025974	0	0.012987	0	0.020779	0.012987	0.005195	0.002597
doc 3971	0.008547	0.006838	0.003419	0.02735	0.051282	0.02735	0.068376	0.025641	0	0.054701	0.557265	0.044444	0.008547	0.006838	0.054701	0.003419	0.010256	0.02906	0.003419	0.008547
doc 3972	0.008247	0.002062	0.02268	0.063918	0.02268	0	0.03299	0.090722	0.018557	0.230928	0.002062	0.004124	0.018557	0	0	0.026804	0.024742	0.012371	0.412371	0.006186
doc 3973	0.004587	0.077982	0.009174	0.013761	0.018349	0.009174	0.105505	0.087156	0.027523	0.087156	0.013761	0.03211	0.041284	0.004587	0.013761	0.041284	0.09633	0	0.307339	0.009174
doc 3974	0.006211	0.012422	0.31677	0.006211	0.012422	0	0.012422	0.012422	0.018634	0.055901	0	0.006211	0.018634	0.006211	0.049689	0.26087	0	0.130435	0.055901	0.018634
doc 3975	0.020408	0.020408	0.006803	0.013605	0	0.006803	0.006803	0.122449	0.013605	0.006803	0.346939	0	0	0	0.244898	0.006803	0.040816	0.136054	0.006803	0
doc 3976	0.05283	0.003774	0.158491	0	0	0.154717	0.015094	0.015094	0	0.003774	0	0.015094	0.018868	0.003774	0.007547	0.007547	0.275472	0.215094	0.003774	0.049057
doc 3977	0.017668	0.007067	0.007067	0.024735	0.04947	0.021201	0.109541	0.010601	0.007067	0.014134	0.017668	0.053004	0.007067	0.003534	0.007067	0.084806	0.508834	0.035336	0.010601	0.003534
doc 3978	0	0.395833	0.2125	0.004167	0.008333	0.029167	0.045833	0.05	0.025	0.004167	0.029167	0	0.004167	0	0.0875	0.066667	0.008333	0.025	0.004167	0
doc 3979	0.006154	0.009231	0.003077	0.209231	0.055385	0.018462	0.04	0.175385	0.021538	0.024615	0.021538	0.024615	0.08	0	0.018462	0.061538	0.006154	0.153846	0.049231	0.021538
doc 3980	0	0.072607	0.0033	0.026403	0.016502	0.135314	0.092409	0.0033	0	0.009901	0.029703	0.039604	0	0	0.026403	0.0033	0.148515	0.148515	0.042904	0.20132
doc 3981	0.003049	0.006098	0.04878	0.02439	0.094512	0	0.033537	0.085366	0.006098	0.079268	0.060976	0.039634	0	0.015244	0.003049	0.036585	0.039634	0.277439	0.128049	0.018293
doc 3982	0	0.015038	0.007519	0.015038	0.007519	0	0.421053	0.052632	0.030075	0.007519	0	0.030075	0.007519	0	0.285714	0.045113	0.037594	0.022556	0.007519	0.007519
doc 3983	0	0	0	0	0.008696	0.008696	0	0	0	0	0	0	0	0.93913	0.008696	0.008696	0.008696	0.008696	0	0.008696
doc 3984	0.02935	0.012579	0.392034	0	0.035639	0.010482	0.020964	0	0.188679	0.018868	0.02935	0.092243	0.025157	0	0.010482	0.016771	0.031447	0.067086	0.004193	0.014675
doc 3985	0.044118	0	0.073529	0	0.176471	0	0.088235	0	0.014706	0.323529	0	0.058824	0	0	0.058824	0.014706	0	0.029412	0.088235	0.029412
doc 3986	0	0.005882	0	0.035294	0.035294	0.005882	0	0.029412	0.035294	0.005882	0	0.064706	0	0	0.252941	0.470588	0.035294	0	0.005882	0.017647
doc 3987	0.03908	0.006897	0.055172	0	0.03908	0.027586	0.025287	0.062069	0.052874	0.009195	0.062069	0.055172	0.025287	0.002299	0.002299	0.022989	0.314943	0.186207	0.009195	0.002299
doc 3988	0.014572	0.045537	0.003643	0.081967	0.016393	0.081967	0.105647	0.010929	0.001821	0.005464	0.428051	0	0.061931	0.003643	0.041894	0.020036	0	0.069217	0.001821	0.005464
doc 3989	0.006173	0.012346	0.009259	0	0.046296	0.003086	0.018519	0	0.003086	0.824074	0.009259	0	0.012346	0	0.009259	0.009259	0.009259	0.027778	0	0
doc 3990	0	0.018868	0.09434	0	0.018868	0.037736	0	0.075472	0	0.150943	0.018868	0.169811	0.018868	0	0.264151	0.113208	0	0.150943	0.018868	0
doc 3991	0.042105	0.005263	0.257895	0.005263	0.005263	0.010526	0	0	0.042105	0.057895	0.026316	0	0	0	0.010526	0.494737	0	0.026316	0	0.015789
doc 3992	0	0	0.021739	0	0.01087	0.01087	0.032609	0.01087	0.076087	0.01087	0.195652	0.141304	0	0	0	0.336957	0	0.065217	0.032609	0.054348
doc 3993	0.008065	0	0.004032	0	0.03629	0.004032	0.294355	0.076613	0.016129	0.012097	0.217742	0.016129	0.032258	0.004032	0.012097	0.092742	0.092742	0	0.024194	0.056452
doc 3994	0	0.022472	0.022472	0.011236	0.280899	0.033708	0.05618	0	0.033708	0.269663	0.022472	0.05618	0	0.022472	0.011236	0.134831	0	0	0	0.022472
doc 3995	0.012658	0.063291	0.004219	0	0.004219	0.21097	0	0.004219	0.012658	0.042194	0.025316	0.092827	0.059072	0.037975	0.244726	0	0.008439	0.008439	0.025316	0.14346
doc 3996	0.014085	0.016432	0.00939	0.002347	0	0.007042	0.00939	0.070423	0.023474	0.018779	0.481221	0.023474	0.002347	0	0.039906	0.025822	0.124413	0.126761	0.002347	0.002347
doc 3997	0	0	0.117155	0	0.004184	0.004184	0.012552	0	0.020921	0	0.008368	0.225941	0.004184	0.004184	0.025105	0.292887	0.096234	0.167364	0.016736	0
doc 3998	0	0	0.008929	0	0	0	0	0	0	0.008929	0	0	0	0.982143	0	0	0	0	0	0
doc 3999	0	0.038278	0.019139	0.002392	0.004785	0.011962	0.619617	0.004785	0.019139	0.014354	0.004785	0.114833	0.016746	0.002392	0.026316	0.033493	0	0.033493	0.028708	0.004785
doc 4000	0.229437	0	0.008658	0.002165	0.015152	0.028139	0.073593	0.010823	0	0.008658	0.008658	0.004329	0.004329	0.004329	0.002165	0	0.060606	0.038961	0.493506	0.006494
doc 4001	0.008368	0.004184	0.196653	0.008368	0.066946	0.004184	0	0.020921	0.016736	0.355649	0.008368	0.066946	0.004184	0.012552	0.008368	0.200837	0.004184	0.008368	0.004184	0
doc 4002	0.003333	0.006667	0.49	0	0	0.003333	0.093333	0.006667	0.02	0	0.016667	0	0.056667	0	0.096667	0.016667	0.026667	0.146667	0.006667	0.01
doc 4003	0.0125	0	0	0.01875	0.04375	0.00625	0.00625	0.00625	0.00625	0.0125	0.025	0.13125	0.15625	0	0.075	0.00625	0.4875	0	0	0.00625
doc 4004	0.082051	0.005128	0.487179	0	0	0	0.015385	0.020513	0	0.015385	0.025641	0.030769	0.005128	0.010256	0.025641	0.082051	0.041026	0.112821	0.041026	0
doc 4005	0.02965	0.005391	0.018868	0	0	0	0.598383	0	0.048518	0.005391	0.018868	0.037736	0.010782	0	0.005391	0.153639	0.016173	0.03504	0.002695	0.013477
doc 4006	0.014493	0.014493	0.003623	0.003623	0.01087	0.014493	0.003623	0.021739	0.003623	0	0.01087	0.003623	0.025362	0.003623	0.036232	0.126812	0.264493	0.293478	0.01087	0.134058
doc 4007	0	0.007634	0.076336	0.015267	0.274809	0.007634	0	0.030534	0	0.091603	0.10687	0.038168	0.038168	0.007634	0.007634	0.10687	0	0.167939	0.007634	0.015267
doc 4008	0.005952	0.041667	0.005952	0	0.029762	0.005952	0	0.011905	0	0.172619	0.041667	0	0	0.005952	0	0	0	0.446429	0.214286	0.017857
doc 4009	0.019704	0.172414	0.152709	0.018062	0.036125	0.024631	0.004926	0	0.006568	0.006568	0.009852	0.082102	0.175698	0.004926	0.123153	0.045977	0.003284	0.090312	0.022989	0
doc 4010	0.004587	0	0.082569	0.009174	0.091743	0.004587	0.073394	0	0	0.004587	0	0.119266	0.013761	0.004587	0.004587	0.004587	0.050459	0.059633	0.050459	0.422018
doc 4011	0.018828	0.002092	0.043933	0.002092	0.062762	0.228033	0.008368	0.016736	0.012552	0.008368	0.100418	0.041841	0.016736	0.002092	0.228033	0.140167	0.002092	0.060669	0.004184	0
doc 4012	0.001887	0.037736	0.003774	0.056604	0.035849	0.00566	0.007547	0.3	0.009434	0.039623	0.003774	0.026415	0.013208	0.018868	0.001887	0.011321	0.018868	0.015094	0.260377	0.132075
doc 4013	0.015625	0.003906	0.042969	0.001953	0.052734	0.304688	0.017578	0.003906	0.228516	0.025391	0.003906	0.046875	0.019531	0	0.021484	0.095703	0.044922	0.052734	0.001953	0.015625
doc 4014	0.017778	0.004444	0.062222	0	0.066667	0	0.004444	0.004444	0.004444	0.008889	0.004444	0.004444	0.004444	0.546667	0	0.004444	0.066667	0.102222	0.093333	0
doc 4015	0	0	0.006944	0	0.013889	0	0.013889	0.006944	0	0	0	0.055556	0.006944	0.625	0.006944	0.006944	0.020833	0.006944	0.159722	0.069444
doc 4016	0.020619	0.010309	0	0.010309	0.046392	0.118557	0	0	0.041237	0.030928	0.010309	0.010309	0.015464	0	0.154639	0.489691	0	0.030928	0.005155	0.005155
doc 4017	0.020833	0.015625	0.505208	0.020833	0.010417	0.005208	0.005208	0.096354	0.067708	0.005208	0.002604	0.005208	0.013021	0	0.015625	0.080729	0.007813	0.033854	0.015625	0.072917
doc 4018	0.017928	0.011952	0	0.095618	0.085657	0.023904	0.02988	0.181275	0.023904	0.047809	0	0	0.003984	0.045817	0	0.011952	0.043825	0	0.318725	0.057769
doc 4019	0.061611	0.018957	0.080569	0.004739	0	0	0.004739	0.004739	0.042654	0.018957	0.004739	0.061611	0.047393	0	0.07109	0.028436	0.042654	0.075829	0.009479	0.421801
doc 4020	0.009709	0.009709	0.02589	0	0.022654	0.145631	0.003236	0	0.022654	0.003236	0	0.05178	0	0.003236	0.330097	0.132686	0.016181	0.200647	0.003236	0.019417
doc 4021	0.027273	0.063636	0.009091	0.013636	0.022727	0	0	0.004545	0.031818	0	0	0	0	0	0.009091	0.045455	0.009091	0.018182	0.004545	0.722727	0.018182
doc 4022	0	0.021739	0.006211	0.009317	0.009317	0.009317	0.009317	0.021739	0	0.009317	0	0	0.096273	0.012422	0.015528	0.009317	0.068323	0.121118	0.015528	0.565217
doc 4023	0	0.140351	0	0.013158	0	0.035088	0.188596	0.013158	0.214912	0	0.087719	0.065789	0.149123	0.004386	0.013158	0	0.039474	0.017544	0.017544	0
doc 4024	0	0.018116	0.007246	0	0.007246	0	0.003623	0.086957	0.108696	0.014493	0.608696	0.021739	0.021739	0	0.036232	0	0.003623	0.050725	0.003623	0.007246
doc 4025	0.032143	0.010714	0	0.028571	0.007143	0.610714	0.010714	0	0.007143	0.003571	0.017857	0.014286	0.014286	0	0.021429	0.014286	0	0.185714	0.021429	0
doc 4026	0.012915	0.035055	0.005535	0.00369	0.053506	0.027675	0.188192	0.184502	0.300738	0.001845	0.119926	0.009225	0.001845	0	0.001845	0.00369	0	0.00369	0.023985	0.02214
doc 4027	0.021898	0	0.072993	0	0.138686	0	0.029197	0	0	0.058394	0.043796	0.029197	0	0.007299	0.036496	0.437956	0.007299	0.065693	0.043796	0.007299
doc 4028	0.01581	0.12253	0.035573	0.003953	0	0.019763	0.003953	0.011858	0.501976	0	0.003953	0	0	0	0.118577	0.059289	0.047431	0.039526	0.007905	0.007905
doc 4029	0	0	0.014815	0.155556	0.022222	0.003704	0.014815	0.014815	0.003704	0.618519	0.096296	0.033333	0	0	0.007407	0.007407	0	0.003704	0.003704	0
doc 4030	0.006289	0	0.283019	0.012579	0.125786	0	0.006289	0	0	0.220126	0	0.056604	0.031447	0	0.006289	0.194969	0.018868	0.012579	0.006289	0.018868
doc 4031	0	0.036667	0.056667	0.053333	0.04	0.05	0.006667	0.03	0	0.013333	0.636667	0.003333	0	0	0.003333	0.003333	0.03	0.02	0.003333	0.013333
doc 4032	0.05098	0.003922	0.019608	0.117647	0	0.498039	0	0.015686	0.015686	0.015686	0.086275	0.015686	0.027451	0	0	0	0.12549	0	0.003922	0.003922
doc 4033	0.004386	0.030702	0.013158	0.039474	0.114035	0.035088	0.048246	0.013158	0	0.048246	0.04386	0.008772	0.04386	0.074561	0	0.267544	0.02193	0.131579	0.061404	0
doc 4034	0.014035	0.319298	0.003509	0.017544	0.007018	0.031579	0.031579	0.017544	0	0.094737	0.003509	0.045614	0.003509	0.017544	0	0.010526	0.364912	0.010526	0	
doc 4035	0	0.052356	0.026178	0.041885	0.015707	0.429319	0.010471	0	0.036649	0	0.17801	0.015707	0.005236	0.005236	0.010471	0.052356	0.04712	0.062827	0.010471	0
doc 4036	0.023952	0.011976	0.209581	0.011976	0.005988	0	0.48503	0.005988	0.047904	0	0.071856	0	0.041916	0	0.023952	0.005988	0.011976	0.005988	0.017964	0.017964
doc 4037	0	0	0	0	0	0	0	0	0	0	0	0.010417	0	0.979167	0.010417	0	0	0	0	0
doc 4038	0.014124	0.022599	0.5	0	0.002825	0	0.016949	0.016949	0.211864	0.050847	0.008475	0.056497	0.00565	0	0.00565	0.002825	0.002825	0.081921	0	0
doc 4039	0.030812	0.016807	0.014006	0.005602	0.011204	0.008403	0.070028	0.008403	0.002801	0.028011	0.002801	0	0.62465	0	0	0.002801	0.005602	0.131653	0.002801	0.033613
doc 4040	0.003906	0.007813	0.007813	0.007813	0.003906	0.191406	0.007813	0	0.039063	0.003906	0.003906	0.109375	0.003906	0	0.066406	0.488281	0.03125	0.003906	0.011719	0.007813
doc 4041	0	0.005952	0.136905	0.035714	0	0.047619	0.005952	0	0.047619	0.005952	0	0.017857	0.02381	0.011905	0.041667	0.107143	0.011905	0	0	0.5
doc 4042	0	0	0	0	0	0	0	0	0	0.012195	0	0	0	0.97561	0.012195	0	0	0	0	0
doc 4043	0.009804	0.029412	0.009804	0	0.019608	0.009804	0.009804	0	0.029412	0.058824	0.009804	0.117647	0.009804	0	0.009804	0.490196	0	0.117647	0.029412	0.039216
doc 4044	0.193182	0	0.007576	0	0.299242	0.056818	0.018939	0	0.079545	0.007576	0.05303	0.003788	0.015152	0	0	0.064394	0.034091	0.003788	0.151515	0.011364
doc 4045	0.003401	0.001701	0	0.001701	0.246599	0.001701	0.028912	0.003401	0.006803	0.02551	0.003401	0.018707	0.02381	0.028912	0	0.008503	0.05102	0.353741	0.119048	0.073129
doc 4046	0.001669	0.015025	0.001669	0.081803	0.158598	0.001669	0	0	0.010017	0.005008	0	0.225376	0.011686	0	0.003339	0	0.370618	0.098497	0.010017	0.005008
doc 4047	0.016949	0.002825	0.081921	0.002825	0.10452	0.002825	0.050847	0.079096	0.022599	0.016949	0.008475	0.011299	0.011299	0.002825	0.00565	0.09322	0.435028	0	0.036723	0.014124
doc 4048	0	0.004032	0.016129	0.032258	0.008065	0.008065	0.008065	0.153226	0.008065	0.193548	0.040323	0.008065	0.032258	0	0.004032	0.096774	0.008065	0.012097	0.366935	0
doc 4049	0	0	0.005747	0.094828	0.002874	0.091954	0	0.014368	0.008621	0.054598	0.491379	0	0.005747	0.005747	0.04023	0.020115	0.020115	0.143678	0	0
doc 4050	0.009063	0.003021	0.021148	0.003021	0.126888	0.084592	0.003021	0.018127	0.356495	0	0.003021	0.069486	0	0.02719	0.066465	0.048338	0.003021	0.054381	0.090634	0.012085
doc 4051	0	0	0.113636	0	0	0.022727	0	0.022727	0	0.045455	0.045455	0.022727	0	0	0.045455	0.454545	0	0.204545	0	0.022727
doc 4052	0	0.014423	0	0	0.014423	0.129808	0	0.004808	0.014423	0.004808	0.028846	0.355769	0.038462	0	0.009615	0.163462	0.168269	0.048077	0	0.004808
doc 4053	0	0.040876	0.018978	0.00146	0.021898	0.10365	0.007299	0.013139	0.017518	0	0.309489	0.084672	0.013139	0	0.059854	0.09781	0.109489	0.071533	0.007299	0.021898
doc 4054	0	0	0	0.021672	0.241486	0.009288	0	0.03096	0.012384	0.455108	0.01548	0.006192	0.024768	0	0.003096	0.040248	0.003096	0.024768	0.068111	0.043344
doc 4055	0.02381	0	0.228571	0.014286	0.071429	0.014286	0.047619	0.009524	0	0.004762	0	0.019048	0	0	0	0.290476	0.138095	0.014286	0.12381	0
doc 4056	0.012698	0.015873	0.073016	0.006349	0	0.003175	0.019048	0.006349	0.114286	0.003175	0.044444	0.003175	0.066667	0	0.457143	0.006349	0.092063	0.060317	0.006349	0.009524
doc 4057	0.4	0.002985	0.140299	0.077612	0.023881	0.01791	0.01791	0.00597	0	0.044776	0.01194	0	0.008955	0	0.098507	0.050746	0.020896	0.047761	0.026866	0.002985
doc 4058	0.048711	0.017192	0.011461	0.008596	0.197708	0.005731	0.005731	0.100287	0.008596	0.088825	0.020057	0.011461	0.022923	0.002865	0	0.005731	0.025788	0.386819	0.025788	0.005731
doc 4059	0.023438	0.523438	0	0.054688	0	0.007813	0.007813	0.023438	0.070313	0	0.039063	0	0	0	0.015625	0.046875	0	0.132813	0.007813	0.046875
doc 4060	0.003257	0.016287	0.006515	0.035831	0.026059	0.081433	0.045603	0.009772	0.04886	0	0.214984	0.003257	0.084691	0.009772	0.172638	0	0.179153	0.029316	0.006515	0.026059
doc 4061	0	0.018987	0.037975	0.012658	0	0.006329	0.006329	0.012658	0	0.018987	0.031646	0	0.563291	0	0	0.075949	0.012658	0.170886	0.006329	0.025316
doc 4062	0.010204	0.010204	0	0	0.255102	0	0.056122	0.010204	0.045918	0.056122	0.02551	0.030612	0.010204	0	0.122449	0.05102	0.005102	0.295918	0	0.015306
doc 4063	0	0	0	0	0	0.011364	0	0.022727	0	0	0	0.022727	0	0.806818	0.011364	0	0.011364	0.068182	0.022727	0.022727
doc 4064	0.342857	0.009524	0.052381	0.038095	0.02381	0.014286	0	0.114286	0.047619	0.028571	0.019048	0.02381	0.07619	0.004762	0.033333	0.028571	0.028571	0.080952	0	0.033333
doc 4065	0.003937	0.023622	0.047244	0.007874	0.019685	0.015748	0.015748	0.043307	0	0.625984	0.003937	0.007874	0	0	0.043307	0.007874	0.011811	0.094488	0.027559	0
doc 4066	0.010336	0.002584	0.436693	0.01292	0.002584	0.015504	0.377261	0	0.036176	0.005168	0	0.01292	0.005168	0.01292	0.046512	0.005168	0	0.007752	0	0.010336
doc 4067	0	0.052632	0.035088	0.017544	0.017544	0	0	0	0.017544	0.087719	0.017544	0.035088	0.017544	0.035088	0	0.614035	0	0	0.052632	0
doc 4068	0.026596	0.031915	0.005319	0.015957	0	0.143617	0.005319	0.026596	0.010638	0.026596	0.489362	0.010638	0.015957	0	0.026596	0.021277	0	0.12766	0.005319	0.010638
doc 4069	0.017544	0	0.131579	0.008772	0	0.061404	0.026316	0.004386	0	0	0.078947	0.013158	0.057018	0.004386	0.179825	0.087719	0.307018	0.017544	0.004386	0
doc 4070	0.02819	0.023739	0.008902	0.014837	0.037092	0.048961	0.005935	0.011869	0.01632	0.002967	0	0.007418	0.235905	0	0.002967	0.017804	0.360534	0.068249	0.008902	0.099407
doc 4071	0.003165	0.003165	0.006329	0.142405	0.193038	0.003165	0	0	0.050633	0.452532	0	0.003165	0.009494	0.003165	0.009494	0.012658	0.003165	0.018987	0.079114	0.006329
doc 4072	0	0	0.035242	0.008811	0.022026	0	0.026432	0.118943	0	0	0	0.008811	0.004405	0.590308	0	0.013216	0.07489	0.004405	0.092511	0

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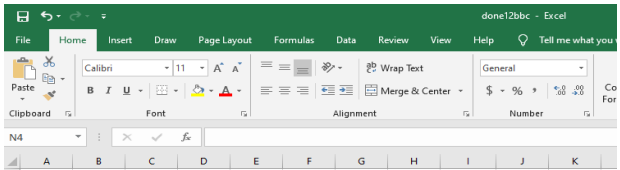
Appendix 3. Preprocessed data randomly attached from Document 0 to Document 5818



	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 t	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 mi	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 hit	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 fui	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	MicroStra	Crypto W	https://w	2022-08-0	2022-08-0	MicroStra	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 jur	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 bri	7/19/2022	22517.1	23407.35
17	doc 15	Bitcoin Fa	Crypto W	https://w	2022-07-0	2022-07-0	The "Bitcc	bitcoin fai	7/1/2022	19922.82	19336.1
18	doc 16	Worldâ,¬	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 bitcc	7/7/2022	20562.57	21647.17
24	doc 22	Bitcoin jus	Crypto W	https://w	2022-06-3	2022-06-3	Bitcoin jus	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 thi	6/29/2022	20278.9	20101.12
27	doc 25	Bitcoin fal	Cryptocur	https://w	2022-06-3	2022-06-3	Crypto hed	bitcoin thi	6/29/2022	20278.9	20101.12
28	doc 26	Charts sug	Mad Mon	https://w	2022-06-2	2022-06-2	"Bitcoin cc	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 mor	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 pli	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 Harne	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	MicroStra	Cryptocur	https://w	2022-06-1	2022-06-1	MicroStra	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 tur	6/12/2022	28415.54	26704.73
42	doc 40	Human rig	Crypto W	https://w	2022-06-0	2022-06-0	Human rig	washingtc	6/7/2022	31380.14	31193.07
43	doc 41	Bitcoin dr	Cryptocur	https://w	2022-06-1	2022-06-1	BitcoinÂ t	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 mi	6/5/2022	29847.33	29909.21
50	doc 48	Bitcoin fal	Cryptocur	https://w	2022-06-1	2022-06-1	Bitcoin is t	bitcoin fe	6/15/2022	22174.8	22490.59
51	doc 49	MicroStra	U.S. Mark	https://w	2022-05-1	2022-05-1	MicroStra	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 rese	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 bitcc	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 exec	5/17/2022	29833.05	30452.62
61	doc 59	Luna Four	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 inv	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 exc	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 bre	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 Si	Crypto W	https://w	2022-04-2	2022-04-2	MicroStra	miami mia	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 exc	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 bitcc	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 inv	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 | N	https://w	2018-01-1	2018-01-1	Millennial	werent da	1/9/2018	34062.89	14710.6
5796	doc 5794	The 10 mo	Careers | N	https://w	2018-01-2	2018-01-2	Education	though co	1/22/2018	34062.89	10917.31
5797	doc 5795	Legendary	Entrepren	https://w	2018-01-2	2018-01-2	Bill Miller	legendary	1/21/2018	34062.89	11481.03
5798	doc 5796	Men most	Money | M	https://w	2018-01-1	2018-01-1	A new GO	financial r	1/15/2018	34062.89	13769.22
5799	doc 5797	Make It's	Money | M	https://w	2017-12-3	2017-12-3	These wei	bitcoin cra	12/30/2017	34062.89	12732.36
5800	doc 5798	Self-made	Money | M	https://w	2018-01-0	2018-01-0	If you hav	want supe	1/4/2018	34062.89	15163.9
5801	doc 5799	GOP tax p	Money | M	https://w	2017-12-2	2017-12-2	"More tha	middle cla	12/19/2017	34062.89	17700.78
5802	doc 5800	3 commor	Careers | N	https://w	2017-12-2	2017-12-2	Your essay	college ap	12/20/2017	34062.89	16599.69
5803	doc 5801	Mark Cub	Money | M	https://w	2017-12-2	2017-12-2	"Shark Tar	year oppo	12/25/2017	34062.89	13965.21
5804	doc 5802	The 8 best	Entrepren	https://w	2017-12-1	2017-12-1	Here are t	heart shar	12/18/2017	34062.89	18931.2
5805	doc 5803	Vanguard	Money | M	https://w	2017-12-1	2017-12-1	"I don't lik	jack bogle	12/12/2017	34062.89	16798.03
5806	doc 5804	Here's ho	Careers | N	https://w	2017-12-2	2017-12-2	The bill co	morning s	12/19/2017	34062.89	17700.78
5807	doc 5805	Here's ho	Money | M	https://w	2017-11-1	2017-11-1	With Andr	billionaire	11/14/2017	34062.89	6647.346
5808	doc 5806	Departme	Careers | N	https://w	2017-10-2	2017-10-2	Criminals	safe cyber	10/23/2017	34062.89	5946.927
5809	doc 5807	Mark Cub	Money | M	https://w	2017-10-2	2017-12-2	Even billic	come sma	10/20/2017	34062.89	6000.943
5810	doc 5808	Success h	Leadershi	https://w	2017-11-0	2017-11-0	Not every	charles bu	11/1/2017	34062.89	6751.17
5811	doc 5809	Billionaire	Entrepren	https://w	2017-10-2	2017-10-2	â¸Â"I wo	peter thie	10/25/2017	34062.89	5725.302
5812	doc 5810	Mark Cub	Money | M	https://w	2017-10-2	2017-10-2	It's "a far t	prefer pay	10/24/2017	34062.89	5526.929
5813	doc 5811	The 9 sure	Leadershi	https://w	2017-09-0	2017-09-0	"Take any	resume te	9/4/2017	34062.89	4224.22
5814	doc 5812	Looks like	Money | M	https://w	2017-08-1	2017-11-1	"We live i	rising hea	8/10/2017	34062.89	3391.23
5815	doc 5813	For the bu	Careers | N	https://w	2017-06-2	2017-06-2	Traveling	corporate	6/20/2017	34062.89	2718.49
5816	doc 5814	This start-	South by S	https://w	2017-03-1	2017-03-1	A former l	marijuana	3/14/2017	34062.89	1240.06
5817	doc 5815	Want to tr	Money | M	https://w	2017-03-2	2017-03-2	An easy, a	brick farm	3/19/2017	34062.89	1038.05
5818	doc 5816	'Shark Tan	Careers | N	https://w	2017-02-2	2017-02-2	The cyber	tempting	2/27/2017	34062.89	1179.03
5819	doc 5817	The Five F	Money | M	https://w	2016-10-2	2016-10-2	If you and	bought so	10/26/2016	34062.89	678.486
5820	doc 5818	Turn your	How I Mac	https://w	2016-05-0	2016-07-0	The Collis	john collis	5/8/2016	34062.89	458.6

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