Spatiotemporal Topic Association Detection on Tweets

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ABSTRACT

The analysis of Twitter data can help to predict or explain many real world phenomena. The relationships among events in the real world can be reflected among the topics on social media. In this paper, we propose the concept of topic association and the associated mining algorithms. Topics with close temporal and spatial relationship may have direct or potential association in the real world. Our goal is to mine such topic associations and show their relationships in different time-region frames. We propose to use the concepts of participation ratio and participation index to measure the closeness among topics and propose a spatiotemporal index to calculate them efficiently. With the topic filtering and the topic combination, we further optimize the mining process and the mining results. The algorithms are evaluated on a Twitter dataset with 27,956,257 tweets.

Categories and Subject Descriptors

H.2.8 [Database Management]: Database Applications—*Data Mining*

Keywords

Hashtag, Participation Index, Topic Association

1. INTRODUCTION

The analysis of Twitter data can help to predict or explain phenomena in many real world applications [1, 3]. Topics on Twitter may potentially be associated in space and time. For example, the hashtags related to the Independence Day *#july4th* are closely related to the hashtags *#firework* and *#beer* in the beginning of July, which directly reveals how people celebrate the Independence Day. The detection of such topic associations can help to improve on-line services such as news recommendation and explain the relationship among real world events.

The goal of this paper is to detect the associations between hashtags (topics) by analyzing the time and location

distributions of tweets which contain these hashtags. We define the topic set of each tweet as the hashtags it contains. So each topic can appear in a number of tweets and each tweet can contain several topics. For example, the right side of Figure 1 shows two tweets. The first tweet is related to the topic/hashtag *#Amazon* and the second one contains two topics *#Job* and *#Houston*. The left side of Figure 1 shows three groups of hashtags represented by three colors. The weights in the graph measure the closeness between the hashtags and the calculation of these weights will be discussed in section 3. Using these relationships, when a user talks about certain topics, such as *#job*, we can recommend the tweets from other related topics based on the topic associations (e.g. *{#job, #hiring, #tweetmyjobs}*) so that the users can get more comprehensive information of what they want. Such close correlated topic associations can also reflect the relations among real world events. For example, the mining process reveals a topic association of *{#nbafinals, #cle, #gsw}*. As a matter of fact, hashtags *#cle* and *#gsw* are the two teams in the NBA finals 2015. The mining process reveals these three topics appearing in space and time proximity.

However, the detection of topic associations has several challenges. First, we need an appropriate measurement to evaluate the closeness between two or more topics. The second challenge is that each topic may have a large number of related tweets. We need algorithms scalable to large number of tweets and topics. More importantly, the closeness of topic associations can be different in different time and region. So we must take time-region frame into consideration to provide a more accurate measurement, which can make the calculation more complex and expensive. Finally, the detection may result in a large number of topic associations. So it is necessary to filter out the less interesting topic associations.

Topic Association First we define the closeness among topics by examining the co-occurrence of tweets containing these topics. Closely related topics may tend to be talked in the similar time and region. Based on this idea, we define the participation index of topic associations. If the tweets of a set of topics tend to be found in the same time and region, they will have a higher participation index. We evaluate this concept in our experiments by comparing the measuring results of participation index with the human judgment. Based on the concept of participation index, we propose three different types of queries to help users to extract topic associations with different semantics in different time-region frames.

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Figure 1: Closeness of topics and topic related tweets.

Mining Topic Association One of the challenges is that the number of tweets can be very large as well as the topics and their combinations. For example, in the sample we collected, there are 364,333 geo-tagged tweets that contain the hashtag *#job* in the U.S. in July, 2015. So how to develop an efficient algorithm to help to calculate the participation index of a set of topics will be the most important step. Here we propose a multi-layer geographic index and a time index to help us to filter the topic sets under the threshold quickly to calculate the participation index.

Optimization Another challenge in our work is the number of topics. Our dataset contains 492,492 hashtags. Any subset of these hashtags can be a potential topic association. To deal with the exponential nature of the hashtag associations, we propose two methods to optimize the mining algorithm: topic filtering and topic combination. In the topic filtering, we will remove some topics which are not affected by other topics or real world events. These topics participate in a large number of associations and the resulting associations are not interesting. Furthermore, we propose an algorithm to combine similar topics to further reduce the complexity.

This paper makes the following contributions:

- We define the participation index of a set of topics by measuring the time and location distributions of tweets containing the topics; We define three types of queries to answer questions related to topic associations;
- By introducing the time and location indexes, we propose an efficient algorithm to calculate the participation index;
- Topic filtering and topic combination methods are developed to optimize the querying results;
- We test our algorithm on a large Twitter dataset which contains 27,956,257 tweets and 492,492 hashtags. The results demonstrate that our method is effective and efficient.

The rest of the paper is organized as follows: In section 2 we introduce the related work. Section 3 provides the definitions of relationship between hashtags and three types of queries. In section 4, we describe the mining algorithm and in section 5, we propose two optimization methods. We evaluate our algorithm in section 6.

2. RELATED WORK

In the recent years, many researchers have shown interest in topic, trend, events and their correlation on social media. Different methods have been used to analyze tweet content including machine learning algorithms, language model, feature-based algorithms, information retrieval and many

more with help from spatiotemporal data mining. Petrovic et al. [15] employ a locality-sensitive hashing (LSH) to detect first story from a stream of tweets. The proposed approach uses hash table to organize new similar tweets in an existing story or labels. Although LSH has been used in nearest neighbor search applications, Protrovic's work makes event detection possible on large-scale tweets dataset. This approach does not differentiate the nature of events and content such as local event, disaster or news. Sakaki et al. [16, 17] classify tweets based on features such as keywords or word number and use a probabilistic spatio-temporal model to detect earthquakes from tweet content. The event location is estimated using Kalman filtering and particle filtering. The assumption of Sakaki's approach, is that only one event takes place in one region at a time and users know the event to set up keyword queries in advance.

Budak et al. [5] proposed a location-topic pair index using both tweet location and user location to detect geo-trends, or trends in different geographic locations in a sliding window. Kamath et al [10] did a thorough study of a tweet's hashtags as a representation of its topic. They did an analysis of the global footprint of hashtags and an exploration of the spatial constraints on hashtag adoption. They measure the hashtag's spatial propagation properties: focus, entropy, and spread. Lee et al. [12] tried to detect events such as traffic jams by using geographical coordinates of geotagged tweets and monitoring the geographical pattern of tweets. Sugitani et al. [20] use a different approach to detect events by using spatio-temporal clustering techniques. Schulz et al. [18] are the first in using a multi-indicator approach to get accurate geographic location of tweets and Twitter users.

Analysis of the time, location and hashtags of tweets can help to extract more meaningful information from real world events, trends, and roles in social networks. In [4], the authors detect trends which related to locations. Hashtags are also defined as topics of tweets here as well as [21] and three different thresholds are introduced to define the correlation between topics and locations. In [22], the authors propose a linear regression based approach to predict the spread of an idea in a given time frame. The hashtags are taken as the idea of tweets. Yang et al. [24] propose measurements to analyze the main factors of how users select hashtags and a machine learning model is used to help to predict the future adoption of hashtags of users. Kywe et al. [11] study the time distribution of hashtags, and then the authors propose a hashtag recommendation method based on collaborative filtering. In [13], the authors propose a geovisual analytics approach to leveraging Twitter in support of crisis management. The hashtags which are related to locations are used to extract more location information of tweets. By study-

Figure 2: Mining topic association in time-region frame $\langle w, r \rangle$. In this case, we set the time window w as the whole time line, which means every tweet is in the time window, and then we set r as the area circled in the dashed line. There are four hashtags (topics) in this example: #healthcare, #tech, #DataViz, and #mPoweringORB. Each topic is contained in several tweets. We firstly generate 3 size-2 (each topic association contains two topics) topic association and then generate a size-3 topic association.

ing the tweets related to 2011 London riots, Glasgow et al. [8] analyze emergent social networks directly relating to response to crisis. Their study shows that the hashtag lifespan may relate to social behaviors and social networks coupled to crisis response. Carter et al. [6] propose a method for translating hashtags, which builds on methods from information retrieval.

Co-location patterns [9, 25, 14] and efficient algorithms have been studied by various researchers. An initial summary of results on general spatial co-location mining was proposed in [19]. The authors proposed the notion of user-specified neighborhoods in place of transactions to specify group of spatial items. By doing so, they can adopt traditional association rule mining algorithms, i.e., Apriori algorithm [2] to find spatial co-location rules. An extended version of their approaches was presented in [9].

3. PROBLEM DEFINITION

In this section, we introduce the definition of participation index of topic association and three kinds of topic association queries. Table 1 gives the notations used in this paper.

Table 1: Notations and parameters

v_i	Tweet i
$t_i, l_i, \mathcal{H}_i$	The time, region and hashtags of tweet v_i
w, r	Time and region windows
W, R	Set of time and region windows
$h, \mathcal{H}$	Topic h and a set of topics $\mathcal{H}$
t, d, θ, k	Thresholds in query

A tweet v_i is represented by a triple $(t_i, l_i, \mathcal{H}_i)$, where t_i is the time when it is shared, l_i is the location where it is shared, and $\mathcal{H}_i$ is a set of hashtags contained in the tweet. For example, in the Figure 1, the triple for the first

tweet $v_1: (t_1, l_1, \mathcal{H}_1)$ has the time information *September 24*, location information l_1 , and the topics list $\{\#amazon\}$.

Definition[Topic] The topics of each tweet are defined as the hashtags it contains. One tweet can relate to several topics.

Let w and r denote time and region windows, and we define the pair of $\langle w, r \rangle$ as a *time-region frame*. Each frame corresponds to a set of tweets $V_{\langle w, r \rangle} = \{v_i | t_i \in w \wedge l_i \in r\}$.

Definition[Related Tweets] For each topic, its related tweets are the tweets which contain this topic. So the set of related tweets of topic h in a time-region frame $\langle w, r \rangle$ can be denoted as: $V_{\langle w, r \rangle}(h) = \{v_i | h \in \mathcal{H}_i \wedge t_i \in w \wedge l_i \in r\}$.

Definition[Topic Set] A topic set is a set of hashtags and denoted as: $\mathcal{H} = \{h_1, h_2, \dots\}$.

3.1 Calculating Participation Index

Definition[Neighbor Relationship] Two tweets, v_i and v_j , are neighbors when: 1) $|t_i - t_j| \leq \varphi$ and $|l_i - l_j| \leq \delta$ where φ and δ are two user given thresholds on time and distance.

Definition[Supporting Tweet] A set $V = \{v_1, v_2, \dots, v_k\}$ of k tweets supports a size- k topic set $\mathcal{H} = \{h_1, h_2, \dots, h_k\}$ if tweets in V are pairwise neighbors and $h_i \in \mathcal{H}_i$ for $i = 1, 2, \dots, k$. Each tweet v_i in the set V is called supporting $\mathcal{H}$ with h_i and the predicate $s(v_i, h_i, \mathcal{H})$ is true.

For example, in Figure 2, there are four topics and each topic has several related tweets. For topic sets $\{\#healthcare, \#tech, \#DataViz\}$, #healthcare.2, #tech.2, and #DataViz.2 are supporting tweets since they can form a size-3 clique.

Definition[Participation Ratio] The participation ratio of topic h in the topic set $\mathcal{H}$ in the time-region frame $\langle w, r \rangle$ is defined as:

$$pr_{\langle w, r \rangle}(h, \mathcal{H}) = \frac{|\{v_i | s(v_i, h, \mathcal{H}) \wedge v_i \in V_{\langle w, r \rangle}\}|}{|V_{\langle w, r \rangle}(h)|} \quad (1)$$

Definition[Participation Index] The participation index

of topic set $\mathcal{H}$ in time-region frame $\langle w, r \rangle$ is defined as:

$$pi_{\langle w, r \rangle}(\mathcal{H}) = \min_{h \in \mathcal{H}} pr_{\langle w, r \rangle}(h, \mathcal{H}) \quad (2)$$

For example, in Figure 2, topic $\#healthcare$ has 4 related tweets in the given time-region frame and topic $\#tech$ has 3. The tweets of them form 3 neighbor relations. Assuming $\mathcal{H} = \{\#healthcare, \#tech\}$, $pr(\#healthcare, \mathcal{H}) = 3/4 = 0.75$ and $pr(\#tech, \mathcal{H}) = 3/3 = 1$. So $pi(\mathcal{H}) = \min\{0.75, 1\} = 0.75$.

Definition[Topic Association] A topic set $\mathcal{H}$ is a topic association if its participation index meets a given threshold, and such topic set will be denoted as $\mathcal{H}_c$.

Figure 3: Vertical query, horizontal query, and super topic association query

3.2 Query

Each query $q(W_q, R_q, \varphi_q, \delta_q, \theta, k)$ contains six constraints: 1) A set of time windows $W_q = \{w_1, w_2, \dots\}$; 2) A set of region windows $R_q = \{r_1, r_2, \dots\}$; 3) Time threshold φ_q ; 4) Distance threshold δ_q and 5) A user given participation index threshold θ ; 6) A rank threshold k . Based on the return of queries, we define two kinds of queries: vertical query and horizontal query. Then we replace k with a topic set to define super topic association query which allows a user to find other topics associated with a topic set that he is interested in.

3.2.1 Vertical Query

A vertical query $q_v(W_q, R_q, \varphi_q, \delta_q, \theta, k)$ includes five constraints and a ranking threshold k . The Cartesian product of W_q and R_q defines a set of time-region frames, which are all the possible combinations of time and region windows, $\{\langle w, r \rangle | w \in W_q \wedge r \in R_q\}$. Each frame corresponds to a set of tweets $V_{\langle w, r \rangle}$. For each time-region frame $\langle w, r \rangle$, we will calculate the participation index of topic sets $\mathcal{H}$ using related tweets in $V_{\langle w, r \rangle}$, and query q_v will return the sets of topic associations with the participation indexes larger than θ and ranking in the top- k among all the topic sets.

3.2.2 Horizontal Query

Similarly, the horizontal query $q_h(W_q, R_q, \varphi_q, \delta_q, \theta, k)$ also has a ranking threshold k . For each topic set $\mathcal{H}$, we calculate its participation indexes $pi_{\langle w, r \rangle}(\mathcal{H})$ in different time-region frames $\langle w, r \rangle$ and then return the time-region frames with top- k highest values of $pi_{\langle w, r \rangle}(\mathcal{H})$. The number of returned frames may be less than k if there are less than k frames having participation index higher than the given threshold θ .

3.2.3 Super Topic Association Query

The super topic association query, $q_h(W_q, R_q, \varphi_q, \delta_q, \theta, \mathcal{H}')$, replaces k with a set of topics/hashtags $\mathcal{H}'$. For each time-region frames $\langle w, r \rangle$ in $W_q \times R_q$, it returns topic associations $\mathcal{H}$ where $\mathcal{H}' \subseteq \mathcal{H}$ and $pi_{\langle w, r \rangle}(\mathcal{H})$ larger than θ .

For example, Figure 3 shows the results of vertical query and horizontal query. W contains two time windows w_1 and w_2 , and R contains two regions r_1 and r_2 . Assuming $\theta = 0.25$, there are several hashtags and they can form topic associations in different time-regions frames. The participation index of each topic association is shown in the figure. For vertical query, assuming $k = 2$, it will return the top-2 topic associations in each frame. For example in $\langle w_1, r_1 \rangle$, it returns $\{\#deal, \#buy\}$ and $\{\#deal, \#bargains\}$ since their participation indexes are larger than the threshold and ranked in the top-2. For the horizontal query, it returns the top related time-region frames. For instance, the topic association $\{\#deal, \#bargains\}$ achieves highest participation index in $\langle w_2, r_2 \rangle$ and $\langle w_1, r_1 \rangle$. So when $k = 2$, it will return these two time-region frames for this topic association. For the super topic association query, assuming that the set of hashtags inputted is $\{\#deal\}$, it will return the associations in different time-region frames which contain $\#deal$.

4. MINING TOPIC ASSOCIATION

Given the definition of the participation index, we now propose algorithms for the queries of mining topic association.

4.1 Calculation of the Participation Index

When considering the neighbor relationship between tweets v_i and v_j , we redefine it as $|t_i - t_j| \leq \varphi_q$ and v_i and v_j are published in the same city because real world events are greatly affected by the geographic boundary. People may be interested in completely different topics in different cities even the distance between the two cities is short. Another reason is that sometimes we do not have an accurate location of tweet. We may only have the city level location from the tweets or from the profiles of authors. Finally, users may have a city level active area and they may publish tweets anywhere in the city they live.

From the definition of the participation ratio and index, we can see the most important step in detecting topic association is counting the number of supporting tweets of each topic h in $\mathcal{H}$ and calculating the participation index. The Algorithm 1 gives the process of this step.

Previous work has developed R-tree based [26] or grid based [23] index for spatial related search engines. In this problem, the tweets $V_{\langle w, r \rangle}(h)$ of each topic h are distributed in a three dimensions space, latitude, longitude, and time. Based on our definition of neighbor relationship, we use the bitmap index as the Topic Geographic Index $\mathcal{I}_T$ as shown in

Algorithm 1: Calculation of Participation Index

Data: Topic geographic index $\mathcal{I}_T$ and Time index $\mathcal{I}_c$,
 set of topics $\mathcal{H}$, time-region frame $\langle w, r \rangle$
Result: Participation index of hashtag set $\mathcal{H}$ in $\langle w, r \rangle$
 Begin:
 $Supporting[h] = 0$;
 Find cities containing topics in $\mathcal{H}$ by index $\mathcal{I}_T$, limited
 by region window r :
 $R(\mathcal{H}) = B(h_1) \cap B(h_2) \cap \dots, h \in \mathcal{H}$;
for Each c in $R(\mathcal{H})$ **do**
 Get the common effective time window by time
 index $\mathcal{I}_c$, limited by time window w :
 $W_{common}(\mathcal{H}) = W_{\langle w, c \rangle}(h_1) \cap W_{\langle w, c \rangle}(h_2) \cap \dots, h \in \mathcal{H}$
 ;
 for $h \in \mathcal{H}$ **do**
 Count the number n of tweets of topic h in
 $W_{common}(\mathcal{H})$ at c by the time index $\mathcal{I}_c$;
 $Supporting[h] = Supporting[h] + n$;
 end
end
 $pr_{\langle w, r \rangle}(h, \mathcal{H}) = \frac{Supporting[h]}{|V_{\langle w, r \rangle}(h)|}$ (Equation 1) ;
 $pi_{\langle w, r \rangle}(\mathcal{H}) = \min_{h \in \mathcal{H}} pr_{\langle w, r \rangle}(h, \mathcal{H})$ (Equation 2) ;
return $pi_{\langle w, r \rangle}(\mathcal{H})$

Figure 4. For each topic h , $\mathcal{I}_T$ contains the index $\mathcal{I}_T(h)$ of h which records the geographic distribution of tweets among cities related to topic h . If we divide the region window r into city level as: $r = \{c_1, c_2, \dots\}$, where c represents a city level region window, we can denote $V_{\langle w, r \rangle}(h)$ as $\{V_{\langle w, c_1 \rangle}(h) \cup V_{\langle w, c_2 \rangle}(h) \cup \dots\}$. Each time index in a city c corresponds to a set of tweets $V_{\langle w, c \rangle}(h)$ if it is not empty (topic h has at least one tweet in region c during the time windows in w), and we denote the set of these cities c as $B(h)$.

Then we apply an Time index $\mathcal{I}_c(h)$ on the time dimension on each set of tweets $V_{\langle w, c \rangle}(h)$ as it is shown in Figure 4. Every tweet v_i of topic h at city c has an “effective period” $[t_i - \varphi_q, t_i + \varphi_q]$ defined by the user given time threshold φ_q in the query. The union of the effective periods of tweets in $V_{\langle w, c \rangle}(h)$ is the total effective periods of topic h in the city c and denoted as $W_{\langle w, c \rangle}(h)$. So based on the definition of neighbor relationship, for a tweet v_j of another topic, if v_j was published at city c and during the period of $W_{\langle w, c \rangle}(h)$, we can find at least one tweet v_i of topic h which has neighbor relation with v_j .

Algorithm 1 provides the process of the calculation of participation index. Given a set of topics $\mathcal{H}$ and the time-region frame $\langle w, r \rangle$, we firstly find the cities which contain tweets of every topic h in $\mathcal{H}$. For each topic h , we have the topic geographic index $\mathcal{I}_T(h)$ to help to get the set of cities which have related tweets of h and we denote the set of cities as $B(h)$. So the intersection of all $B(h)$, $h \in \mathcal{H}$, is the set $R(\mathcal{H})$ of cities containing related tweets of every topic in $\mathcal{H}$.

Based on our definition of neighbor relation, for a tweet $v_i(t_i, l_i, \{h_i\})$, $l_i \in c$, we can find a neighbor v_j related to another topic h_j only when h_j has tweets published in city c and $t_i \in W_{\langle w, c \rangle}(h_j)$. For a set of topics, we can calculate the effective period $W_{\langle w, c \rangle}(h)$ of each topic in a city c . The common effective period of the topics is denoted as $W_{common}(\mathcal{H})$. For each topic h in $\mathcal{H}$, if it has a related tweet v published in $W_{common}(\mathcal{H})$ in city c , we can find

Figure 4: Calculation of participation index of topic sets $\mathcal{H}$: There are two topics in this example, $\#Topic A$ and B . $\#Topic A$ has related tweets distributed in two cities. We use the bitmap index $\mathcal{I}_T$ to record cities which has tweets related to $\#Topic A$. For the tweets in each city, e.g. the tweets related to $\#Topic A$ in $City.3$, we will use the Time Index $\mathcal{I}_c$ to record the beginning and ending time of the effective period and the tweets published during these periods.

at least one neighbor tweet from other topics in $\mathcal{H}$. So v will be a supporting tweet for $\mathcal{H}$. In Algorithm 1, for each city c in $R(\mathcal{H})$, we use the time index of tweets in city c of topic h , $\mathcal{I}_c(h)$, which records the begin and end time of each effective period and the tweets published during the period, to achieve the common period $W_{common}(\mathcal{H})$. Tweets of each topic in $W_{common}(\mathcal{H})$ will be counted as supporting tweet for $\mathcal{H}$. After scanning all the cities in $R(\mathcal{H})$, we can calculate the participation ratio of h by the number of supporting tweets and get the participation index of $\mathcal{H}$.

4.2 Calculation of Horizontal Query

For the horizontal query, we need to generate all the topic associations in each time-region frame. Algorithm 2 provides this process. For each $\langle w, r \rangle$ frame in $W_q \times R_q$, we firstly put every topic in the set of a size-1 topic association $\{\mathcal{H}_c\}_1^{\langle w, r \rangle}$. In each loop, we use the apriori-gen algorithm [2] to generate size- n topic association candidates $\{\mathcal{H}\}_n$ by size- $(n-1)$ topic association $\{\mathcal{H}_c\}_{n-1}^{\langle w, r \rangle}$. Then we use the Algorithm 1 to calculate the participation index of every candidates and get the size- n topic association. After generating topic associations in every $\langle w, r \rangle$ frames, we will return every topic association $\mathcal{H} \in \{\mathcal{H}_c\}$ and the top- k frames which $\mathcal{H}$ achieves the highest participation index.

4.3 Calculation of Vertical Query

As shown in Algorithm 3, for each time-region frame $\langle w, r \rangle$, after we generate size- n topic association, we will prune the topic association by removing the association ranking out of k in $\{\mathcal{H}_c\}^{\langle w, r \rangle}$ because such topic association cannot be a subset of a topic association which has a higher participation index.

4.4 Calculation of Super Topic Association Query

The algorithm of super topic association query is based on the method of vertical query. The difference is that the process will begin at generating size- $(|\mathcal{H}'| + 1)$ topic association candidates and these candidates must contain all the hashtags in $\mathcal{H}'$.

Algorithm 2: Horizontal Query

Data: Tweets $vt, l, \mathcal{H}$, topic geographic index $\mathcal{I}_T$, time index $\mathcal{I}_c$, set of topics $\mathcal{H}$, time-region frame $\langle w, r \rangle$, query $q_h(W_q, R_q, \varphi_q, \delta_q, \theta, k)$
Result: Topic association $\{\mathcal{H}_c\}$ and top-k $\langle w, r \rangle$ frames with highest participation index of each topic association $\mathcal{H}_c$

initialization;
 $\{\mathcal{H}_c\} = \phi$;
for $\langle w, r \rangle \in W_q \times R_q$ **do**
 $\{\mathcal{H}_c\}^{\langle w, r \rangle} = \phi$;
 Add all topics to $\{\mathcal{H}_c\}_1^{\langle w, r \rangle}$;
 for $n = 2; \{\mathcal{H}_c\}_{n-1}^{\langle w, r \rangle} \neq \phi; n++$ **do**
 $\{\mathcal{H}\}_n = \text{apriori} - \text{gen}(\{\mathcal{H}_c\}_{n-1}^{\langle w, r \rangle})$ //Generate new topic association candidates ;
 for $\forall \mathcal{H} \in \{\mathcal{H}\}_n$ **do**
 Calculate the participation index of $\mathcal{H}$ by Algorithm 1 ;
 end
 $\{\mathcal{H}_c\}_n^{\langle w, r \rangle} = \{\mathcal{H} | pi_{\langle w, r \rangle}(\mathcal{H}) \geq \theta \wedge \mathcal{H} \in \{\mathcal{H}\}_n\}$;
 end
 $\{\mathcal{H}_c\}^{\langle w, r \rangle} = \cup_n \{\mathcal{H}_c\}_n^{\langle w, r \rangle}$;
 $\{\mathcal{H}_c\} = \{\mathcal{H}_c\} \cup \{\mathcal{H}_c\}^{\langle w, r \rangle}$;
end
for $\mathcal{H} \in \{\mathcal{H}_c\}$ **do**
 Get the top-k $\langle w, r \rangle$ frames with highest $pi_{\langle w, r \rangle}(\mathcal{H})$;
end
return $\{\mathcal{H}_c\}$ and top-k $\langle w, r \rangle$ frames for $\mathcal{H} \in \{\mathcal{H}_c\}$

Algorithm 3: Vertical Query

Data: Tweets $vt, l, \mathcal{H}$, topic geographic index $\mathcal{I}_T$, time index $\mathcal{I}_c$, set of topics $\mathcal{H}$, time-region frame $\langle w, r \rangle$, query $q_v(W_q, R_q, \varphi_q, \delta_q, \theta, k)$
Result: Top-k topic association with highest participation index in every time-region frames

initialization;
for $\langle w, r \rangle \in W_q \times R_q$ **do**
 $\{\mathcal{H}_c\}^{\langle w, r \rangle} = \phi$;
 Add all topics to $\{\mathcal{H}_c\}_1^{\langle w, r \rangle}$;
 for $n = 2; \{\mathcal{H}_c\}_{n-1}^{\langle w, r \rangle} \neq \phi; n++$ **do**
 $\{\mathcal{H}\}_n = \text{apriori} - \text{gen}(\{\mathcal{H}_c\}_{n-1}^{\langle w, r \rangle})$ //Generate new topic association candidates ;
 for $\forall \mathcal{H} \in \{\mathcal{H}\}_n$ **do**
 Calculate the participation index of $\mathcal{H}$ by Algorithm 1 ;
 end
 $\{\mathcal{H}_c\}_n^{\langle w, r \rangle} = \{\mathcal{H} | pi_{\langle w, r \rangle}(\mathcal{H}) \geq \theta \wedge \mathcal{H} \in \{\mathcal{H}\}_n\}$;
 $\{\mathcal{H}_c\}^{\langle w, r \rangle} = \cup \{\mathcal{H}_c\}_n^{\langle w, r \rangle}$;
 Prune topic association in $\{\mathcal{H}_c\}^{\langle w, r \rangle}$ and $\{\mathcal{H}_c\}_n^{\langle w, r \rangle}$ by only keeping the topic association with the participation index ranking in the top-k in $\{\mathcal{H}_c\}^{\langle w, r \rangle}$;
 end
end
return $\{\{\mathcal{H}_c\}^{\langle w, r \rangle} | \langle w, r \rangle \in W_q \times R_q\}$

5. OPTIMIZATION OF QUERYING RESULT

5.1 Topic Combination

Many topic pairs or groups refer to the same thing or same event. These topics may share similar words and be talked in same area and same time (e.g. *#amazonwishlist* and *#amazoncart*). Some official Twitter accounts even list several hashtags and tell users that all these hashtags are related to the same thing, for example, *#choicetvchemistry* and *#choicetvcliplock* in Table 2. If such a hashtag group contains n hashtags, it may generate 2^n topic associations. It increases computation time and leads to a huge number of redundant associations. So before we apply our algorithm, we will combine some hashtags which are related to the same thing together to make the algorithm more efficient, and less number of detected results can help to extract useful topic associations more easily.

We combine the hashtags in two steps: First, we build a hashtag similarity graph. Each hashtag is a node in this graph and there is an edge between every hashtag pair. We assign each edge a weight as:

$$\begin{aligned} \text{Weight}(\text{hashtag}_1, \text{hashtag}_2) \\ = \frac{|\text{Total longest common substring}|}{\max\{|\text{hashtag}_1|, |\text{hashtag}_2|\}} \end{aligned} \quad (3)$$

We follow the method in [7] to get the longest substring. We remove the longest common substring of the two hashtags iteratively until there is no common substring longer than 1. For example, the longest substring of *#amazonwishlist* and *#amazoncart* is “amazon” and the weight of the edge is 0.43.

Then we run the hierarchical clustering algorithm on this graph. The distance between two clusters is defined as the average weight of edges between hashtags in these two clusters. However, we have two other problems: 1) when we stop the hierarchical clustering, some hashtags share long common substrings but actually they do not refer to the same thing (e.g. *#braves* and *#travel*). Table 2 lists more examples. All these examples are similar strings but their participation index is 0.

To solve these problems, we introduce the participation index here. Before we combine two clusters together, we will calculate the participation index of the new cluster. If it is less than the threshold, we won’t combine them and we will go to next two clusters with highest average weight of edges. If all the top-N candidates cannot meet the requirement, we will stop the hierarchical clustering. Table 2 shows that the use of participation index in topic clustering can filter out hashtags “similar in appearance but dissimilar in spirit”.

5.2 Topic Filtering

Many topics follows a rhythm of a typical day. For example, they happen more when there are more people using Twitter such as lunch time. These topics such as job advertisement are white noises and do not related to other topics. Here we propose a method to filter out these topics to prevent them from participating in most topics associations.

In a time-region frame $\langle w, r \rangle$, we calculate the correlation coefficient between topic h and all the topics by their distributions of number of tweets in each city c in r during the time window w as:

Table 2: Apply participation index in topic combination

Topic Pairs	Wt	PI
<i>tamuc, tamuk</i>	0.8	0
<i>longlivelya, longlivejr</i>	0.8	0
<i>rays, raya</i>	0.75	0
<i>live, livy</i>	0.75	0
<i>freedom, freedex</i>	0.71	0
<i>amazoncart, amazonwishlist</i>	0.42	0.95
<i>phillies, philly</i>	0.625	0.81
<i>travelnursing, travelhealthcare</i>	0.375	0.68
<i>nationaldonutday, nationaldoughnutday</i>	0.84	0.48
<i>choicetvchemistry, choicetvcliplock</i>	0.47	0.43

Figure 5: The distribution of tweets of different topics in New York and Austin.

$$Cor(h, \mathcal{H}_{total}) = \frac{\sum_{u=1}^n (|v_u^h| - |\overline{v_u^h}|)(|v_u^{\mathcal{H}}| - |\overline{v_u^{\mathcal{H}}}|)}{\sqrt{\sum_{u=1}^n (|v_u^h| - |\overline{v_u^h}|)^2 \sum_{u=1}^n (|v_u^{\mathcal{H}}| - |\overline{v_u^{\mathcal{H}}}|)^2}} \quad (4)$$

Here, $V_{\langle u, c \rangle}(h) = \{v_1^h, v_2^h, \dots\}$, $V_{\langle u, c \rangle}(\mathcal{H}) = \{v_1^{\mathcal{H}}, v_2^{\mathcal{H}}, \dots\}$, and u denotes a unit of time, such as one day.

When a topic correlates with total volume of the tweets above a threshold, there tweets are considered as uninteresting and are excluded from the topic association mining. Figures 5(a) shows that *#nyc* is a topic highly correlated to the number of tweets in New York during a day while *#texas* (correlation index of 0.87) is not. In Austin however as shown in Figure 5(b), *#texas* is a highly correlated topic (correlation index of 0.87) while *#nyc* and *#nbafinals* are not. *#job* is a highly correlated topic in both cities. So the topics like *#job* will not be considered in topic association

mining since such topics are not effected by other topics or real world events.

6. EXPERIMENT

In this section, we first introduce the data set used in the experiment. Then we evaluate the effect of parameters of queries by comparing the running time of each query. Finally, we demonstrate the experiment results in some time-region frames to explain the meaning of the topic association. We show the results of topic filtering. We compare the results produced by our algorithms with human judges.

6.1 Data

We collected tweets published from May 21 to June 15, 2015 using Twitter Streaming API¹ with the spatial bounding box $[24^\circ 3'N, 127^\circ 7'W, 48^\circ 8'N, 65^\circ 5'W]$, which covers U.S. mainland. The dataset consists 27,956,257 tweets from 492,492 topics. We removed the topics with less than 1,000 related tweets, and finally we selected 10,201,960 tweets which contain both geotag and hashtag from 2,000 topics.

6.2 Detecting Topic Association

Firstly, we evaluate the effect of different parameters on the running time. Table 3 gives the list of parameters and the default values.

Number of Topics

Figure 6(a) shows the running time of vertical query and horizontal query under different number of topics. More topics means more topic associations under the same settings and the increase of number of topic associations can be exponential in the worst case. The running time in Figure 6(a) shows this trend. In our algorithm, each topic will have a time index in each city and a geographic index to record its distribution. So the increase of the number of topics will take more memory to store the indexes but it has little influence on the running time of calculating the participation index.

Time-region Frame

In this experiment, we use four parameters to describe the time-region frame. W_q and R_q are largest time and region frame and W_{gran} and R_{gran} are used to divide the largest time and region frames into smaller ones, i.e. we divide W_q and R_q based on the length of W_{gran} and R_{gran} .

Firstly, we test the influence of the region window R_q . We divide the cities in U.S. into 1 to 32 groups equally and record the average querying time on these groups. Figure 6(b) gives the results of this experiment. The numbers on x-axis represent the R_{gran} proportion of each group of the total region window. For example 1/2 means that we divide the whole area of the U.S. into two groups and y-axis is the average running time of the queries on these two groups. The results show that the running time has a linear relationship with the scope of the region window, e.g. the running time of two groups is about half of the “total” case and twice as much as the “1/4” case. The two queries perform differently in the “city” case, where we set each city as the region window. Running the queries in city granularity will generate a large number of topic associations. So the horizontal query has

¹<https://dev.twitter.com/streaming/overview>

Table 3: Parameters used in queries

Parameter	Definition	Default value	Test scope
$N_{\mathcal{H}}$	The total number of topics used	1,000	[100, 2000]
W_q	The total time windows	20 days	[1, 20]
R_q	The total region window	US	[city level, U.S.]
W_{gran}	The granularity of time window	1	[1, 20]
R_{gran}	The granularity of region window	1	[city level, U.S.]
φ_q	Time threshold in the definition of neighbor relation	1 hour	fixed
δ_q	Distance threshold in the definition of neighbor relation	City level	fixed
θ	The threshold of the participation index	0.8	[0.04 0.8]
k	The ranking threshold of the query	40,000	[500 40,000]

Figure 6: Running time under different setting of parameters.

a longer running time since vertical query can prune more topic association candidates. We will provide more analysis in the following section.

The influence of time window size is shown in Figure 6(c). Similar as the results of changing the total region window, the running time has linear relationship with the time window. The increase of time and region window needs additional indexes to record the distribution of new tweets. If we only increase the region window, for each topic set, we need to scan more cities to calculate the participation. If we increase the time window only, for each city we need to scan a larger time window by the time index. That explains why the running time increases linearly with the region and time window.

Then we fixed the largest time and region windows and change the granularity of the sub-time and sub-region windows. If we set smaller smaller time or region window, each query will be faster, but the query needs to be executed more times. When changing the granularity of the region window (Figure 6(d)), we can see that the total running time does not change too much. It only increases in the “state” case because some state only contains one city and the query will take longer time. Figure 6(e) is the results of the running time of different time window granularities. The total running time can be smaller when we set a longer time window granularity. Actually, we can estimate the results in Figure 6(d) and 6(e) by the results in Figure 6(b) and 6(c).

Threshold on Participation Index

The threshold of the participation index greatly affects the number of topic associations. As shown in Figure 6(f), with the decreasing of the value of the threshold θ , the running time increase quickly since there will be an exponential growth of the number of topic associations. Here the ranking threshold k of the vertical query is big enough, so the optimization is not useful and the running time of both the two queries is similar.

Top-K Selection

In Figure 6(g) and 6(h), we test the influence of the ranking threshold k of vertical query. In these two experiments, we set the value of the threshold of participation index θ as 0.8 and 0.12 separately. In both the two cases, the ranking threshold greatly affects the running time. So when this threshold is not large enough, during the generating step, we can prune a part of topic associations which have their participation index larger than the threshold θ . So the running time of the vertical query will be much smaller than the horizontal query. With the increase of the ranking threshold k , the gap of the running time of the two queries becomes smaller.

6.3 The Topic Association

In this experiment, we use the results of the two queries

Table 4: Vertical Query

City:	New York	Chicago	Houston
1	braves, bruins	rockets, rays	traffic, houstonastros
2	nationaldonutday, uclfinal	astros, rockets	traffic, houstontexans, houstonastros
3	sundayfunday, sunday	astros, rockets, rays	traffic, houstontexans
4	gsw, nbafinals2015	astros, rays, texasedmfamilly	houstontexans, houstonastros
5	nbafinals, cle	rockets, rays, texasedmfamilly	whodatnation, gramfam

to show that our algorithm can detect meaningful topic associations. We also compare the results with/without the topic filtering method.

Vertical Query

Table 4 shows the top-5 topic associations (sorted by participation index) in New York, Chicago, and Houston from May 25 to Jun 15. The relationship between hashtags in most topic associations can be easily revealed by investigating the real world event they refer to. For example, “#gsw, #nbafinals2015” and “#nbafinals, #cle”, #gsw and #cle refer to the two teams which play against in the NBA final, 2015.

Horizontal Query

Table 5: Horizontal Query

	gsw, nbafinals2015	nbafinals, cle
Frame 1	New York, June 7	New York, June 7
Frame 2	New York, June 4	New York, June 4
Frame 3	New York, June 16	New York, June 14

Table 5 shows examples of horizontal query results. Here we select two topic associations in Table 4, *gsw, nbafinals2015* and *nbafinals, cle*. For the first topic association, the days when it achieve highest participation indexes is June 7, 4, and 16, and for the second example, they are June 7, 4, and 14. If we check the schedule of NBA finals in 2015, we will find that there exists a match in all these days. So we can see that the horizontal query will return the most related time-region frames.

Super Topic Association Query

Table 6 lists two examples for super topic association query. We set $\mathcal{H}'$ as $\{\#nbafinals\}$ and $\{\#amazoncart\}$ and the query returns the topic associations containing those hashtags.

Table 6: Super Topic Association Query

#nbafinals	PI	#amazoncart	PI
#gsw	0.79	#amazonwishlist	0.95
#cle	0.76	#einkaufen	0.94
#nbafinals2015	0.71	#bargains	0.92

Topic Filtering

In Table 7 we compare the querying results with and without the topic filtering. We apply the same settings with the experiment for vertical query. Here we list the top-5 topic associations which have the highest participation indexes in

New York from May 25 to Jun 15. If we do not apply the topic filtering method, we will detect lots of topic associations including *nyc, newyork* and *job, hiring*. They have a very high participation index because people discuss about them every often and they can form supporting cliques easily. After we filter such topics, we can see that Wthe new results are more meaningful. Most of them are caused by some real world event.

Table 7: Topic Filtering

Before Filtering	After Filtering
nyc, newyork	braves, bruins
job, hiring	nationaldonutday, uclfinal
job, nyc	sundayfunday, sunday
job, newyork	gsw, nbafinals2015
hiring, jobs	nbafinals, cle

6.4 Effectiveness of Participation Index

To verify the effectiveness of participation index, which greatly effects the final results, we compare the experiment results with human judgment in this experiment. Since it is difficult to give an appropriate measurement to judge the tightness between topics, we only compare the tightness of topic sets. First we create topic set groups. Each topic set group contains 5 topic sets and each topic sets contain two topics. The participation indexes of these five topic sets should be in the range of $(0, 0.05]$, $(0.05, 0.15]$, $(0.15, 0.3]$, $(0.3, 0.45]$, and $(0.45, 1]$ respectively. The gap of participation indexes of each two topic set should be larger than 0.05. Based on the participation indexes, we can get a rank of these topic sets X . Then we manually compare the tightness of topic sets in the same group and give a rank Y based on their judgment. To make the judgment easier and more accurate, the topic sets in the same group will share a common topic. Finally, we use Spearman’s rank correlation coefficient to compare the human judgment with the experiment (rank based on the participation index).

$$\rho = 1 - \frac{6 \sum (x_i - y_i)^2}{n(n^2 - 1)} \quad (5)$$

The x_i and y_i is the ranking of the i th element in the topic set group given by participation index and human judgment. Since we fix the size of topic set group as five, the value of n is 5. The average value of the Spearman’s rank correlation of our 200 cases is 0.68, which illustrates that the participation index can measure the tightness of topics effectively. Figure 7 shows the distribution of the values of the Spearman’s rank correlation coefficient. Most cases have the Spearman’s rank correlation coefficient larger than 0.4 and 40 percent cases have the value larger than 0.8.

Figure 7: Compare the ranking based on the participation indexes with the human judgment.

7. CONCLUSION

In this paper, we apply participation index as the measurement of topic closeness. We define three different kinds of queries to mining the topic association. For each query, we design the algorithm for it. Two optimization methods, topic filtering and topic combination are used to help getting a better query results. We test our method on a large Twitter data set with 27,956,257 tweets which contain both hashtags and geo-tag. The results of the experiment show that the mining algorithms are effective and efficient. We also compare the experimental results with human judgment to verify the effectiveness of using participation index to measure the closeness among topics.

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