Clustering short status messages: A topic model based approach

by

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ABSTRACT

Title of Thesis: Clustering short status messages: A topic model based approach

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Recently, there has been an exponential rise in the use of online social media systems like Twitter and Facebook. Even more usage has been observed during events related to natural disasters, political turmoil or other such crises. Tweets or status messages are short and may not carry enough contextual clues. Hence, applying traditional natural language processing algorithms on such data is challenging. Topic model is a popular method for modeling term frequency occurrences for documents in a given corpus. A topic basically consists of set of words that co-occur frequently. Unsupervised nature allows topic models to be trained easily on datasets meant for specific domains.

We use the topic modeling feature of MALLET - a machine learning tool kit, to generate topic models from unlabelled data. We propose a way to cluster tweets by using the topic distributions in each tweet. We address the problem of determining which topic model is optimal for clustering tweets based on its clustering performances. We also demonstrate a use case wherein we cluster Twitter users based on the content they tweet. We back our research with experimental results and evaluations.

Keywords: topic models, clustering, social media, Twitter.

Dedicated to Aai, Baba and Amit.

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Chapter 1

INTRODUCTION

In this chapter we present an introduction to the online social media. We will discuss the need for clustering the data that is available on such social media sites and present a formal thesis definition.

1.1 Online Social Media

Recently online social media has emerged as a medium of communication and information sharing. Status updates, blogging, video sharing and social networking are some of the ways in which people try to achieve this.

Popular online social media sites like Facebook[1], Orkut[2] or Twitter[3] allow users to post short message to their homepage. These are often referred as micro-blogging[4] sites and the message is called a *status update*. Status updates from Twitter are more commonly called as tweets. Tweets are often related to some event, specific topic of interest like music, dance or personal thoughts and opinions. A tweet can contain text, emoticon, link or their combination.

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[1] http://www.facebook.com/
[2] http://www.orkut.com/
[3] http://twitter.com/
[4] http://en.wikipedia.org/wiki/Microblogging

Tweets have recently gained a lot of importance due to their ability to disseminate information rapidly. Popular search engines like Google[5] and Bing[6] have started including feeds from Twitter in their search results. Researchers are actively involved in analyzing these micro-blogging systems. Some research areas include understanding usage and communities (Java *et al.* 2007), discovering user characteristics (Dongwoo *et al.* 2010), detecting spam (Yardi *et al.* 2010) and so on.

1.2 Motivation - why do we need to cluster tweets?

Analysis of micro blogging sites during crises situation has seen a rising interest as discussed in (Starbird *et al.* 2010) and (Vieweg *et al.* 2010). Content oriented analysis by applying traditional natural language techniques using syntactic and semantic model is difficult due to reasons described in (Kireyev, Palen, & Anderson 2009). These can be summarized as

- Tweets are very short in length with the message length being about 140 characters. Such a short piece of text provides very few contextual clues for applying machine learning techniques.
- Tweets are written in informal style and often consist of simple phrases, sentence fragments andor ungrammatical text. They contain abbreviations, internet slang and mispelled words.
- Tweets may contain implied references to locations as described in (Vieweg *et al.* 2010). Hence, named entity recognition using off the shelf named entity recognizers yield poor results.

[5]http://www.google.com/
[6]http://www.bing.com/

We believe that clustering of tweets will help to easily categorize them based on their content. Using such clusters we would be able to identify the topic or particular event about which the tweet is.

In this work, we would thus like to define a process that will classify an incoming tweet to one of the clusters existing in the system using topic model approach. Currently, we have analyzed the clusters generated using differently trained topic models. These topic models vary in size of training data, training data itself and number of topics.

1.3 Thesis contribution

The thesis contribution can be briefly stated as follows:

1. We determine the topic model configuration that is optimal to cluster tweets. Typically, in machine learning a model is trained using data that belongs to the same domain as the test data. For example, a named entity recognition system for biology related data is trained on biological data. But as mentioned above the short nature and esoteric form of tweets makes it necessary to explore if a topic model trained on twitter can yield better performance compared to a topic model trained on new wire text which has more contextual information.

2. We then evaluate the decisions made in point 1 by clustering a new set of tweets and also estimate the accuracy of the results. We compare the accuracy obtained with a baseline approach to show the merit of topic model based approach.

3. We show that the use of topic model to cluster Twitter users based on their status updates. We show the merit of topic model based approach to cluster Twitter users.

Chapter 2

BACKGROUND AND RELATED WORK

Generative models[1] have been popular for document analysis. A generative model is a model for randomly generating observable data, typically given some hidden parameters. It specifies a joint probability distribution over observation and label sequences. Often these generative models talk about a special type called topic model. There has been some work around analysis of Twitter data using topic models. In this chapter, we will explain few background concepts that are necessary to understand this thesis work. We will also review some recent research about analyzing online social media using topic models.

2.1 Topic models

Topic models are generative models and a popular method for modeling term frequency occurrences for documents in a given corpus. The basic idea is to describe a document as mixture of different topics. A topic is simply a collection of words that occur frequently with each other.

Latent Dirichlet allocation (Blei, Ng, & Jordan 2003) is a generative model that allows sets of observations to be explained by unobserved groups which explain why some parts of the data are similar. For example, if observations are words collected into documents,

[1] http://en.wikipedia.org/wiki/Generative_model

it posits that each document is a mixture of a small number of topics and that each word's creation is attributable to one of the document's topics.

Latent semantic analysis (Landauer, Foltz, & Laham 1998) is a technique in natural language processing, in particular in vectorial semantics, of analyzing relationships between a set of documents and the terms they contain by producing a set of concepts related to the documents and terms.

2.1.1 Properties of topic model

As discussed in (Kireyev, Palen, & Anderson 2009), topic models have certain properties that make it suitable to analyze Twitter data. These are summarized below:

Topic models do not make any assumptions about the ordering of words (Steyver & Griffiths 2007). This is known as bag-of-words model[2]. It disregards grammar as well. This is particularly suitable to handle language and grammar irregularities in Twitter messages.

Each document is represented as a numerical vector that describes its distribution over the topics. This representation is convenient to compute document similarity and perform clustering.

Training a topic model is easy since it uses unsupervised learning. It saves the effort required on creating labeled data and training classifiers using such labeled data.

Topic models are useful for identifying unobserved relationships in the data. This makes dealing with abbreviations and misspellings easy by using topic models.

2.2 Clustering

Clustering is an unsupervised learning techniques that takes a collection of objects such as tweets and organizes them into groups based on their similarity. The groups that are

[2]http://en.wikipedia.org/wiki/Bag_of_words_model

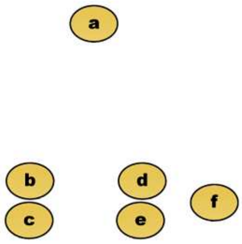


FIG. 2.1. Raw data for hierarchical clustering (figure courtsey: Wikipedia)

formed are known as clusters. Let's take a look at two main types of clustering algorithms.

2.2.1 Hierarchical clustering algorithms

This type of clustering algorithms can be divided into two types.

Agglomerative (bottom-up): Agglomerative algorithms begin with each individual document as a separate cluster, each of size one. At each level the smaller clusters are merged to form a larger cluster. It proceeds this way until all the clusters are merged into a single cluster that contains all the documents.

Divisive (top-down): Divisive algorithms begin with the entire set and then the splits are performed to generate successive smaller clusters. It proceeds recursively until individual documents are reached.

The agglomerative algorithms are more frequently used in information retrieval than the divisive algorithms. The splits and merge are generally done using a greedy algorithm. A greedy algorithm is an algorithmic approach that makes the locally optimal choice at each stage of its run with the hope of finding the global optimum. The results are often represented using a dendrogram as shown in Figure 2.2.

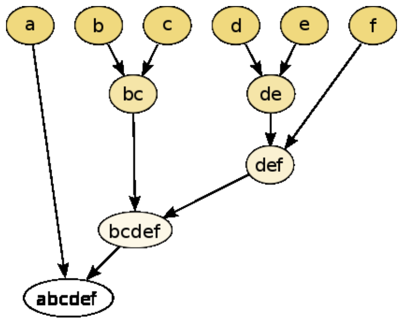


FIG. 2.2. Dendrogram representation for hierarchical clustering (figure courtsey: Wikipedia)

2.2.2 Partitional clustering algorithms

Partitional clustering algorithms typically determine all clusters at once. The k-means clustering algorithm belongs to this category. It starts off with choosing 'k' clusters and then assigning each data point to the cluster whose center is nearest. The algorithm as described in (MacQueen 1967) is as follows:

```
1. Choose the number of clusters, k.
2. Randomly generate k clusters and determine the cluster
   centers, or directly generate k random points as
   cluster centers.
3. Assign each point to the nearest cluster center, where
   "nearest" is defined with respect to one of the
   distance measures discussed above.
4. Recompute the new cluster centers.
5. Repeat the two previous steps until some convergence
   criterion is met (usually that the assignment
   hasn't changed).
```

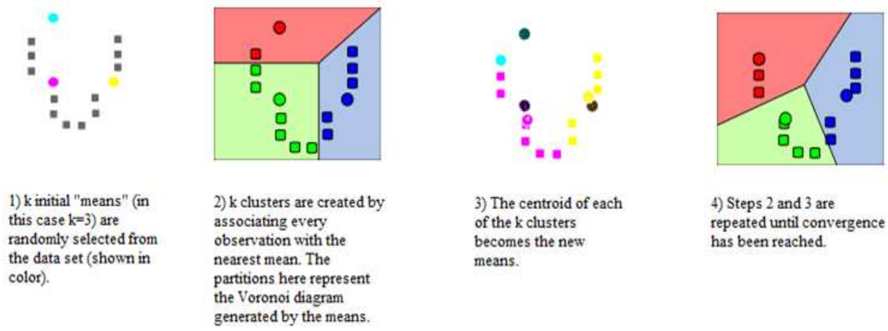


FIG. 2.3. Demonstration of k-means clustering (figure courtsey: Wikipedia)

The main advantages of k-means are its simplicity and speed when applied to large data sets. The most common hierarchical clustering algorithms have a complexity that is at least quadratic in the number of documents compared to the linear complexity of k-means. K-means is linear in all relevant factors: iterations, number of clusters, number of vectors and dimensionality of the space. This means that k-means is more efficient than the hierarchical algorithms as described in (Manning, Raghavan, & Schutze 2008). Figure 2.3 gives a demonstration for a k-means algorithm.

2.3 Related Work

Topic models have been applied to a number of tasks that are relevant to our goal of clustering Twitter status messages. We will briefly describe three categories and cite a few examples in each.

2.3.1 Topic models for information discovery

There has been some work with regards to using topic models for information discovery. (Phan, Nguyen, & Horiguchi 2008) presents a framework to build classifiers using both a set of labelled training data and hidden topics discovered from large scale data collections.

It provides a general framework to be applied across different data domains. (Griffiths & Steyvers 2004) presents a generative model to discover topics covered by papers in PNAS[3]. These topics were then used to identify relationships between various science disciplines and finding latest trends. An unsupervised algorithm described in (Steyvers, Griffiths, & Smyth 2004) extracts both the topics expressed in large text collection and models how the authors of the documents use those topics. Such author-topic models can be used to discover topic trends, finding authors who most likely tend to write on certain topics and so on. Author-Recipient-Topic model (McCallum, Corrada-Emmanuel, & Wang), is a Bayesian model for social network analysis that discovers topics in discussions conditioned on sender-recipient relationships in the corpus.

2.3.2 Text categorization

Another set of research deals with similarity and categorization of texts. Use of Wikipedia concepts to determine closeness between texts was explained in (Gabrilovich & Markovitch 2007). Text categorization based on word clustering algorithms was described in (Bekkerman *et al.* 2003). k-means clustering for sparse data was introduced in (Dhillon & Modha 2001). A topic vector based space model for document comparison was introduced in (Kuropka & Becker 2003). (Lee, Wang, & Yu) explores supervised and unsupervised approaches to detect topic in biomedical text categorization. It describes the Naive Bayes based approach to assign text to predefined topics. It performs topic based clustering using unsupervised hierarchical clustering algorithms.

[3]Proceedings of the National Academy of Sciences of the United States of America, http://www.pnas.org/

2.3.3 Topic models and online social media

As described in Chapter 1, most of the work related to Twitter and online social media in general has been focused on understanding usage and communities (Java *et al.* 2007), the role of micro-blogging (Zhao & Rosson 2009) and other such aspects related to community and network structure. Recent research has started to look at content related aspects of online social media and specifically Twitter. Smarter BlogRoll (Baumer & Fisher), uses text mining techniques to augment a blogroll with information about current topics of the blogs in that blog roll. The use of a partially supervised learning model (Labeled LDA) to characterize Twitter data and users is presented in (Ramage, Dumais, & Liebling). It classifies tweets based on roughly four dimensions like substance, style, social and status. Topic based clustering approach mentioned in (Kireyev, Palen, & Anderson 2009) identifies latent patterns like informational and emotional messages in earthquake and tsunami data sets collected from Twitter.

Chapter 3

SYSTEM DESIGN AND IMPLEMENTATION

In this chapter we will explain a high level design and implementation of our system. In the first section we explain the system components that have most direct influence on the system. We then describe the datasets, libraries and packages that we used to build this system.

3.1 System Design

Figure 3.1 provides an architectural overview of our system.

3.1.1 Topic modeler

This is the most important block in our system. A topic modeler consists of three stages.

Input stage: This stage involves converting the training corpus into an acceptable format. MALLET (McCallum 2002) that we used to build our system provides a special input command for converting the training data into MALLET's special internal format. We also remove certain stop words from the corpus during this stage. Since we have build topic models from new wire corpus and Twitter corpus which we describe in the next section; we have used two different lists of stop words as shown in Table 3.1. We also remove url's

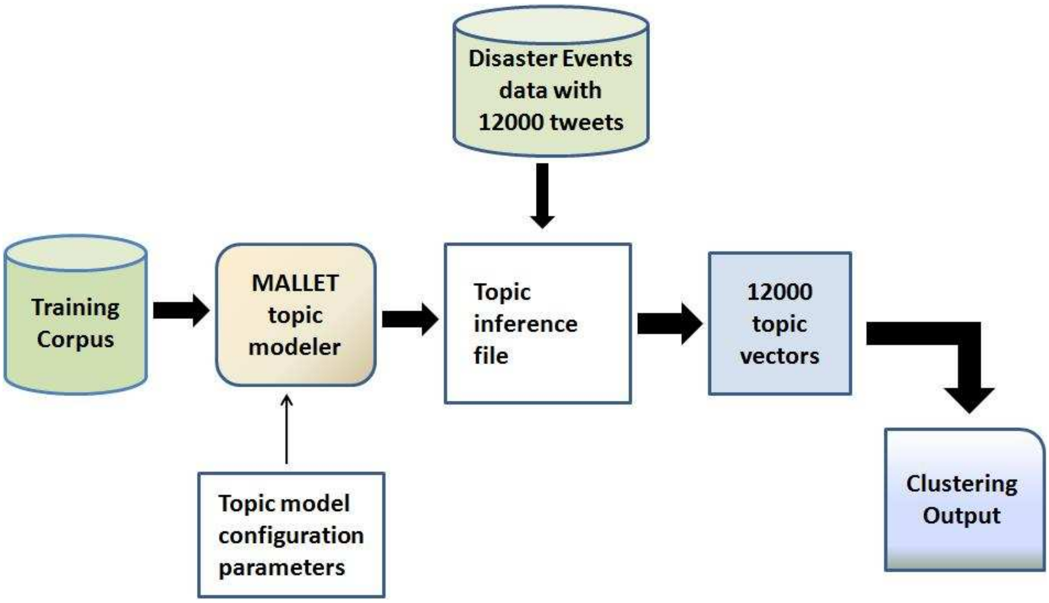


FIG. 3.1. System architecture

Corpus	Stop Words
News wire	eng, ldc, news, afp, apw, cna, ltw, nyt, rey, xin, the, is, as, and, ...
Twitter corpus	twitter, hey, hi, lol, lo, i, get, with, the, ...

Table 3.1. Stop words list

and @ sign tags from the training data if it's from the Twitter corpus.

Training stage: Once the data is available in MALLET's internal format we train a topic model on this input data. We build a topic model using MALLET's 'train-topics' command. We also supply the number of topics to be used. The MALLET's documentation for topic modelling recommends that a value in the range 200 to 400 gives reasonably fine-grained results.

Output Stage: The output from a topic modeler is typically an inference file and a file containing top 'k' words associated with each topic. We use this inference file to infer topics from disaster data set. In our system k=10, i.e., the default value in MALLET. Figure 3.2 gives an insight about top words associated with some of the topics for the news wire

```
0	0.25	kenya violence kibaki people kenyan odinga opposition country president nairobi police political december election crisis annan told
government african
1	0.25	minister prime government cabinet foreign ministers pm office deputy told premier country parliament finance affairs meeting defence
political resignation
2	0.25	united chelsea league liverpool arsenal england manchester football season ferguson champions players team side manager wenger game club
ronaldo
3	0.25	gold olympic world olympics medal men women games won beijing final team champion medals bronze silver swimming record athens
4	0.25	monday tuesday story week day weekend sunday due ahead expected days late early set announced start earlier taking latest
5	0.25	percent share points index shares billion market yuan shanghai investors dealers turnover prices closed rose stocks securities fell
benchmark
6	0.25	percent points market index stock wall shares street markets stocks dow investors fell jones london european trading average bond
7	0.25	world swiss switzerland story cup won super ahead place year francs race season sunday event finished saturday slalom downhill
8	0.25	black fashion wearing white show red hair blue wear man style young dressed image dress traditional clothes shoes designer
9	0.25	cup world team final football match coach players tournament group play champions finals teams semi matches game round asian
10	0.25	internet online website microsoft yahoo google video people site search users information posted web software advertising based youtube
computer
11	0.25	milan inter roma ac champions football league match season home italian points story italy top back serie sunday fiorentina
12	0.25	army killed fighting camp clashes al people militants troops soldiers wounded forces fire fighters area city spokesman civilians security
13	0.25	world champion olympic year won final athletics record time olympics gold championships race men women marathon title metres jump
14	0.25	golf round open par tour woods lead shot back hole year holes birdies play tournament masters pga championship event
15	0.25	week term long analysts recent remain expected strong short ahead continue analyst coming major expect remains past positive good
16	0.25	newspaper daily wrote times letter published media paper newspapers interview press story magazine jones editorial article journal page
post
17	0.25	rangers celtic league football scottish cup group champions african side scotland smith result story final match club round home
18	0.25	film star movie hollywood actor films actress director oscar story stars place top office awards box drama role year
19	0.25	rights human group international groups freedom government activists amnesty watch based political abuses torture authorities violations
called activist law
20	0.25	space mission launch station shuttle nasa satellite earth iss agency astronauts international endeavour crew launched astronaut moon rocket
orbit
21	0.25	deal talks agreement negotiations agreed signed accord end sides reached pact sign agree issues reach parties signing discussions progress
22	0.25	south korea korean north lee kim seoul won koreans roh skorea border yonhap park jong myung il agency samsung
23	0.25	bayern side league football munich german germany striker win bremen champions bundesliga coach group season euro midfielder top goals
24	0.25	meeting summit leaders conference talks meet ministers discuss president countries minister nations attend held hold foreign forum agreed
meetings
```

FIG. 3.2. Word to topic association for our training data set

corpus we used.

3.1.2 Topic models generated from various configurations

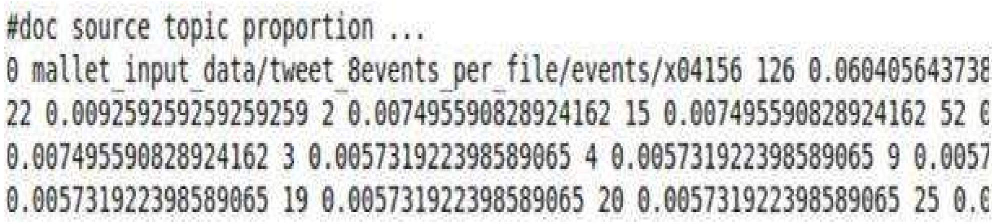
We use MALLET to generate different topic models. The topic models differ in:

Training data used: We use both new wire data and Twitter domain data. We explain these datasets in detail in the next section.

Size of training corpus: We vary the corpus size for Twitter trained models from 5 million tweets up to 20 million tweets.

Number of topics: We build topic models with number of topics varying from 200 to 400 for each of the above combination.

Additionally, we build two more models each with 40 million tweets and with 200 and 300 topics respectively. Each model has it's own inference file that is used to infer topics from the disaster events dataset.



```
#doc source topic proportion ...
0 mallet_input_data/tweet_8events_per_file/events/x04156 126 0.06040564373E
22 0.009259259259259259 2 0.007495590828924162 15 0.007495590828924162 52 0
0.007495590828924162 3 0.005731922398589065 4 0.005731922398589065 9 0.0057
0.005731922398589065 19 0.005731922398589065 20 0.005731922398589065 25 0.0
```

FIG. 3.3. Topic vectors snapshot for # topics = 200

3.1.3 Topic Vectors

MALLET provides an option to use a previously generated inference file as an inference tool. The output is a topic vector which gives a distribution over each topic for every document. Figure 3.3 gives a snapshot of topic vectors generated for one such document from a topic model trained on news wire corpus and 200 topics.

3.1.4 Clustering

We use R (R Development Core Team 2010), a system for statistical analysis and graphics for clustering the tweets based on their topic vectors. We first convert the file containing topic vectors to comma-separated values (CSV) format so that it is suitable for processing with R's commands. We then perform multidimensional scaling (MDS) (Cox & Cox 2001) on this data to reduce it to two dimensions using R's *cmdscale* function. MDS is a common way to visualize an N-dimensional data for exploring similarities and dissimilarities in it. We then perform clustering on these reduced dimensions using R's *k-means* function. Figure 3.4 provides a closer look at the clustering stage.

The *k-means* command in R returns a vector containing cluster association for each document in the dataset. We run a program to collect together all the documents with same cluster numbers. For such an induced cluster, if more than 50% of the documents belong to a particular original cluster then we assign the induced cluster with that event name.

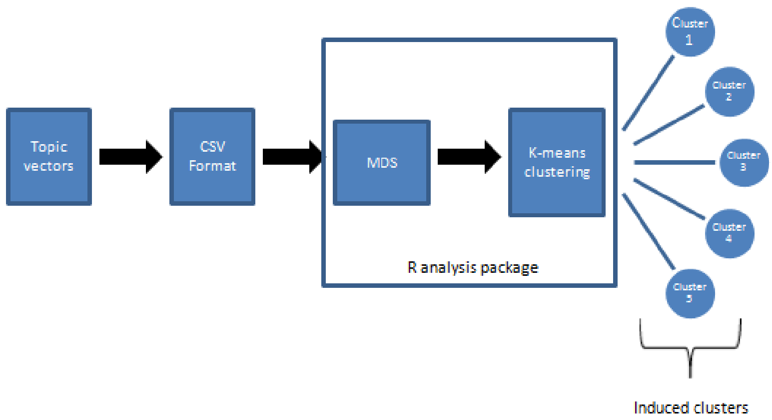


FIG. 3.4. Clustering stage

The original cluster here means the cluster in the disaster events dataset that we explain in Section 3.2.3.

3.2 Datasets

In this section we describe four different datasets that we have used in order to train the topic models as well as to test the performance of the topic models. All the four datasets contain tweets which are in English language. Except for the first dataset, i.e., twitterdb which is stored in PostgreSql database the other datasets are stored as plain text files.

3.2.1 Twitter dataset (twitterdb)

This is one of the two datasets the we used to train our topic models. The total collection is about 150 million tweets from 1.5 million users, collected over a period of 20 months (during 2007 to 2008). The distribution of tweets collected per unit time is shown as a histogram below in Figure 3.5. Our source changed data collection methods in mid-2008, which makes for many more tweets collected per day. The language detection performed on this dataset by (Murnane 2010) gave the distributions as showed in Table 3.2. The 32%

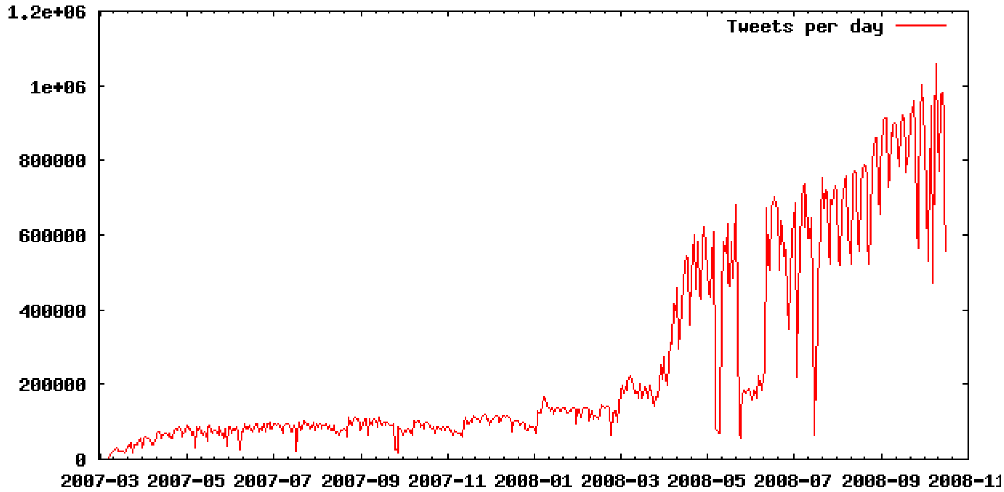


FIG. 3.5. Distribuition of tweet collection in twitterdb

detection rate for English in turn makes around 48 million English tweets available to train our topic models. Table 3.3 lists top hash tags and user tags present in this dataset.

3.2.2 TAC KBP news wire corpus

This is the other dataset we used to train our topic models. This was basically 2009 TAC KBP corpus with approximately 377K newswire articles from Agence France-Presse

Language	**Percentage**
English	32.4%
Scots	12.5%
Japanese	7.4%
Catalan	5.2%
German	3.9%
Danish	3.1%
Frisian	2.5%
Portugese	2.3%
Latin	2.3%

Table 3.2. Languages with more than 2% detection rate

Hashtags	1, 2, 1:, news, 3news, rnc08, elecoes, 080808, dnc08, lastfm
Usertags	chrisbrogan, garyvee, commuter, harunyan, leolaporte, lynmock, kazusap, kevinrose, Scobleizer, Hemi

Table 3.3. Top 10 hashtags and usertags

(AFP). About half articles were from 2007 and half from 2008 with a few (less than 1%) from 1994-2006.

3.2.3 Disaster events dataset

This dataset includes tweets for 8 disaster events as shown in Table 3.4. We collected 1500 tweets for each of these events which gave us a total of 12,000 tweets in this dataset. The tweets for two events, namely, *California Fires* and *Gustav Hurricane* were from our Twitter dataset. We exclude these tweets while training the model using Twitter dataset. The tweets for the other six events were obtained from Twitter's public timeline using twitter4j [2]. We have used a number of Twitter search operators to get the most accurate query for the events. Here are some of the examples queries.

- Using words, hashtags and date ranges for querying
  Haiti earthquake in Jan 2010: haiti earthquake # haiti since:2010-01-12 until:2010-01-16

- Using words, date ranges and location
  Washington DC snow blizzard in Feb 2010: snow since:2010-02-25 until:2010-02-28 near:"Washington DC" within:25mi

A manual scan for tweets from five events, namely *Afghanistan war, China mine blasts, California fires, Haiti earthquake* and *DC snow* indicates that more than 97% tweets

[2] http://twitter4j.org/en/index.html

Event name	Source
DC snow	Twitter search API's
NE thuderstorm	Twitter search API's
Haiti earthquake	Twitter search API's
Afghanistan war	Twitter search API's
China mine blasts	Twitter search API's
Gulf oil spill	Twitter search API's
California fires	twitterdb
Gustav hurricane	twitterdb

Table 3.4. Disaster events dataset

Event	#Tweets
Hurricance Alex	624
China earthquake	376

Table 3.5. Supplementary test dataset

are actually related to those particular events. Thus we can infer that this data contains eight clusters. We call this as 'original clusters' in further chapters.

3.2.4 Supplementary test dataset

We collected 1000 tweets which were a mixture of tweets from Hurricane Alex of June 2010 and China earthquake of May 2008. We manually went through all these 1000 tweets and confirmed their relevance to either of the events. Table 3.5 shows the tweet distribution.

3.3 Tools and libraries

3.3.1 MALLET

MALLET stands for MAchine Learning for LanguagE Toolkit and is a opensource software toolkit. It provides a Java-based package to do various machine learning tasks. We use the topic modeling features as described in previous section. It provides a fast and scalable implementation of Gibbs sampling and topic inferring tools.

3.3.2 Twitter4j

It provides a opensource Java library for Twitter API's. We used it to collect tweets related to disaster events. We have primarily used Search, Query and QueryResult implementation from the twitter4j package.

3.3.3 R analysis package

The R analysis package is a free software environment for statistical computing and graphics. We typically use R's *dist* command to perform distance matrix computations, *cmdscale* command for multidimensional scaling and *k-means* command for clustering. R provides other commands that help to obtain within cluster sum of squares for each cluster, cluster centroids, cluster size and a vector containing integers to indicate cluster association for each data point.

Chapter 4

EXPERIMENTAL ANALYSIS AND RESULTS

In this chapter we present the results of the experiments performed for selecting the best topic model for clustering Twitter data. We also present the clustering results for this best topic model. We also provide results of our experiments to cluster Twitter users using this topic model.

Most of the code was in Java with some file handling and regular expression matching done using Perl scripts or shell commands. Clustering scripts were written in R language. Clustering experiments were performed on Sun Solaris machine running Ubuntu OS with about 40 GB RAM. Topic models were created on Linux machine with about 4 GB RAM.

4.1 Definitions, computation techniques and analysis

4.1.1 Residual Sum of Squares (RSS)

As defined in (Manning, Raghavan, & Schutze 2008), RSS is the squared distance of each vector from it's cluster centroid summed over all vectors in the cluster. It gives a measure of how well the centroid represents a cluster. It's a heuristic method to calculate number of clusters for k-means clustering algorithm. It's the objective funciton for k-means and a smaller value of RSS indicates tighter clusters. RSS for the k^{th} cluster is given by equation 4.1.

$$RSS_k = \sum_{\vec{x} \in \omega_k} |\vec{x} - \vec{\mu}(\omega_k)|^2 \quad (4.1)$$

where $\vec{x}$ represents a distance vector of a document in cluster ω and $\vec{\mu}(\omega_k)$ represents the centroid of cluster ω_k given by equation 4.2.

$$\vec{\mu}(\omega_k) = \frac{1}{|\omega|} \sum_{\vec{x} \in \omega} \vec{x} \quad (4.2)$$

Hence, the RSS for a particular clustering output with say K clusters is given by

$$RSS = \sum_{k=1}^{K} RSS_k \quad (4.3)$$

4.1.2 Cluster Cardinality

As mentioned above we use a heuristic based approach to calculate value of k for k-means clustering. We use the steps mentioned in (Manning, Raghavan, & Schutze 2008) to find k.

- Perform i (we use i = 10) clusterings with a said value of k. Find the RSS in each case as defined by equation 4.3.
- Find the minimum RSS value. Denote it as RSS_{min}.
- Find RSS_{min} for different values of k as k increases.
- Find the 'knee' in the curve i.e. the point where successive decrease in this value is the smallest. This value of k indicates the cluster cardinality.

Table 4.1 shows RSS_{min} for different values of k obtained for clustering using twitterdb trained topic model with 200 topics. Figure 4.1 shows the corresponding plot of

$\mathbf{RSS_{min}}$	**k**
0.6903	3
0.4220	4
0.3662	5
0.2581	6
0.2391	7
0.2192	8
0.2098	9
0.1594	10
0.1469	11
0.1204	12
0.0999	13

Table 4.1. RSS_{min} and k for twitterdb trained topic model with 200 topics

RSS_{min} v/s k. It can be clearly observed from table 4.1 as well as Figure 4.1 that at $k = 8$ the curve flattens the most. Hence, $k = 8$ is the optimal cluster cardinality.

4.1.3 Cluster centers and iterations

As mentioned in Chapter 3, we use k-means command from R analysis package for clustering. We use the following command syntax:

```
kmeans(dist, centers)
```

where,

dist : data matrix,

centers : number of cluster centers i.e. k

Cluster centers are randomly chosen from the set of rows available in dist. The number of iterations performed to reach convergence is by default set to ten. We generated over 27 topic model configurations and have performed clustering. We found that barring just three cases convergence was achieved with this setting. For these three cases we had to set this value to 15 to allow k-means to reach convergence. The (Hartigan & Wong 1979) k-means

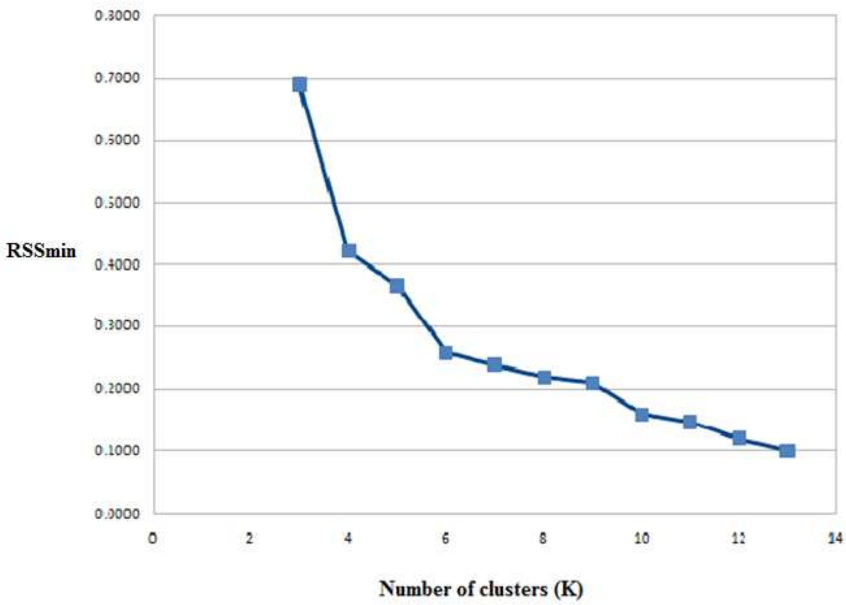


FIG. 4.1. RSS_{min} v/s k

clustering algorithm is used by default. Figure 4.2 shows the k-means clustering for our disaster event dataset with $k = 8$ using topic model trained on TAC KBP news wire corpus with 200 topics.

4.1.4 Cluster validation criterion

We validate the quality of induced clusters on:

- Cluster cardinality computed as in Section 4.1.2
- Similarity between clusters induced using k-means and original clusters (tweets from eight different events) in the dataset using the Jaccard similarity coefficient

Jaccard similarity coefficient

Jaccard coefficient (Jaccard 1901) is a classic statistical measure for similarity in sets. It is defined as:

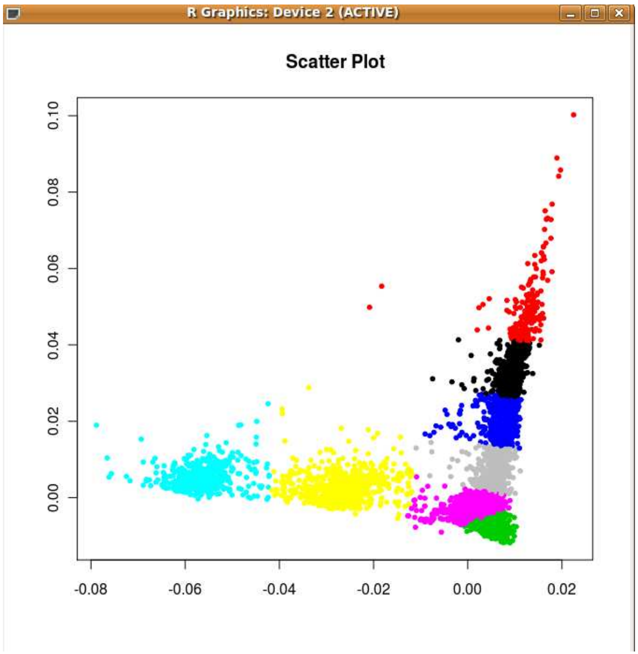


FIG. 4.2. Clustering with k = 8 on disaster events dataset using topic model trained on TAC KBP news wire corpus with # topics=200

$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$

Practically, it can be easily computed by counting $N_{AB} = |A \cap B|$ and N_A and N_B as the data elements that belong only to set A and B respectively so that $N_A + N_B + N_{AB} = |A \cup B|$ and hence

$J(A, B) = \frac{N_{AB}}{N_A + N_B + N_{AB}}$

In further sections, we use Jaccard coefficient as a measure for clustering performance of a topic model. Higher the Jaccard coefficient value, more is an induced cluster similar to an original cluster for the same kind of event.

4.1.5 Clustering Accuracy

As described in (Choudhary & Bhattacharyya) we measure clustering accuracy using the formula:

$Accuracy = \frac{Number of documents correctly clusterd}{Total number of documents}$

We determine accuracy on the test dataset and the results are published in Section 4.5.

4.2 Effect of change in topic model parameters on Jaccard coefficient

We conducted three separate experiments to observe the effect of change of training data size, training data type (twitterdb or news wire data) and changing the number of topics to build a topic model on the Jaccard similarity coefficient. The Jaccard similarity coefficient was calculated based on the comparison between induced clusters and original clusters in the disaster events dataset as described in Section 3.2.3. In these experiments we consider only those topic models that give us induced cluster count same as original cluster count i.e 8. We address the case of inequality in induced cluster count and original cluster count in Section 4.7.

4.2.1 Effect of change in training data size

We build nine different topic models using varying size of twitterdb data to train the model. All the models have topic number fixed to 200. In one case, the topic model trained on 15 million tweets from our twitterdb returned nine induced clusters on our disaster events dataset. We ignore this particular case for this experiment.

Table 4.2 shows various topic models we trained using varying number of tweets from our twitterdb collection. All the topic models shown have 200 topics. These topic models were then used to perform clustering on the disaster events dataset which contained tweets from eight events as described in Section 3.2.3. We calculate Jaccard similarity coefficient in each case and the results are as shown in Table 4.3.

We then plot a bar graph as show in Figure 4.3 for the results in Table 4.3. It can

Topic model	Number of tweets used (in millions)
Case 1	5
Case 2	10
Case 3	16
Case 4	17
Case 5	18
Case 6	19
Case 7	20
Case 8	40

Table 4.2. Topic models with 200 topics trained using varying number of tweets from twitterdb

Jaccard Coefficient								
Event Name	**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 5**	**Case 6**	**Case 7**	**Case 8**
DC snow	0.36	0.378	0.381	0.387	0.388	0.386	0.387	0.388
California Fire	0.378	0.4	0.402	0.409	0.415	0.41	0.412	0.411
NE thunderstorm	0.389	0.425	0.428	0.431	0.443	0.441	0.44	0.439
China mine blasts	0.344	0.355	0.372	0.366	0.377	0.373	0.368	0.368
Afghan War	0.374	0.382	0.385	0.391	0.401	0.393	0.391	0.394
Gulf Oil Spills	0.267	0.327	0.33	0.329	0.334	0.333	0.331	0.333
Gustav Hurricane	0.23	0.276	0.28	0.285	0.29	0.288	0.288	0.287
Haiti Earthquake	0.326	0.354	0.343	0.35	0.357	0.354	0.355	0.356

Table 4.3. Jaccard coefficient for various topic models with 200 topics trained using twitterdb

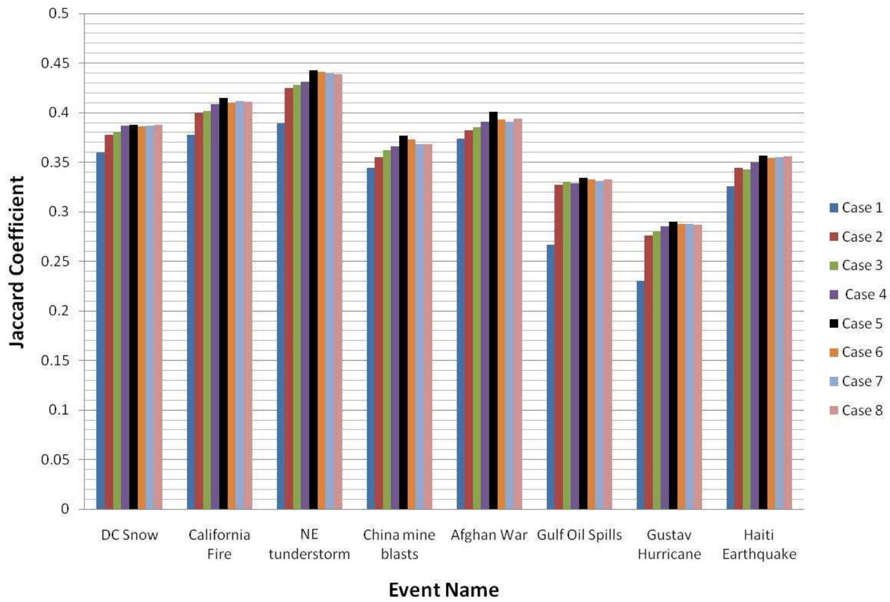


FIG. 4.3. Effect of change in size of training corpus on Jaccard coefficient

be easily seen that the Jaccard coefficient increases steadily upto Case 5 for each of the disaster events and then more or less remains constant. Figure 4.4 shows a plot of Jaccard coefficient values for each of these events. Case 5 (black bar) thus indicates a threshold beyond which the topic models cease to give improved performance in terms of Jaccard coefficient. Thus we can infer that Case 5 with 18 million tweets is the optimal topic model amongst those trained on twitterdb with 200 topics.

4.2.2 Effect of change in training data corpus

This experiment tried to understand the change in Jaccard coefficient when topic models trained on twitterdb and news wire corpus were used. We compare the best case from above i.e. Case 5 against a topic model trained on our TAC KBP corpus keeping the number of topics fixed i.e. 200.

Table 4.4 shows the Jaccard coefficient for the two models. AFP_200 is the model

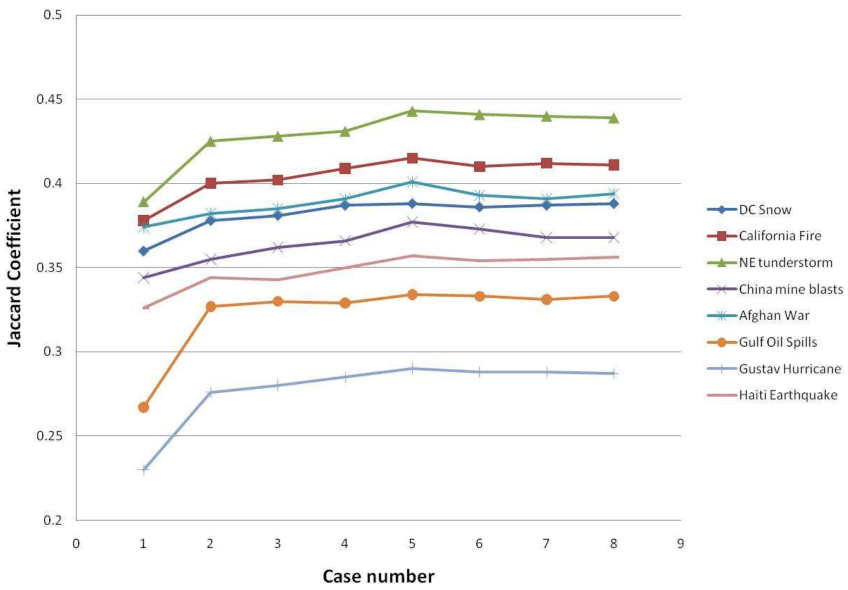


FIG. 4.4. Scatter plot of Jaccard coefficient for the disaster events dataset

	Jaccard Coefficient	
Event Name	**Case 5**	**AFP_200**
DC snow	0.388	0.428
California Fire	0.415	0.43
NE thunderstorm	0.44	0.479
China mine blasts	0.377	0.415
Afghan War	0.401	0.421
Gulf Oil Spills	0.334	0.395
Gustav Hurricane	0.29	0.405
Haiti Earthquake	0.357	0.406

Table 4.4. Jaccard coefficient for Case 5 and topic model trained on TAC KBP news wire corpus

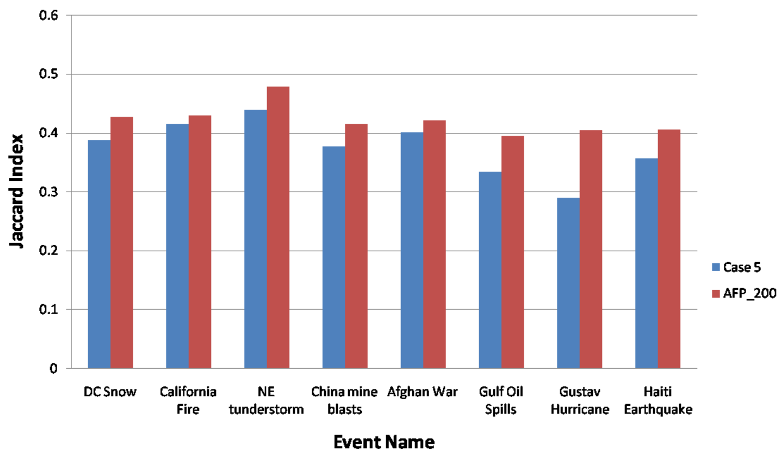


FIG. 4.5. Effect of change in training data corpus on Jaccard coefficients for Case 5 and news wire trained topic model

trained on TAC KBP corpus with 200 topics. Figure 4.5 shows a bar graph used to compare the models. As we can see, news wire corpus gave good cluster similarity measure compare to Case 5. We observed a similar behavior with topic models having 300 topics. Thus in general we can infer that models trained on news wire corpus performed better compared to models trained on Twitter data. Thus result gains added evidence from the fact that tweets are short and esoteric and have very less contextual content compared to news wire text as mentioned in Chapter 1.

4.2.3 Effect of change in number of topics

In this experiment we compared the Jaccard coefficients obtained by keeping the training corpus size and data constant and build topic models with 200, 300 and 400 topics. Table 4.5 shows the Jaccard coefficient values obtained for topic models trained using same 16 million tweets from our twitterdb but varying the topic numbers.

	Jaccard Coefficient		
Event Name	**T_200**	**T_300**	**T_400**
DC snow	0.381	0.391	0.385
California Fire	0.402	0.419	0.409
NE thunderstorm	0.428	0.447	0.435
China mine blasts	0.372	0.382	0.38
Afghan War	0.385	0.4	0.396
Gulf Oil Spills	0.33	0.353	0.349
Gustav Hurricane	0.298	0.388	0.324
Haiti Earthquake	0.343	0.369	0.353

Table 4.5. Effect of change in number of topics

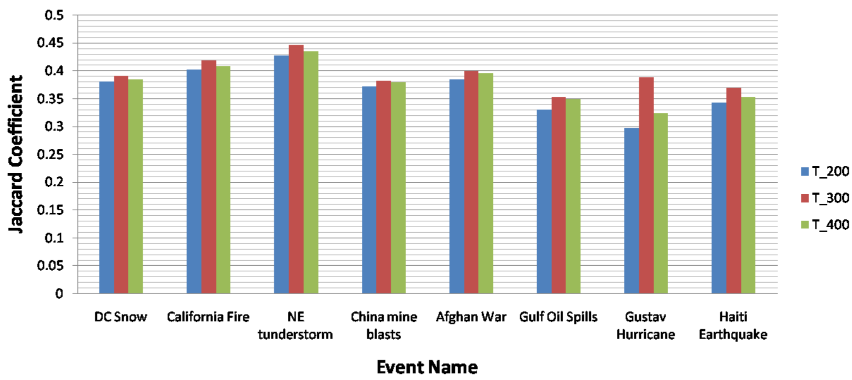


FIG. 4.6. Jaccard coefficient for topic models with varying topic number

It can be seen from the graph in Figure 4.6 that topic model (T_300 indicated with red bar) with 300 topics gives a peak performance. Experiments using news wire corpus also yielded similar results. We found this result similar to those discussed in (Griffiths & Steyvers 2004) and (Steyvers, Griffiths, & Smyth 2004), where a topic model with 300 topics was found to be optimal.

4.3 Selecting an optimal topic model

Section 4.2 demonstrates effect of changing various topic model parameters on the Jaccard coefficient. Table 4.4 clearly shows that a topic model with 200 topics trained on

Topic model	Number of tweets used (in millions)
Case 1	5
Case 2	15
Case 3	16
Case 4	17
Case 5	18
Case 6	19
Case 7	20
Case 8	40

Table 4.6. Topic models with 300 topics trained using varying number of tweets from twitterdb

news wire corpus performed better clustering than any of the topic models with 200 topics trained using twitterdb. Also, as seen from Section 4.2.3 and Table 4.5 a topic model with 300 topics yielded better clustering.

This gave us an intuition that a topic model with 300 topics and trained on news wire corpus will give us better performance compared to any of the model configurations that we tried. We verified this by measuring Jaccard coefficient for various topic models with 300 topics trained on twitterdb.

Table 4.6 shows different cases that we considered. As seen from the graph in Figure 4.7, the clustering performance deteriorates after Case 3 (green bar). This is the best performance we could get out of model trained on twitterdb. Even a topic model built from news wire corpus with 200 topics betters this. We then plot a bar graph of Jaccard coefficients obtained from news wire trained topic models with 200 topics (AFP_200), 300 topics (AFP_300) and 400 topics (AFP_400).

Table 4.7 shows the Jaccard coefficients for both the models and Figure 4.8 clearly shows that our intuition was correct since AFP_300 (pink bar) gives the best clustering performance.

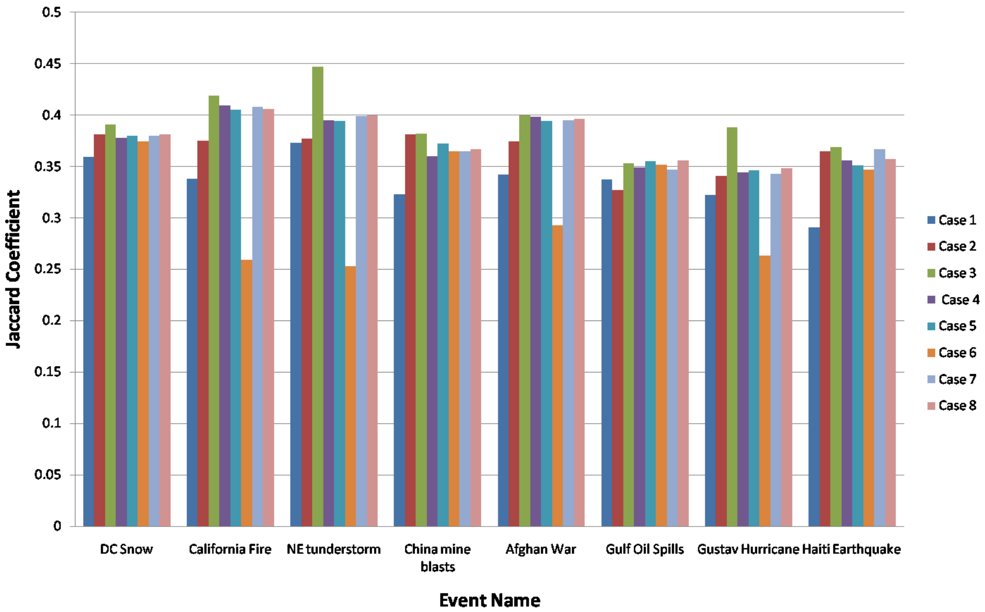


FIG. 4.7. Jaccard coefficient for topic models with 300 topics trained on twitterdb

	Jaccard Coefficient		
Event Name	**AFP_200**	**AFP_300**	**AFP_400**
DC snow	0.428	0.505	0.43
California Fire	0.43	0.483	0.439
NE thunderstorm	0.479	0.498	0.491
China mine blasts	0.415	0.546	.439
Afghan War	0.421	0.49	0.441
Gulf Oil Spills	0.395	0.527	0.421
Gustav Hurricane	0.405	0.492	0.439
Haiti Earthquake	0.406	0.499	0.429

Table 4.7. Jaccard coefficient for news wire corpus trained topic models

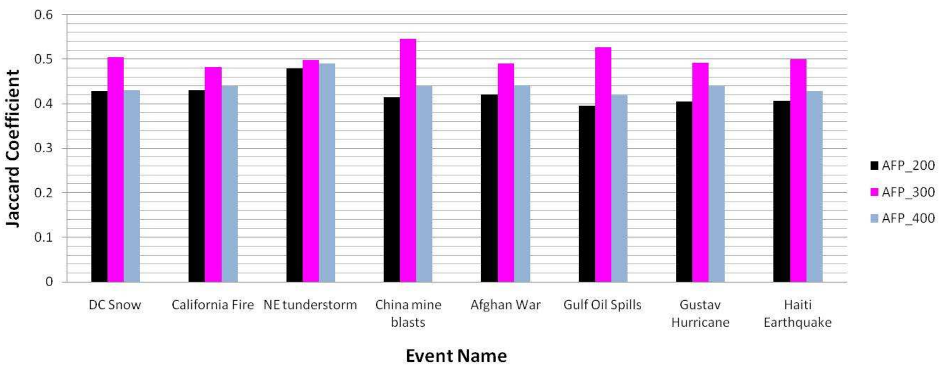


FIG. 4.8. Comparing news wire trained topic models for 200, 300 and 400 topics

	Original Clusters							
	DC snow	California Fire	NE Thunderstorm	China mine blasts	Afghan War	Gulf Oil Spills	Gustav Hurricane	Haiti Earthquake
Induced Clusters								
DC snow	0.505	0.028	0.231	0.016	0.009	0.046	0.12	0.048
California Fire	0.024	0.483	0.042	0.127	0.139	0.08	0.046	0.061
NE thunderstorm	0.141	0.012	0.498	0.004	0.016	0.111	0.213	0.009
China mine blasts	0.008	0.092	0.016	0.546	0.21	0.024	0.003	0.101
Afghan War	0.019	0.124	0.026	0.136	0.49	0.016	0.097	0.098
Gulf Oil Spills	0.089	0.071	0.009	0.066	0.117	0.527	0.018	0.083
Gustav Hurricane	0.178	0.061	0.18	0.037	0.002	0.096	0.492	0.101
Haiti Earthquake	0.051	0.134	0.003	0.108	0.09	0.101	0.014	0.499

Table 4.8. Jaccard coefficient matrix for AFP_300

4.4 Jaccard coefficient matrix

In the previous section we concluded that AFP_300 has the best performance for the task of clustering tweets. Table 4.8 provides us an insight about what proportion of each events is an induced cluster made up of.

We observed that the induced cluster for *NE thunderstorm* has the second highest contribution from tweets related to *Gustav Hurricane*. Similar was the case with induced clusters for *Afghan War* having second highest contribution from tweets related to *California Fire* and vice versa. To analyze this behavior we generated a list of top five most frequent words for these events from our disaster events dataset by ignoring the proper nouns. For example, we ignore proper nouns like California, CA, USA and Gustav. We then investigated the topic keys generated by MALLET for AFP_300 topic model. We found that in

Induced Cluster for	Top 5 most frequent words from disaster events dataset	topic keys generated by MALLET
Afghan War	war, fires, army, terrorist, kill	fire, california, fires, damage, police killed, shot, attack, died, injured, wounded
California Fire	fire, burn, smoke, damage, west	
NE thunderstorm	storm, winds, rain, warning, people	storm, people, hurricane, rain, rains, flooding, flood coast mexico, areas
Gustav Hurricane	hurricane, storm, floods, heavy, weather	

Table 4.9. Relation between most frequent words and topic keys

Cluster Name	Size of induced cluster (A)	Correctly clustered tweets (A ∩ B)	Original Size (B)	Jaccard Coefficient	Accuracy
Hurricane Alex	572	403	624	0.508	64.58%
China earthquake	428	263	376	0.486	69.94%

Table 4.10. Clustering accuracy for test dataset

some topics these words co-occurred. Table 4.9 shows the most frequent words and related topic keys.

4.5 Accuracy on test dataset

We determined the accuracy of AFP_300 by using it to cluster test dataset described in Section 3.2.4. We obtained an accuracy of about 64% for clustering tweets from *Hurricane Alex* and about 70% for clustering tweets from *China earthquake*.

The baseline we chose was the framework built to classify sparse and short text by (Phan, Nguyen, & Horiguchi 2008). It uses a a training corpus of around 22.5K documents for training and 200 topics with Gibbs sampling. They had an accuracy of around 67% to classify short pieces text from medicinal domain.

We present these results in Table 4.10. It can also be observed that the Jaccard coefficient values for *Hurricane Alex* and *China earthquake* are similar to those for *Gustav Hurricane* and *Haiti Earthquake* respectively as shown in Table 4.7 for AFP_300.

4.6 Applying topic model to cluster Twitter users

We use AFP_300 to perform an experiment of clustering Twitter users based on their tweets. We identified 21 well known Twitter users across seven different domains - sports,

Domain	Twitter user
Sports	@ESPN, @Lakers, @NBA
Travel Reviews	@Frommers, @TravBuddy, @mytravelguide
Finance	@CBOE, @CNNMoney, @nysemoneysense
Movies	@imdb, @peoplemag, @RottenTomatoes, @eonline
Technology News	@TechCrunch, @digg_technews
Gaming	@EASPORTS, @IGN, @NeedforSpeed
Breaking News	@foxnews, @msnbc, @abcnews

Table 4.11. Twitter users

travel reviews, finance, movies, technology news, gaming and breaking news. We used Twellow[1] to obtain Twitter users. It's like a yellow pages for Twitter. Table 4.11 shows the Twitter users we selected for this experiment. We collected 100 tweets for each user using Twitter API.

We generate topic vector for a user by aggregating the topic dimensions across all the tweets for that user. Table 4.12 shows the clustering results. $k = 6$ was experimentally obtained as the optimal value of k by performing cluster cardinality analysis as described in Section 4.1.2.

@EASPORTS consisted more tweets about it's new NBA and football game release. It ended up being clusterd with other sports domain users. Technology news related users and breaking news got clustered together with @msnbc ending up with other finance domain users.

4.7 Limitations

We are aware of two limitations in our work. The first concerns our approach for evaluating the accuracy of the induced clusters which, in some cases, could not be applied. The second involves the lack of tests for the statistical significance of some of our results.

[1]http://www.twellow.com/

Cluster #	Twitter users
1	@CBOE, @msnbc, @CNNMoney, @nysemoneysense
2	@IGN, @NeedforSpeed
3	@EASPORTS, @ESPN, @Lakers, @NBA
4	@Frommers, @TravBuddy, @mytravelguide
5	@imdb, @peoplemag, @RottenTomatoes, @eonline
6	@foxnews, @abcnews, @TechCrunch, @digg_technews

Table 4.12. Twitter user clusters

Cluster Type	K-means (A)	Original (B)	A ∩ B	Jaccard index
DC snow	1531	1500	824	0.373
China mine blasts	1568	1500	811	0.36
Haiti earthquake	1425	1500	777	0.361
Afghan War	1762	1500	854	0.354
unidentified	2689			
Gulf oil spills	1472	1500	745	0.334
California Fire	1553	1500	838	0.378

Table 4.13. Jaccard coefficient calculations for Case C

Cluster numbers

In Section 4.2 we considered only those topic models that gave eight clusters. During our analysis and experiments we came across four topic model configurations that yielded optimal cluster cardinality other than eight. Table 4.13 lists all such configurations.

We study Case C which generates seven induced clusters and Case D which generates eleven induced clusters. Table 4.14 shows the Jaccard coefficient calculations for Case C. We could identify an event type with six of the induced clusters and one remained unidentified. It was a mostly a collection of tweets from Gustav Hurricane and NE thunderstorm with some mix of tweets from other events.

Table 4.15 shows the Jaccard coefficient for Case D. We were able to ascertain the type for eight out of eleven clusters. The remaining three clusters were a mix of tweets from three to four events. This lowered the Jaccard coefficient for clusters with type *California Fire*, *Afghan War*, *NE thunderstorm* and *Gustav Hurricane*. This is clearly evident in Figure

Topic model	Trained on	topic #	Induced clusters #
Case A	15 million tweets	200	9
Case B	5 million tweets	300	10
Case C	10 million tweets	300	7
Case D	19 million tweets	300	11

Table 4.14. Topic model configurations with cluster cardinality $\neq 8$

Cluster Type	K-means (A)	Original (B)	$A \cap B$	Jaccard index
DC snow	1483	1500	813	0.374
Haiti Earthquake	1464	1500	765	0.347
China mine blasts	1530	1500	811	0.365
Gulf Oil Spills	1485	1500	778	0.352
California Fire	1012	1500	517	0.259
Afghan War	1245	1500	623	0.293
NE thunderstorm	986	1500	501	0.253
Gustav Hurricane	1009	1500	523	0.263
unidentified	780			
unidentified	481			
unidentified	525			

Table 4.15. Jaccard coefficient calculations for Case D

4.7 where Case 6 (orange bar) represents Case D. Clustering performance from such models was suboptimal and hence we ignored them. We feel that this problem could be tackled by using the ClusterMap (Cheng & Liu 2004) approach. ClusterMap address the problems of labeling irregular shaped clusters, distinguishing outliers and extending cluster boundaries.

Test of statistical significance

The results that we show in Section 4.2 where we experiment the effect of change in topic model parameters on Jaccard coefficient values were obtained for a single run. We have not done a statstical significance test on the results that we got in Section 4.2. We mention a way in which this could be done in Chapter 5 under Section 5.2.

Chapter 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

We proposed and described an approach to determine the most suitable topic model to cluster tweets. We analyzed the effect of change in topic model parameters like training corpus size, type of training data and number of topics on its clustering performance. We also considered various clustering parameters like residual sum of squares (RSS), cluster validation in terms of cluster cardinality (k) and Jaccard coefficient. We compared various topic model configurations based on the variations in these parameters. Based on our experiments and analysis it was evident that the topic model with 300 topics trained on news wire corpus (TAC KBP) performed better than the topic models trained on twitterdb corpus. We used this model to cluster tweets from test dataset and had an clustering accuracy of 64.58 % and 69.94% for the two events under consideration. Our approach also provides a way to graphically survey the induced clusters via the R analysis package as show in Figure 4.2. Such a topic model will definitely be useful for the research community by saving the effort on clustering tweets based on their content similarity. In Section 4.6 we also demonstrate a use case for this topic model by clustering twitter users based on the content they tweet about. This is definitely helpful to identify twitter users who have an interest in particular topic.

5.2 Future Work

During our experiments we observed that the step that performs k-means clustering is slow. For future work, we would like to use a faster implementation of k-means algorithm such as the one that uses coresets to quickly determine clusterings of the same point set for different values of k. The current model does not sufficiently address the case where some of the clusters are of 'unidentified' type as seen in Section 4.7 We would require more complex analysis for such cases. There is always a trade off between complexity of system and ease of analysis. For results obtained in Section 4.2 a statistical significance could be provided by performing muliple runs for each case and then use a test like paired ttest for statistical significance.

We feel that clustering twitter users could be extended in a way where a new user could decide to follow only those users that post content that is of any interest to him. Similarly, the work could be extended to cluster hashtags. This will help a user to follow the topics he is interested in. Though we presented all our work for clustering tweets from disaster events, our work may be extended to cluster Facebook status updates as well. Lastly, we should scale the infrastrucure so that we could collect tweets in real time and and perform clustering on them.

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