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Adaptive Model for Dynamic and Temporal Topic Modeling from Big Data using Deep Learning Architecture

Ajeet Ram Pathak [1], Manjusha Pandey[1], Siddharth Rautaray[1]
[1]School of Computer Engineering, Kalinga Institute of Industrial Technology University (KIIT), Bhubaneswar, India
E-mail: {ajeet.pathak44, manjushapandey82, sr.rgpv}@gmail.com

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Abstract—Due to freedom to express views, opinions, news, etc and easier method to disseminate the information to large population worldwide, social media platforms are inundated with big streaming data characterized by both short text and long normal text. Getting the glimpse of ongoing events happening over social media is quintessential from the viewpoint of understanding the trends, and for this, topic modeling is the most important step. With reference to increase in proliferation of big data streaming from social media platforms, it is crucial to perform large scale topic modeling to extract the topics dynamically in an online manner. This paper proposes an adaptive framework for dynamic topic modeling from big data using deep learning approach. Approach based on approximation of online latent semantic indexing constrained by regularization has been put forth. The model is designed using deep network of feed forward layers. The framework works in an adaptive manner in the sense that model is extracts incrementally according to streaming data and retrieves dynamic topics. In order to get the trends and evolution of topics, the framework supports temporal topic modeling, and enables to detect implicit and explicit aspects from sentences also.

Index Terms—Aspect detection, big data, deep learning, latent semantic indexing, online learning, regularization, topic modeling.

I. INTRODUCTION

The emergence of social media platforms lead to increase in posting of text in the form of reviews, opinions on the web, and heavily contribute for unprecedented growth of big data [1]. Many natural language processing applications such as summarization, user profiling, product recommendation, event tracking, text classification, collaborative filtering, similarity finding, sentiment analysis, etc. need to discover latent semantic topics from large text corpora. In such applications, topic modeling is the foremost step. Extracting the latent topics at large scale is challenging due to sparseness of text, spelling and grammatical errors, slangs, or jargons, unstructured data, and interrelated data discussed under different domains, etc.

Microblogging sites such as Twitter, Tumblr, Pinterest, Reddit, Yammer, etc stream large amount of short and long normal texts with substantial growth in due course of time. Streaming data are characterized by temporal order. Temporal information is necessary to get the notion of evolution and spread of domain-specific latent topics. Moreover, instead of processing large collection of time-stamped datasets with using off-line fashion in batch mode; it is more crucial for many natural language applications to analyze, summarize and extract valuable insights on the go in an online manner. Batch algorithms are not suitable for extracting topics from large scale and streaming data. Also such algorithms need to repeatedly scan the data for topic learning and need to keep the model up-to-date when new data arrives. Therefore, online algorithms are preferred for topic learning.

Online algorithms are able to handle large scale data efficiently since they only store small chunks of data for updating the model when new data arrives. This makes them more efficient than batch counterparts. For example, due to some worldwide event, many social media platforms gets flooded with comments of people, news feeds, etc and this requires automated systems to extract and track current topics of specific interest and identify emerging trends discussed on social media platforms. If extracted topics correspond to suspicious activities or alarming scenarios, then quick actions can be taken by authorized personnel for proactive measures. Hence, use of temporal topic model which works in online mode to infer dynamically generated topics from streaming data is the need of the hour.

Considering all the aforementioned motivation, this paper proposes an adaptive Framework for deep learning based dynamic and temporal topic modeling from big data. The proposed approach works in online manner for topic modeling and therefore, it is intrinsically scalable to large datasets. The work is contributed as follows.

- We have proposed a deep learning model for detection of dynamically generated topics from streaming data by online version of Latent Semantic Indexing (LSI) constrained by regularization.

- The approach is scalable to large collection of datasets. It is flexible to support both long normal text and short text for modeling the topics.
- The model is adaptive and it is updated incrementally and performs temporal topic modeling to get notion of evolution and trends of topics over time.
- It supports extraction of implicit and explicit topics from sentences also.

The rest of the paper is portrayed as follows. Section II deals with discussion of conventional topic models, topics models based on deep learning paradigm and relation of the existing work with the proposed approach. Section III focuses on statistical environment, proposed architecture and algorithms for dynamic and temporal topic modeling and user query evaluation. The experimentation details encompassing exploratory data analysis and correspondence analysis and results are discussed in section IV. Section V gives conclusion and future directions of the research.

II. Related Work

Topic modeling is a statistical technique and provides automated approach for extracting latent semantic topics from documents. In classical settings, document is considered as a mixture of latent topics i.e. multinomial distribution over topics and topic is viewed as probability distribution over words.

Topic Modeling algorithms have been extensively developed for text analysis since the past decade [2]. Manually identifying the topics is not efficient and scalable due to huge size of data, wide variation, and dynamically changing nature of topics. Therefore, topic models such as Latent Dirichlet Allocation (LDA) [3], probabilistic Latent Semantic Analysis (PLSA) [4], and Latent Semantic Indexing (LSI) [5] have been put forth for automatically extracting the topics at large scale. Various topic modeling algorithms have been used for inferring the hidden topics from short texts [6-8] and normal long texts [9-10].

LDA model put forth by Blei et al. [3] is the most popular probabilistic generative model for topic modeling. Approximate technique namely convexity-based variational method is used for inference since exact inference is intractable. For estimating Bayes parameters, expectation maximization algorithm is used in LDA model. Due to probabilistic and modular nature, LDA models can be easily fit into complex architectures. This property is not supported by LSI [5] model.

LSI model [5] uses Singular Value Decomposition (SVD) to capture variance in the document collection. This approach captures implicit semantic structure among the terms in documents for identifying relevant documents based on terms present in queries. It maps high dimensional count vectors to lower dimensional latent semantic space.

The improved version of standard latent semantic analysis model has been put forth in [4]. Probabilistic latent semantic analysis model - PLSA (aspect model) follows statistical latent class model, and it is an unsupervised learning method. A method for generalization of maximum likelihood estimation, namely, tempered expectation maximization has also been proposed in [4].

Many topic modeling approaches have been put forth by modifying basic topic models like LDA, PLSA, and LSI. Hoffman et al. [11] extended LDA by proposing online variational Bayes (VB) algorithm for topic modeling over streaming data.

Scaling to large dataset of document collection is one of the most challenging tasks in topic modeling. Topic modeling approaches based on LDA and LSI pose challenges related to scalability when such methods are employed to solve real-world tasks. For an instance, it is very difficult to update term-topic matrix simultaneously for satisfying the criterion of probability distribution when the dataset is large. In case of LSI, due to orthogonality assumption, problem needs to be solved using SVD, and it is difficult to parallelize the procedure for SVD. Also topic models like LDA and PLSA assumes document as a mixture of topics and models document-level word co-occurrences. Wang et al. [12] came up with novel model based on regularized latent semantic indexing (RLSI) for scalable topic modeling. RLSI is different from LSI method. It uses regularization to constrain the solutions instead of using orthogonality as adopted by LSI techniques.

The online version of LDA has been put forth in [13]. This approach works on non-Markovian Gibbs sampling. The weight-matrix history is maintained in the generative process of the method according to homogeneity of domain. It does not handle inter-topic differences and drifts within same topics. Topic model for temporally sequenced data has been proposed in [14]. This model dynamically predicts future trends for data and is scalable in nature.

Some topic modeling approaches assume that words have equal weights. This results into selection of topics having highest frequency of terms in documents. But, this may cause selection of meaningless words like domain-specific stop words which are not useful for further processing. Li et al. addressed this issue by proposing conditional entropy based term weighing scheme in which entropy is measured by word co-occurrences [15]. To infer more effective topics during topic inference phase, meaningless words are assigned lower weights and informative words are assigned higher weights. This scheme is applied with Dirichlet Multinomial Mixture (DMM) model [8] and LDA model [3] to infer topics from shorts texts and normal long texts respectively.

Kuhn put forth structural topic modeling approach and captured correlation among topics pertaining to single domain [16]. Brody and Elhadad [17] employed unsupervised approach for aspect detection. They used local version of LDA working at sentence level and assumed each sentence as a document.

With success of deep learning approaches in computer vision tasks [18-20], deep learning models have also been devised for natural language processing tasks. Language model based on recurrent neural network (TopicRNN) [21] follows semi-supervised approach to capture syntactic dependency and semantic dependency of document using RNN and latent topic model respectively. This model can be considered as alternative to LDA for topic modeling. Li et al. [22] used an attention mechanism of neural networks for modeling contents and topics to recommend the hashtags.

Generative topic models usually do not consider the contextual information while performing the task of topic extraction. A Document Informed Neural Autoregressive Distribution Estimator (iDocNADE) [23] takes into account the contextual information using language models having backward and forward references. LDA-based generative topic model proposed in [24] performs incremental updating of parameters over consecutive windows, and enables faster processing by adaptive window length.

Word embeddings have found to be useful for distributed representation of words and capturing semantic and syntactic information in many natural language processing tasks such as parts-of-speech tagging, parsing, named entity recognition, etc. Enlightened by same, word embedding models have also been used for topic modeling. Zhang et al. [25] used word2vec embedding model for feature extraction from large range of bibliometric data and coupled it with k-means algorithm for improving the performance of topic extraction. Topic modeling approaches working on short texts from social media platforms suffer from data sparsity, noisy words and word sense disambiguation problems. Gao et al. [26] addressed the issue of word sense disambiguation by utilizing local and global semantic correlation provided by word embedding model. Conditional random field is used in inference phase for short text modeling. Approach in [27] introduced common semantic topic model designed using mixture of unigram models for capturing the semantic and noisy words from short texts. Weibull distribution based hybrid autoencoding inference process for deep LDA has been put forth in [28] to get hierarchical latent representation of big data for scalable topic modeling.

Considering the relation of proposed work with the existing literature, this paper proposes scalable topic modelling approach based on deep learning. The proposed model has capability to infer the dynamic topics from streaming data and provides notion of evolution and trends of topic over time.

III. Methodology

This section describes statistical environment and proposed architecture for topic modeling.

A. Statistical environment

Following matrices are used in the proposed approach.

- Terms Γ, $\Gamma \in \mathbb{R}^{M}$

$$\Gamma \equiv [\Gamma_1, \Gamma_2, .. \Gamma_M]$$

where M denotes number of terms.

- Sentences $\$_i$

Sentences can be represented as set of terms

$$\$_i \equiv [\Gamma_1, \Gamma_2, .. \Gamma_J]$$

where $i = 1,2,..,P$ and P is number of sentences. The number of terms J in a sentence are less than total number of terms i.e. $J < M$.

- Topics u_i, $u_i \in \mathbb{R}^{K\times 1}$

$$u_i \equiv \{u_1, u_2, \dots, u_K\}$$

where $i = \{1,2,..,K\}$ and K denotes number of topics.

- Term-document Matrix D, $D \in \mathbb{R}^{M\times N}$

$$D \equiv [d_1, d_2, \dots, d_N]$$

where M denotes number of terms, and N denotes number of documents. The values in term-document matrix are calculated using TF-IDF score.

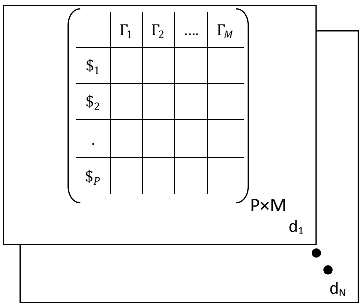
$$\left(\begin{array}{c|c|c|c|c} & d_1 & d_2 & \dots & d_N \\ \hline \Gamma_1 & & & & \\ \hline \Gamma_2 & & & & \\ \hline . & & & & \\ \hline \Gamma_M & & & & \end{array}\right)_{M\times N}$$

- Sentence-term matrix W, $W \in \mathbb{R}^{P\times M\times N}$

$$W \equiv [\mathrm{w}_1, \mathrm{w}_2, .. \mathrm{w}_N]$$

where P denotes number of sentences, M denotes number of terms and N denotes number of documents. For documents $d_1, d_2, \dots, d_N$, sentence-term matrix *'W'* is shown as three dimensional matrix. The values in sentence-term matrix *'W'* are calculated using 2 ways.

- Presence or absence of terms in each sentence can be represented by 1 or 0 respectively in sentence-term matrix
- Term frequency–inverse document frequency (TF-IDF) score can be used for calculating the values in a sentence-term matrix



- Term-topic matrix U, $U \in \mathbb{R}^{M\times K}$

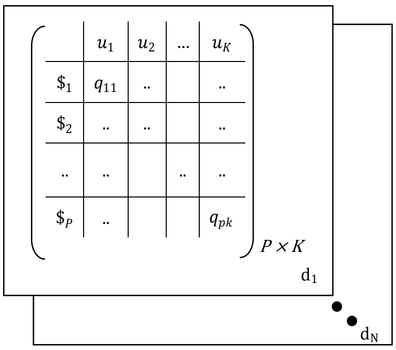
where M is number of terms, K is number of topic. Entries in the term-topic matrix correspond to the weight of mth term in topic 'k' which is denoted by u_{mk}. At sentence level, term Γ gives name of the aspect if term belongs to the topic i.e. corresponding weight of the term u_{mk} is higher for the given topic u_i. Term-topic matrix shows strength of belongingness of each term to topic.

$$\begin{pmatrix} & u_1 & u_2 & \dots & u_K \\ \Gamma_1 & u_{11} & .. & .. & .. \\ \Gamma_2 & .. & . & & \\ .. & .. & & . & \\ \Gamma_M & .. & & & u_{mk} \end{pmatrix} \quad M\times K$$

- Sentence-topic Matrix O, $O \in \mathbb{R}^{P\times K\times N}$

$$O \equiv [o_1, o_2, \dots, o_N]$$

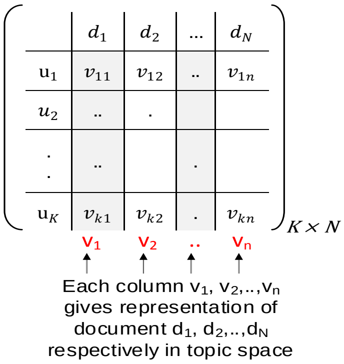
where P denotes number of sentences, K denotes number of topics and N denotes number of documents. For documents $d_1, d_2, \dots, d_N$, three dimensional sentence-topic matrix is shown where q_{pk}denotes weight of each k^{th} topic in a sentence.



- Topic-document Matrix V, $V \in \mathbb{R}^{K\times N}$

$$V \equiv [v_1, v_2, \dots, v_N]$$

where K denotes number of topics, N denotes number of documents, v_{kn}denotes weight of k^{th} topic in document d_N. As shown in term-document matrix, each column $v_1, v_2, \dots v_n$ gives the representation of document $d_1, d_2, \dots d_N$ in the topic space.



B. Proposed architecture

Fig. 1 shows the proposed methodology of topic modeling. The architecture is divided into 4 main modules. The model works on steaming data. For building the prototyped model, we collected the dataset. Initially, data cleaning and tokenization has been performed using R, Python and SpaCy packages. After data preprocessing, exploratory data analysis (EDA) and correspondence analysis (CA) has been performed. EDA is used to infer useful information from data, understand the behaviour of data and check usefulness of data for further phase of topic modelling.

We have done correspondence analysis as a generalization of principal component analysis (PCA), and SVD. We analysed the data using heat map, scree plots, factor score and most contributing variable. We designed the topic model for temporal analysis by online latent semantic indexing constrained by regularization using deep learning approach. We designed the model using dense network of feed forward network layers.

Use of sentence level topic modeling yields to detect both implicit and explicit topics mentioned in sentences. We applied algorithm 1 for training the model incrementally.

Due to online learning, only one document remains in memory at a time. Therefore space complexity is given by $DocLength + K$ where $DocLength$ stands for document length and K is number of topics. For initial construction of 'U' and 'V' matrices, space complexity is $DocLength \times N + KN$. For processing document at time t, the time for updating 'U' and 'V' matrices as shown in equation (3) is significant, therefore, time complexity is given by $C \times M \times K^2$ where C denotes number of times the algorithm iterated, M is number of terms and K is number of topics.

When user sends a query for inferring the topics, algorithm 2 is followed. The topics associated with terms mentioned in query and other implied latent topics are returned by model as output of the query evaluation.

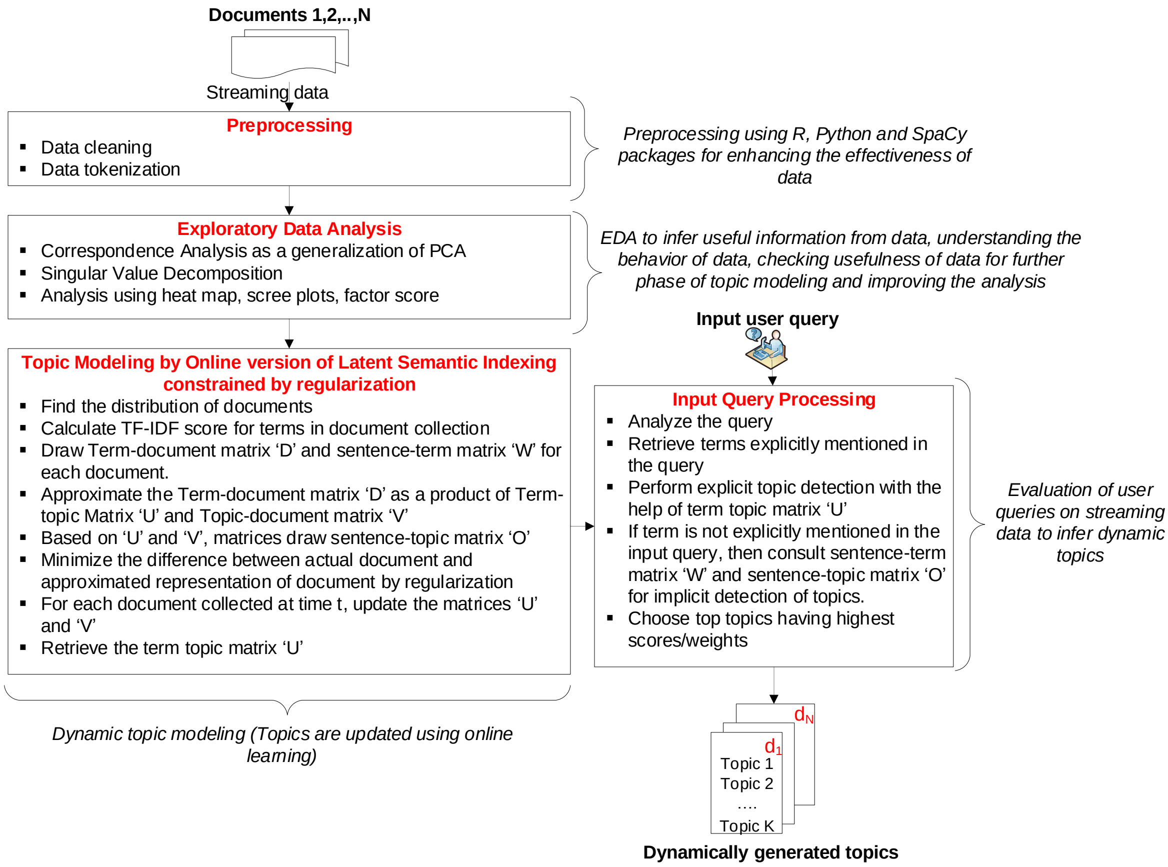


Fig.1. Proposed architecture for topic modeling

Algorithm 1: Temporal Topic Modeling by Online Latent Semantic Indexing constrained by regularization
Model Training
Input: Streaming Data
Output: Trained model obtained using online learning

- Find the distribution of documents $d_1, d_2, \dots, d_N$.
- Calculate TF-IDF score for terms in document collection using equation (1).

$$TFIDF = \frac{c(\Gamma,d)}{|d|} \times \log \frac{|D|}{|\{d \in D : \Gamma \in d\}|} \quad (1)$$

  where, $c(\Gamma, d)$ is a count that term Γ occurs in document d, $|d|$ is Length of document d, $|D|$ is Total count of documents in document collection, and $|\{d \in D: \Gamma \in d\}|$ is total count of documents in which term Γ occurs
- Draw term-document matrix *'D'* and sentence-term matrix 'W' for each document.
- Approximate term-document matrix *'D'* as a product of term-topic Matrix *'U'* and topic-document matrix *'V'*.

$$d_n \approx U v_n \quad (2)$$

  where d_n is document, $'U'$ is term-topic matrix, v_n is Representation of document d_n in the topic space.
- Based on *'U'* and *'V'* matrices, draw sentence-topic matrix *'O'*.
- Minimize the difference between actual document and approximated representation of document by $\ell 2$ regularization according to Eq. (3)

$$\|d_n - U v_n\|_2^2 \quad (3)$$

- For each document collected at time *t*, update the matrices *'V'* and *'U'* by approximating latent semantic indexing model using Eq. (3).
- Retrieve the term topic matrix *'U'* and topic-document matrix *'V'*

Algorithm 2: Query Evaluation
Input: User Query
Output: Dynamically generating topics

- Analyze the query
- Retrieve terms explicitly mentioned in the query
- Perform explicit topic detection with the help of term topic matrix 'U'
- If term is not explicitly mentioned in the input query, then consult sentence-term matrix 'W' and sentence-topic matrix 'O' for implicit detection of topics.
- Choose top topics having highest scores/weights

IV. Experimentation Details

For topic modeling, real word dataset related to 3 hashtags has been collected using Twitter APIs. Tweets associated with the hashtags #bitcoin, #ethereum, and #facebook are captured from 3-3-2018 to 3-5-2018. Tweets are analyzed weekly according to the duration of data collected. For experimentation, Python, and R programming languages have been used. We also used SpaCy for advanced natural language processing task and developed the model in the TensorFlow framework.

Based on the collected dataset in .csv format having 3 major hashtags, we converted the duration into weeks i.e. from 9 to week 18 of the year. Out of 22 attributes of the dataset (*viz. 'Tweet ID, Conversation ID, Author Id , Author Name, isVerified, DateTime, Tweet Text, Replies, Retweets, Favorites, Mentions, Hashtags, Permalink, URLs, isPartOfConversation, isReply, isRetweet, Reply To User ID, Reply To User Name, Quoted Tweet ID, Quoted Tweet User Name, Quoted Tweet User ID'*), we only focused on attributes - *DateTime*, *Tweet Text* and *Hashtags*. The reason behind choosing these 3 attributes out of 22 attributes is that our aim is to perform temporal topic modeling from Tweet text to get the notion of evolution and trends of topics discussed under various hashtags over time. Therefore, we are considering 3 attributes (*DateTime*, *Tweet Text* and *Hashtags*) for topic modeling.

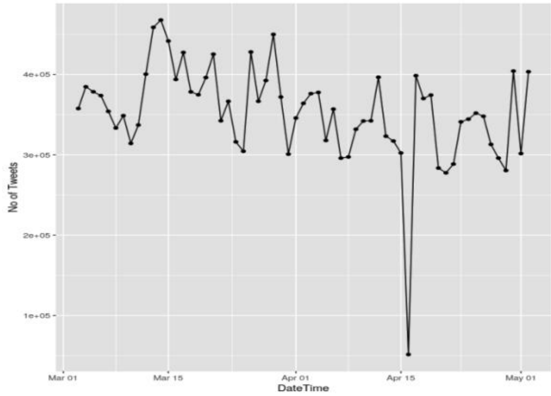
A. Exploratory Data Analysis

As a first step towards topic modeling, Exploratory Data Analysis has been performed. All the steps in EDA have been carried out on aforementioned dataset having 3 main hashtags. The main objective of EDA is to understand how much useful information does dataset hold. Therefore, we first calculated the five-number summary statistics for the '*DateTime'* attribute to understand the distribution of words over weeks. After that we calculated frequency of words against each month. Fig. 2 - (a), (b) and (c) shows the frequency of words against each month from March, to May for hashtags #ethereum, #facebook and #bitcoin respectively. Frequency of occurrence of words is calculated using Eq. (4). Table 1 shows the frequency of words based on weeks.

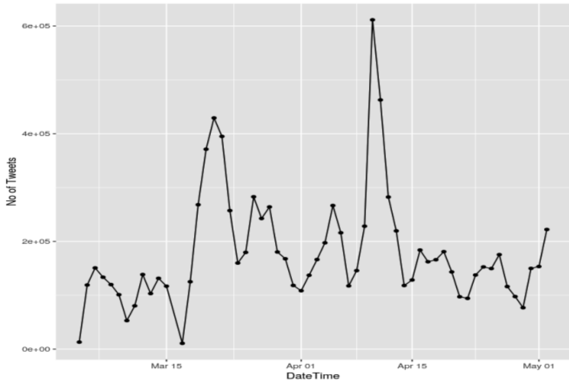
$$Frequency = \frac{n}{total\_words} \tag{4}$$

where n denotes number of times specific word occurs in a week, $total\_words$ denote total number of words appeared in a week.

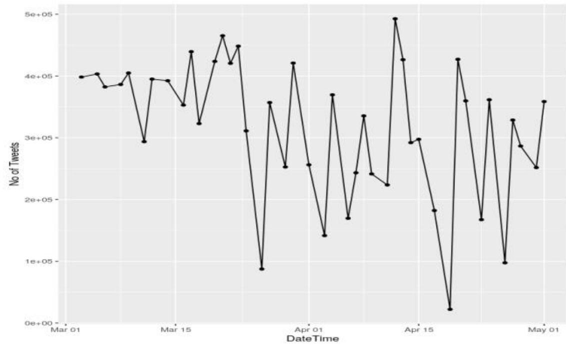
To get clear notion of appearance of words in corresponding weeks, tables 1, 2 and 3 show the count and frequency of words weekly for the hashtags #bitcoin, #ethereum, and #facebook respectively. From tables 1, 2 and 3, it can be observed that value of frequency is very low. This is the major issue related to big data. To overcome this issue, correspondence analysis has been done considering the count of terms occurred in a week instead of frequency of terms. Tables 4, 5 and 6 show the count of words discussed under the hashtags #ethereum, #facebook and #bitcoin respectively in tweets per week.



(a) #ethereum



(b) #facebook



(c) #bitcoin

Fig.2. Frequency of words against each month for (a) #ethereum, (b) #facebook, and (c) #bitcoin (X-axis represents time in terms of date and Y-axis represents count of tweets)

Table 1. Weekly Frequency of Words for #Ethereum

week	word	freq	n	total
9	#ethereum	0.039225512	29118	742323
9	#eth	0.033369571	24771	742323
9	#btc	0.028740858	21335	742323
9	#bitcoin	0.028646560	21265	742323
9	#ico	0.023175895	17204	742323
9	#blockchain	0.022731345	16874	742323
9	#cryptocurr	0.022020064	16346	742323
⋮	⋮	⋮	⋮	⋮

Table 2. Weekly Frequency of Words for #Facebook

week	word	freq	n	total
9	#facebook	0.073163210	949	12971
9	#twitter	0.012335209	160	12971
9	#instagram	0.011795544	153	12971
9	en	0.009251407	120	12971
9	de	0.008711742	113	12971
9	facebook	0.007246935	94	12971
9	#socialmedia	0.006475985	84	12971
⋮	⋮	⋮	⋮	⋮

Table 3. Weekly Frequency of Words for #Bitcoin

week	word	freq	n	total
9	#bitcoin	0.067669116	26952	398291
9	#cryptocurr	0.023540577	9376	398291
9	#blockchain	0.021306030	8486	398291
9	#ethereum	0.020575408	8195	398291
9	#crypto	0.019721761	7855	398291
9	#btc	0.018283115	7282	398291
⋮	⋮	⋮	⋮	⋮

B. Correspondence Analysis

For extracting useful information from dataset which is represented using contingency table, reducing the data by focusing on important information and analyzing the patterns in data, we have performed singular value decomposition and decomposition of positive semi-definite matrices. For handling the qualitative variables, Principal Component Analysis has been generalized as Correspondence Analysis [29].

CA is used for visualizing the salient relationship between categorical variables in low-dimensional space. Rows and columns of the contingency table can be depicted in same plot, and work in symmetrical manner [30, 31]. Correspondence Analysis has been carried out on count of words associated with hashtags instead of frequency of terms to address the issue of big data problem (High dimensionality). This is because value of frequency obtained from tables 1, 2 and 3 is very low, and we can't find any pattern from such low valued attribute. We are doing correspondence analysis to see which topics started to converge closer to each other for which week.

This would mean that something important happened during that week that brought different words closer to each other, and therefore, we are just using highest frequency word as topic.

For CA, the whole dataset with 3 hashtags, namely, #ethereum, #facebook and #bitcoin and associated terms have been displayed in row-column manner in which rows represent terms associated with hashtags and columns represent weeks. Entries in contingency table represent how many times the given terms have been discussed on Twitter in a given week. Table 7 shows contingency table of terms associated with 3 hashtags along with their occurrence in weeks from 9 to 18.

1) *Singular Value Decomposition*

For reducing data size, SVD finds new components which are derived from original variables using linear combinations. The first component exhibits as much as large variance as possible. This component explains the largest part of inertia of table. Subsequent principal component is obtained having large variance with a constraint that it is orthogonal to the preceding component. These new variables used for deriving the components are called as factor scores. Factor scores can be assumed as projections of observed data onto the principal components. We have used Correspondence Analysis via ExPosition. To reduce dimensions, we used SVD, and got new axis for all weeks as shown in the table 8.

2) *Heat Map Analysis*

It can be noted from histogram that count of terms #bitcoin1, #ethereum, and #facebook is very high (shown in red color) compared to other terms.

3) *Scree Plots*

As we only need to infer the useful information, the problem is how many components need to be considered for correspondence analysis. Scree plots give an intuition which components represent data in best possible way. Scree plots may or may not give best components since this procedure is somewhat subjective.

For scree plot analysis, Eigen values are plotted according to their size. Then an elbow point is decided such that slope of graph becomes flat from steep one. The points before this elbow point are kept for further analysis. These points represent the data in best possible manner. Three points above elbow point best represent the data as shown in figure 4. Based on scree plot, only two dimensions possessing large amount of data variability are selected for further analysis.

4) *Factor Scores*

Factor scores represent the proportion of the total inertia ‘‘explained’’ by the dimension. Factor score obtained from scree plot asymmetrically and symmetrically for both dimensions are plotted in figures 5 and 6 respectively where λ represents Eigen values and τ represents percentage of data explained by the dimension.

Table 4. Weekly Frequency of Words for #Ethereum

Word	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
#ada	4909	8017	22093	8335	7913	4790	4459	5966	5662	3024
#airdrop	8803	26098	52520	35142	36588	23695	23437	17425	22093	10432
#altcoin	5252	15007	20565	19074	24754	15769	16140	15630	14965	7212
#bch	1676	5532	0	0	5837	4847	0	4335	6812	3517
#binanc	2100	6885	5777	6301	5311	5388	6872	4604	8544	3573
#bitcoin	21265	74625	86687	80112	88349	80468	78405	75880	74117	35899
#bitcoincash	0	0	0	0	0	0	0	5292	7042	4591
#blockchain	16874	63634	77100	76298	86977	73230	74537	62033	70407	33964
#bounti	4349	13399	23040	18379	23916	12641	15873	12443	12209	4913
#btc	21335	63269	85576	62158	66565	55042	56945	48847	55188	25308
#bts	0	0	0	5602	0	0	0	4577	0	0
#coin	0	0	0	0	8583	4176	0	0	0	0
#crowdfund	1649	0	0	0	0	0	6617	4170	4572	0
#crowdsal	0	4511	0	5034	4876	5252	6068	4020	4487	0
#crypto	16057	49975	64539	57773	64473	57169	63050	54821	60671	28176
#cryptocurr	16346	55146	67646	65178	72530	64913	65206	60007	58497	27540
#cryptonew	0	0	0	4878	0	4196	4725	0	0	0
#dash	2216	6034	6165	6053	6340	6508	4518	4540	5847	2968
#digitizecoin	0	0	0	0	0	0	4733	0	0	0
#earn	0	0	0	0	5741	0	0	0	0	0
#elsalvador	0	0	0	0	0	0	0	0	0	3205
#energytoken	5921	8852	0	0	0	0	0	0	0	0
#eo	4481	9439	0	4646	6158	4802	0	4102	8049	4669
#erc20	1385	0	5729	6245	7331	4942	4706	4441	5897	3412
#escort	0	0	0	0	0	0	0	3786	0	3628
#etc	1643	6167	0	0	0	0	0	0	0	0
#eth	24771	74637	99115	77422	87220	71144	73107	58282	67597	32730
#ether	3120	11848	13683	14143	18291	19046	16220	11351	11154	5596
#ethereum	29118	108179	123037	114655	121189	113522	110730	99528	100171	48708
#fintech	0	0	0	0	0	0	0	0	3928	0
#xrp	9686	26943	24497	20066	19455	17269	16319	14031	22588	10513
#xvg	5386	10978	30172	11820	9724	6645	5888	8167	5656	3131
airdrop	3652	8952	17883	10533	7212	6779	7201	4515	6496	2585
blockchain	0	0	0	4972	4746	4063	4967	4187	4662	0
btc	4896	16187	15886	18275	16913	14503	16235	14673	18964	9716
chanc	0	0	10243	0	0	0	0	0	0	0
crypto	0	5167	0	4677	4995	4536	4821	4134	4342	0
cryptocurr	0	0	0	0	0	0	4375	0	0	0
de	0	0	0	0	0	0	0	0	0	3674
earn	2223	5665	0	0	0	0	0	0	0	0
eth	2629	8605	8347	9307	8228	6775	6539	5530	6726	3568
free	4869	12371	22354	9599	5688	4401	4254	0	0	0
friend	1510	0	11701	0	0	0	0	0	0	0
goal	0	0	9690	0	0	0	0	0	0	0
ico	0	4522	0	5096	0	4069	5552	3911	0	0
join	5105	15739	15012	11259	10457	8495	8946	7508	6947	2836
link	0	0	8352	5435	0	0	0	0	0	0
mani	0	0	10111	0	0	0	0	0	0	0
offer	0	0	5691	0	0	0	0	0	0	0
peopl	0	0	10731	0	0	0	0	0	0	0
platform	0	4424	0	4653	4636	4337	4483	3521	0	0
price	0	4429	0	0	4457	0	0	0	0	0
project	2154	8793	19084	11368	10908	10298	10595	8079	8053	3245
reach	0	0	9778	0	0	0	0	0	0	0
refer	0	0	5695	0	0	0	0	0	0	0
regist	0	0	13344	4883	0	0	0	0	0	0
share	0	0	14946	4499	0	0	0	0	0	0
start	0	0	7559	0	0	0	0	0	0	0
time	0	0	7462	4589	0	0	0	0	0	0
token	4541	13866	41710	19947	13665	11690	13544	7998	11945	4653

Table 5. Weekly Frequency of Words for #Facebook

Word	9	10	11	12	13	14	15	16	17	18
#actu	33	1887	1719	0	2248	2178	0	2046	2078	1070
#amazon	0	985	706	0	0	0	0	0	1223	0
#busi	29	1283	1041	0	0	0	0	1566	1457	712
#cambridgeanalyt	0	0	0	5004	1658	0	0	0	0	0
#cambridgeanalytica	0	0	780	13947	4700	4102	6515	1851	1307	826
#congress	0	0	0	0	0	0	2309	0	0	0
#data	0	0	0	3958	2986	2558	3721	1867	1233	0
#date	0	0	0	0	0	0	0	0	0	832
#deletefacebook	0	0	0	5732	3050	1797	2762	0	0	0
#digitalmarket	0	895	710	0	0	0	0	1356	1218	0
#f8	0	0	0	0	0	0	0	0	0	1318
#facebook	949	50748	41961	130670	86932	76678	128772	63718	57189	32773
#facebookdatabreach	0	0	0	0	1635	0	2683	0	0	0
#facebookdataleak	0	0	0	0	0	0	2801	0	0	0
#facebookg	0	0	0	3196	0	0	0	0	0	0
#faitsdiv	33	1882	1717	0	2241	2173	0	2037	2069	1067
#follow	18	0	0	0	0	0	0	0	0	0
#gdpr	0	0	0	0	0	0	0	1499	0	0
#googl	42	2779	2532	4691	5555	3372	4228	3154	3154	1144
#hiphop	21	1249	950	0	0	0	0	0	1102	0
#info	35	1918	1747	2435	2295	2217	0	2101	2118	1077
#instagram	153	7778	5601	8764	7736	7760	8403	7887	7987	3791
#justic	35	1962	1773	2452	2316	2263	2288	2205	2266	1125
#linkedin	23	1091	948	0	0	0	0	1384	1390	0
#maga	0	0	0	0	0	0	2999	0	0	0
#market	36	2763	1954	3032	2726	2457	2865	2591	2902	1449
#markzuckerberg	0	0	0	3952	0	1805	7903	0	0	0
#music	46	2458	2201	3045	2798	2846	3027	2820	2985	1497
#new	0	974	803	0	1616	1734	0	1525	1459	763
le	0	0	0	2617	1695	0	2817	1396	1059	834
les	19	0	0	0	0	0	0	0	0	725
live	18	917	808	0	0	0	0	0	0	0
los	0	0	0	0	0	1652	0	0	0	0
mark	0	0	0	2944	0	0	6420	0	0	0
market	30	990	0	0	0	0	0	0	1092	0
media	33	1383	1208	3226	2058	1885	3156	1705	1494	672
million	0	0	0	0	0	1853	0	0	0	0
moment	26	1072	964	0	0	0	0	1193	1192	0
news	0	1296	827	0	1615	1580	0	0	0	703
page	66	2644	2094	3646	2885	2674	3505	2364	2321	1154
para	20	1126	805	0	1709	1636	0	1655	1425	1028
peopl	18	0	0	3429	1921	2004	3763	0	0	0
person	0	0	0	2847	0	0	0	0	0	0
post	32	1751	1211	2450	2007	1685	2311	1629	1722	898
privaci	0	0	0	2567	2799	2136	4267	1673	0	780
question	0	0	0	0	0	0	3826	0	0	0
radiocapitol	25	997	922	0	0	0	0	0	1091	0
scandal	0	0	0	3077	1805	1632	0	0	0	0
senat	0	0	0	0	0	0	3569	0	0	0
share	0	0	0	2457	0	1833	2849	0	0	0
social	60	2131	1766	5031	3234	2631	4526	2540	2228	1072
su	0	0	0	0	0	0	0	1254	0	0
sur	0	914	0	0	0	0	0	0	0	0
time	28	0	0	3166	1627	0	2645	0	0	0
tip	19	0	0	0	0	0	0	0	0	0
user	0	0	0	4479	2942	3965	5084	2144	1281	895
video	18	1236	766	0	0	0	0	0	1042	0
zuckerberg	0	0	0	4690	1625	2486	11162	1224	0	763

Table 6. Weekly Frequency of Words for #Bitcoin

Word	9	10	11	12	13	14	15	16	17	18
#ada	533	0	3477	0	0	0	0	0	0	0
#airdrop	2638	10038	12507	11880	7421	5107	7985	3490	3742	2120
#altcoin	3324	12295	13478	14894	10800	7325	13349	6072	7680	3825
#bch	580	0	0	0	0	1866	0	0	1953	0
#binanc	867	3603	3463	4556	2974	3130	4372	2906	3326	1713
#bitcoin	26952	129250	130504	142416	93379	88906	139196	70279	84378	40098
#bitcoincash	805	3329	3176	3487	2468	2912	3852	2703	4746	3084
#bittrex	0	0	0	0	0	0	0	1327	0	0
#blockchain	8486	41274	44567	49860	32235	28574	45937	20584	28864	15041
#bounti	1602	5557	9347	9114	5793	3129	6389	2043	0	1003
#btc	7282	32320	34138	33660	24708	21475	34979	15436	21689	10554
#bts	0	0	0	4123	0	0	0	0	0	0
#busi	0	0	0	0	1989	0	0	0	0	0
#coin	544	2564	0	0	3963	0	0	0	0	0
#coinbas	674	0	0	0	0	1647	2644	0	0	0
#costarica	0	0	0	0	0	0	0	0	0	1258
#crowdfund	0	0	0	0	0	0	2577	0	0	0
#crowdsal	0	0	0	2824	0	0	3536	0	0	0
#crypto	7855	34970	36987	38793	23964	23958	39727	20486	26705	14038
#cryptocurr	9376	42126	46774	52489	35009	30402	51495	26833	33424	16409
#cryptonew	0	2919	2865	3296	2009	1834	3759	0	1773	0
#cybersecur	2396	8491	9800	12639	9689	11301	15782	8265	4301	0
#dash	645	2524	2959	2779	0	1904	0	1410	1925	0
#earn	0	0	0	0	2774	0	0	0	0	0
#elsalvador	0	0	0	0	0	0	0	0	0	1816
#eo	0	0	0	0	0	0	0	0	2121	1056
#escort	0	0	0	0	0	0	0	1298	2142	2168
#eth	4133	15872	19390	18999	14174	11231	17540	6999	9486	4917
#ether	1081	5281	5903	6822	5362	5166	8506	2842	3459	1954
#ethereum	8195	37482	40265	45831	32256	27772	47159	23838	28119	15209
#vip	0	0	0	0	0	0	0	0	0	1822
#xrp	1483	6590	4916	5638	3961	3662	5279	3034	3997	2064
#xvg	651	0	3361	3226	0	0	2917	1353	0	0
000guarium	0	0	0	0	0	0	0	1311	0	0
airdrop	620	0	0	0	0	0	0	0	0	0
bitcoin	2711	14780	14408	13655	7537	7178	11675	5826	8137	3793
blockchain	679	3830	3165	4987	2127	1920	3561	1643	2414	1368
btc	3013	12069	13080	14361	8529	7151	11433	6156	8969	4928
buy	0	0	3049	3092	2252	1773	2703	2144	2452	1038
crypto	1098	5655	5945	5495	3300	3129	4997	2410	3177	1661
cryptocurr	956	5092	5437	5222	3318	3026	4341	2091	2740	1309
de	0	0	2536	2867	2198	1581	2924	2074	2880	2359
eth	612	2817	2844	3870	0	0	2595	1287	1797	1191
exchang	0	3077	0	2945	0	1639	2622	0	0	0
free	939	4028	3615	3340	0	1680	0	1327	1846	0
hour	0	0	0	0	0	1838	2616	0	0	0
ico	0	2604	2803	2955	0	0	2969	1251	0	0
invest	0	2545	0	0	0	0	0	0	0	0
join	974	4141	4132	3385	2055	1808	2598	1706	1813	0
market	792	3984	4242	4148	3030	2923	3997	1837	3124	1311
mine	0	2674	2724	0	0	0	0	0	0	0
price	1243	6543	6949	7200	4701	4847	7262	3282	4641	1921
project	0	2565	2527	3030	2006	1927	2912	1275	0	0
secur	564	0	0	0	0	0	0	0	0	0
sell	0	0	0	0	0	0	0	1423	0	0
start	0	2745	0	0	0	0	0	1323	0	0
telegram	557	0	0	0	0	0	0	0	0	0
token	808	3766	3547	3890	2380	1864	2717	1329	1852	0
trade	730	3604	3056	2933	0	1966	0	1375	1859	0
world	0	0	0	3240	0	0	0	0	0	0

Table 7. Contingency table of hashtags along with their occurrence in weeks from 9 to 18

	Weeks									
Words	9	10	11	12	13	14	15	16	17	18
↓	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
#bitcoin	21265	74625	86687	80112	88349	80468	78405	75880	74117	35899
#blockchain	0	63634	0	76298	86977	73230	74537	62033	70407	33964
#btc	21335	63269	85576	0	0	0	0	0	0	0
#crypto	0	0	0	0	0	0	0	0	60671	28176
#cryptocurr	0	0	0	0	0	0	0	60007	0	0
#eth	24771	74637	99115	77422	87220	71144	73107	58282	67597	32730
#ethereum	29118	108179	123037	114655	121189	113522	110730	99528	100171	48708
#ico	17204	0	80290	75305	76068	68794	70205	0	0	0
#cambridgeanalytica	0	0	0	13947	0	0	0	0	0	0
#facebook	949	50748	41961	130670	86932	76678	128772	63718	57189	32773
#instagram	153	7778	5601	0	0	7760	0	7887	7987	3791
#twitter	160	8199	6384	0	9690	8526	0	8848	8827	3895
#zuckerberg	0	0	0	0	0	0	18855	0	0	0
#Data	0	0	0	13700	8052	0	11498	0	0	0
#De	113	6790	5513	21954	13265	12369	19778	10902	8529	5478
#En	120	5497	0	0	0	0	0	7677	6994	0
#Facebook	0	0	4555	15673	10760	8853	15829	0	0	3817
#bitcoin1	29118	154708	159088	165500	107381	109707	176790	81169	95962	43737
#blockchain1	9196	49535	54362	58028	37199	35756	59092	24153	32865	16337
#btc1	0	0	0	0	28262	0	0	0	0	0
#crypto1	8461	41888	44723	44898	0	29718	50492	23863	30424	15276
#cryptocurr1	10076	49910	57015	60767	40541	37868	65620	31307	37879	17766
#ethereum1	8774	45341	49824	54141	37640	35016	60999	28025	32138	16575

Table 8. SVD applied for weeks from 9 to 18

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]	[,8]	[,9]
9	-2.39704392	0.7504260	0.7867228	-0.135401766	0.29029054	-1.24858593	2.06928320	-0.3540769	-5.07620094
10	-1.18154968	-0.8508375	-0.2612808	0.352639099	0.96122721	1.79196491	-0.95563582	-0.7434918	-0.14423827
11	-1.71436241	0.5768373	0.4915485	-0.111930135	-0.00433863	-1.20364721	-0.27991729	0.3793571	1.32622634
12	0.96792692	0.7903582	-0.2512851	-1.511792640	1.47251661	-0.20953824	-0.11017653	-0.1786082	-0.03855474
13	-0.07089537	1.0562556	-0.9800645	0.003870922	-0.94707575	1.37464399	1.31150418	0.9377378	0.31156602
14	0.41491830	0.3527319	-0.3414070	-0.452840703	-1.97879656	-0.30870141	-1.33951583	-1.3002880	-0.48019706
15	0.99273302	0.6564433	1.1705694	1.782179233	0.32616232	-0.01323828	-0.02534604	-0.1235730	-0.02066347
16	0.39084956	-1.2953340	-2.1881072	1.090122086	0.36505431	-1.40700008	0.10876275	0.4659193	-0.16846302
17	0.38071378	-1.8370036	1.0445893	-0.724527422	-0.47709338	-0.03915036	1.68439157	-0.8721054	0.65668085
18	0.53355439	-1.4318975	1.3527783	-0.899883061	-0.64115617	0.32671801	-1.53862175	3.3660138	-1.01199859

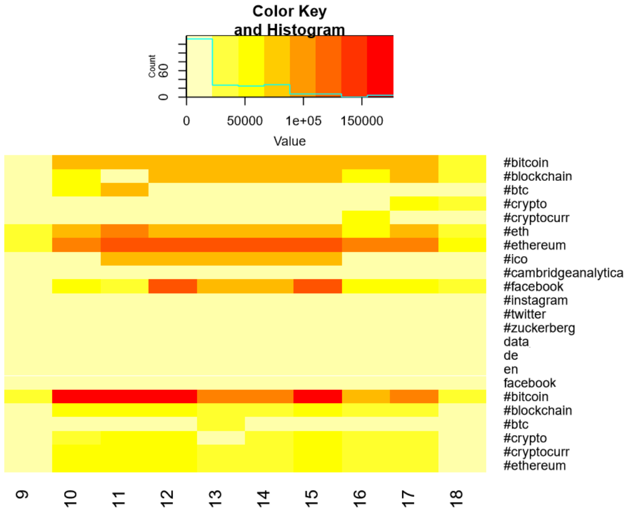


Fig.3. Heat map analysis

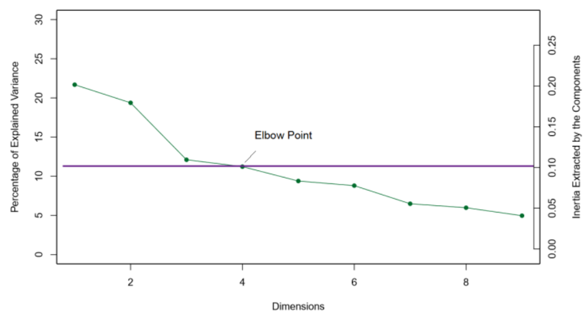


Fig.4. Scree plot

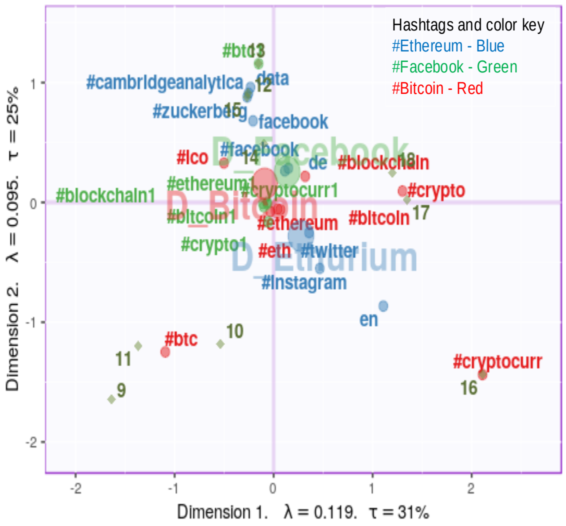


Fig.5. Factor Score (Asymmetric plot)

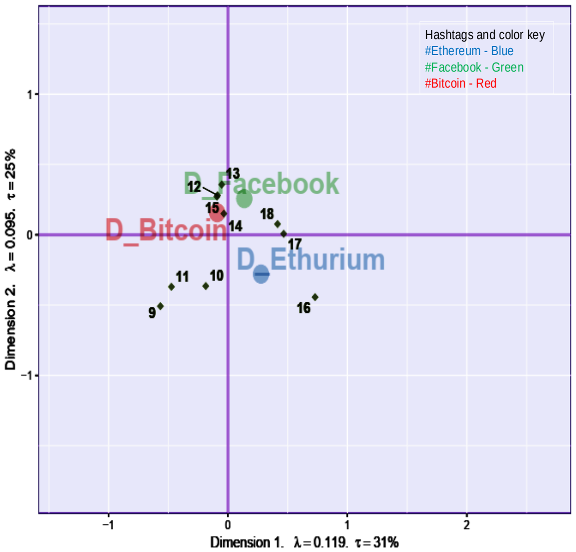


Fig.6. Factor Score (Symmetric plot)

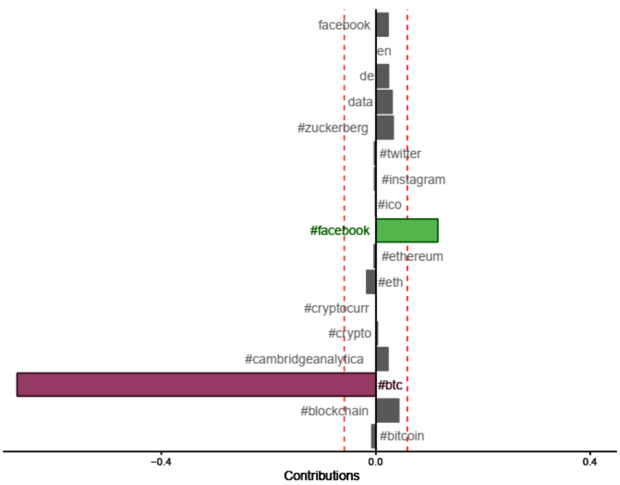


Fig.7. Most Contributing Variables

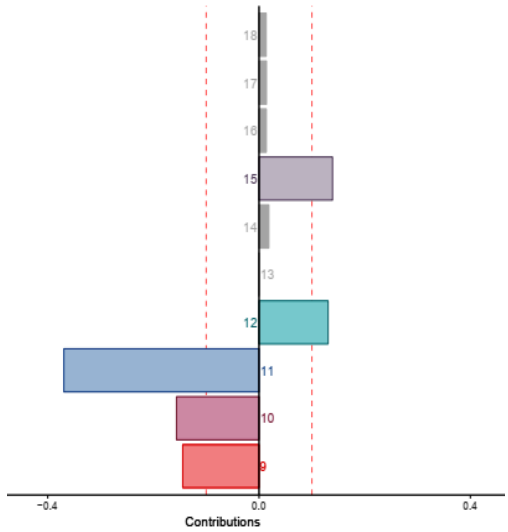


Fig.8. Contribution of all weeks

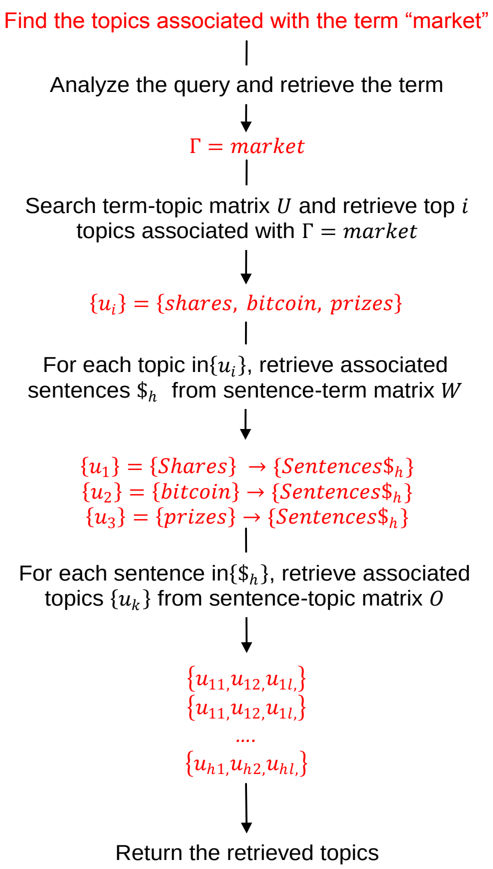


Fig.9. Query evaluation scenario for topic extraction

31% and 25% of total inertia has been explained by dimensions 1 and 2 respectively. More the data points are away from the center, more the inertia (variance) they possess. If distance between data points is more, then they carry good pattern among themselves. For example, #cambridgeanalytica has been discussed more in weeks 12 and 15 under hashtag #facebook. So, this visualization gives notion of information and patterns among data points. In order to check whether variables associated with data points really possess good information, the plot of most contributing variables in depicted in figure 7. Variable associated with #cryptocurr (shown in blue color) under #facebook category and #crypto (shown in red color) under #bitcoin are the most contributing variables.

Figure 8 shows the plot of weeks according to their contribution for topics being discussed in respective week. Weeks 9, 10, 11, 12, and 15 are important. It shows something happened in News during these weeks that caused the words closer to these weeks behave similarly.

C. Results Discussion

After performing EDA and CA, we applied our proposed approach – online latent semantic indexing constrained by regularization on Twitter data. Tweets are associated with the hashtags #bitcoin, #ethereum, and #facebook. Table 9 shows the top 5 topics extracted in each week from 9 to 18 for the hashtags #bitcoin, #ethereum, and #facebook.

Figure 9 shows the query evaluation scenario when user sends query to get the topics associated with a given term. Let us say, uses sends a query: Find the topics associated with the term "market". Initially, the query is analyzed and terms directly mentioned in query are retrieved. Therefore, for the given example, the term-topic matrix *'U'* is searched and top i topics associated are retrieved, i.e. top topics $\{shares, bitcoin, \text{and } prizes\}$ are retrieved. For each topic, retrieve the sentences from sentence-term matrix *'W'* assuming each topic as a term. For each sentence, choose topics $\{u_k\}$ from sentence-topic matrix *'O'*, and return retrieved topics. These topics are the topics related to the term $\Gamma = market$. The extracted topics are given as

$$u_{11}, u_{12}, \dots, u_{1l}$$
$$u_{21}, u_{22}, \dots, u_{2l}$$
$$\dots \dots$$
$$u_{31}, u_{32}, \dots, u_{3l}$$

With the help of both sentence-term matrix *'W'*and sentence-topic matrix *'O'*, the approach also performs extraction of topics implicitly present.

Table 9. Top 5 topics extracted using proposed approach for each week from 9 to 18

(a) Topics extracted with #bitcoin

Week 9	Week 10	Week 11	Week 12	Week 13	Week 14	Week 15	Week 16	Week 17	Week 18
Dominance	Market	croatia	recent	market	bitcoin	destroy	supporters	Lacklustre	Blockchain
project	Change	Bitcoin	audit	Bounce	scammers	value	Contactez	Markets	Telephone
CRYPTO	Masterminds	rank	payment	water	account	Crypto	reward	Bitcoin	Electron
successs	Bitcoin	Space	sagolsun	Analysis	news	Madness	Hublot	Cash	future
investors	Ripple	quality	cryptocurrency	Dogecoin	livestramers	podcast	decentralisedsystem	crypto	investment
Altcoin	CryptoCashbackRebate	pembeli	BitLicense	Support	akan	Transtoken	cash	trading	History

(b) Topics extracted with #facebook

Week 9	Week 10	Week 11	Week 12	Week 13	Week 14	Week 15	Week 16	Week 17	Week 18
download	Clarification	Google	Shkreli	deactivated	Censoring	fight	Cryptocorner	Unbearably	technologies
Hype	guide	failed	Brotheers	Optimization	virus	content	Market	Snapchat	Market
Facebook	teenager	edumacated	Zuckerberg	socialmedia	catie	brother	drop	video	fund
archive	Business	broadcasting	friend	Regulating	Scanning	privacy	Facebook	lol	suspend
Retargeting	uploaded	live	million	Cryptocurrency	Messenger	graduation	friday	data	Stock

(c) Topics extracted with #ethereum

Week 9	Week 10	Week 11	Week 12	Week 13	Week 14	Week 15	Week 16	Week 17	Week 18
Altcoin	CryptoCashbackRebate	pembeli	BitLicense	Support	akan	Transtoken	cash	trading	History
airdropping	Kapsus	Cryptocurrency	terjual	VertChain	wallet	free	future	Darico	currency
hedgefund	Localcoin	Food	crypto	Airdrop	cryptocurrency	market	RAXOM	crypto	Binance
Limited	Bitcoin	Ico	price	happy	sidechain	Casper	airdrop	Ethereum	Bitcoin
investment	price	Blockchain	drop	shopping	beacon	revolutionary	Truffle	Mining	Exchange

V. Conclusion

We have proposed a deep learning model for explicit and implicit detection of dynamically generated topics from streaming data by online version of Latent Semantic Indexing constrained by regularization. The approach mentioned is scalable to large dataset. It is flexible to support both long normal text and short text for modeling the topics. The model is adaptive such that it is updated incrementally and performs temporal topic modeling to get notion of evolution and trends of topics over time. Topic modeling approach supports extraction of implicit and explicit topics from sentences also. This model can be treated as first step towards implicit and explicit aspect detection for aspect based sentiment analysis on social media data.

We have performed exploratory data analysis and correspondence analysis on real world Twitter dataset. Results state that our approach works well to extract topics associated with a given hashtag. Given the query, the approach is able to extract both implicit and explicit topics associated with the terms mentioned in the query. The next step would be to perform the performance analysis with reference to standard performance metrics.

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Authors' Profiles

Ajeet Ram Pathak is currently pursuing Ph.D. from School of Computer Engineering, KIIT University, Bhubaneswar, India. He received his Master of Engineering degree in Computer Engineering from University of Pune, India in 2014. His research interests include big data analytics, cloud computing, information security, and deep learning. He has published more than 15 international journal and conferences as the first author. He also received best paper awards for research work.

Manjusha Pandey is presently working as Assistant Professor at School of Computer Engineering, KIIT University, Bhubaneswar, India. She received her Ph.D. degree from Indian Institute of Information Technology (IIIT), Allahabad, India. Her research interests include big data analytics, Wireless Sensor Networks, Human-Computer Interactions. She has published more than 70 academic papers in peer-reviewed international journals and conferences.

Siddharth S. Rautaray is presently working as Assistant Professor at School of Computer Engineering, KIIT University, Bhubaneswar, India. He received Ph.D. degree from Indian Institute of Information Technology (IIIT), Allahabad, India. His research interests include Computer Vision, Image Processing, Big data analytics, Human-Computer Interactions, and User Interface Design. More than 75 international journals and conference papers are to his credit.

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