Time-series Visualization of Twitter Trends

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Abstract: Twitter provides a function called "trend" that presents popular words and hashtags. Typically, one trend word or hashtag is related to thousands of tweets. It is difficult to understand such thousands of tweets in a short time by using the standard sort methods and the standard display method provided by Twitter. Most of previous studies analyzed and visualized tweets by using text-based clustering methods. However, these methods suffer from the accuracy of clustering results, because a typical tweet has only poor textual information. This paper presents a Twitter trend analysis system that combines retweet clustering and time-series visualization to allow users to understand flows of topics in a Twitter trend in a short time. This system also provides a list of effective legends and a display of individual tweets with photos in order for users to further understand topics in a trend. To illustrate the effectiveness of this system, this paper presents the results of experiments on the analysis of Twitter trends related to a popular sport event and a popular music program.

1 INTRODUCTION

Twitter provides a function called "trend" that presents popular words and hashtags (Twitter, inc., 2017). Twitter trends are determined from words that appear in many tweets (that are messages in Twitter) by Twitter's specialized algorithm, and they are provided to users based on the accounts that they follow and their locations and interests. One trend is typically related to thousands of tweets and sometimes to over one hundred thousand tweets. It is difficult to understand such thousands of tweets in a short time by using the standard sort methods like "Top" or "Latest" and the standard display method that shows tweets in one line.

Most of previous studies analyzed and visualized tweets by using text-based clustering methods. However, these methods suffer from the accuracy of clustering results, because a typical tweet has only poor textual information. Twitter restricts the length of a tweet to at most 140 characters for certain Asian languages and to at most 280 characters for other languages. In addition, many tweets have only short sentences, and many other tweets have only photos and links to web pages. Therefore, it is difficult to classify these tweets correctly by text-based clustering methods.

In this paper, we present an interactive Twitter trend analysis system that combines retweet clustering and time-series visualization to allow users to understand flows of topics in a Twitter trend in a short time. Retweet is a quotation function in Twitter; when a user retweets a tweet, a new tweet that has a link to the original tweet is posted to the user's account, and the user can spread and discuss the tweet. We use a retweet clustering method (Uchida, Toriumi, & Sakai, 2017) that classifies tweets based on degrees of similarities. Retweet clustering determines a degree of similarity between a pair of tweets by the multiplicity of the users who retweeted both tweets, and then it generates clusters so that their similarity degrees are small. We regard such a cluster as a distinct topic and consider that a cluster has a unique topic. To show flows of topics in a simple and clear manner in chronological order, we use a time-series visualizing method called ThemeRiver (Harve, Hetzler, Whitney, & Nowell, 2002).

It is still difficult to understand the result because each cluster has little information that describes its topic. To solve this problem, we additionally generate effective legends, which is one of our main contributions. We use morphological analysis to extract typical words and show such words as legends.

To generate such legends, we use a set of documents, each of which consists of all text of tweets in a cluster except URLs and the corresponding Twitter

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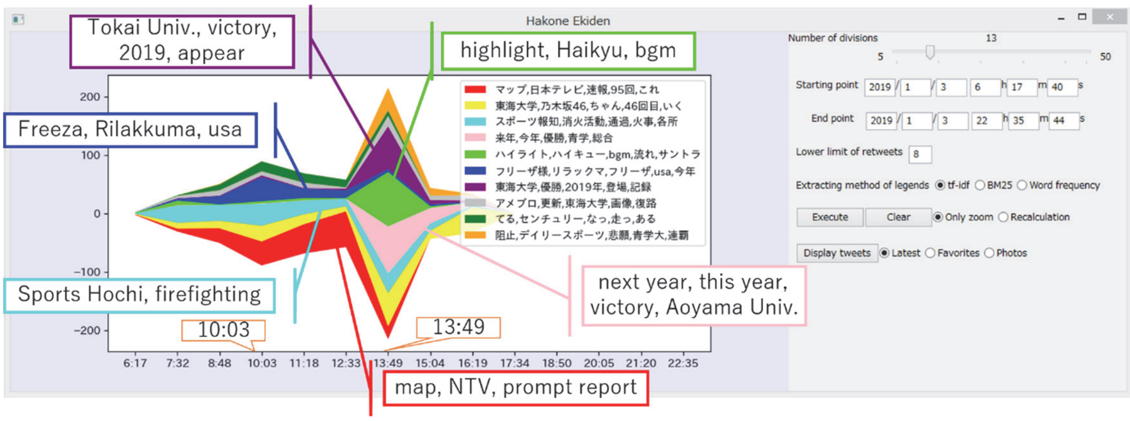


Figure 1: Visualization of tweets related to a Twitter trend “Hakone Ekiden” with legends extracted with tf-idf.

trend keyword. We present multiple methods for extracting words, and the user can switch them if the user wants. This system also supports the analysis of tweets by changing conditions, the lowest number of retweets, and the range and the number of division of time scales, which allows the user to obtain different interesting results. In addition, the system displays individual tweets including photos and URLs by multiple methods for ordering tweets. We also present a function for zooming in an interested area based on the values specified by the user.

Our experimental results showed that this system made it easy to understand flows of topics in Twitter trends in a short time. In a clustering result, tweets that did not have the same words in their text but that essentially had the same topic were classified in the same cluster. We support the users in understanding these clusters by a display of individual tweets because it is sometimes difficult to understand these clusters only from generated legends. We also visualize flows of topics in further detail by narrowing the range of time scales and zooming in an interested area.

2 RELATED WORK

2.1 Twitter’s Trend Function

There have been a few studies related to Twitter’s trend function. [1] Gillespie evaluated the reliability of Twitter’s algorithm for extracting trends (Gillespie, 2011). He mentioned that hashtags such as “#occupywallstreet” and “#wikileaks” did not appear as Twitter trends in spite of the fact that they seemed to become popular in Twitter. Zubiaga et al. classified Twitter trends into four specific themes (i.e., news, ongoing events, memes, and commemoratives) in real time (Zubiaga, Spina, Matrinez, & Fresno, 2014). Their classification was based on early tweets that were potential for yielding Twitter trends, in order to classify Twitter trends as early as possible. Unlike our work, they did not perform the analysis of tweets inside Twitter trends.

2.2 Time-series Visualization of Twitter

There has been much research on the time-series visualization of Twitter. Senticompass (Wang, Sallaberry, Klein, Takatsuka, & Roche, 2015) visualized a classification result in one period of time as a ring-shaped histogram that put it in chronological order on a concentric circle. EvoRiver (Guodao, et al., 2014) employed a river metaphor visualization and represented a topic as a strip. It used multidimensional information, and painted the positive/negative competition and other types of opinion leaders in different colors. OpinionFlow (Wu, Liu, Yan, Liu, & Wu, 2014) visualized the diffusion of opinions among many users in topics. It used two visualizing methods, a stacked tree for showing the hierarchical structure of topics and a combination of a Sankey diagram with a density map to display the dynamics of opinion flows. Xu et al. visualized relations between opinion leaders and topics by using ThemeRiver (Xu, et al., 2013). It displayed strengths of topics in gray scales and types of opinion leaders in colors. These two studies visualized topics across users.

[1] We mean “trends” that are provided as part of Twitter’s social networking service and are widely used by many Twitter users. In this paper, we do not consider trends in a more general sense.

3 RETWEET CLUSTERING

We use Uchida et al.'s retweet clustering method (Uchida, Toriumi, & Sakai, 2017) to classify tweets. This method decides the degree of similarity between a pair of tweets by the multiplicity of the users who retweeted both tweets. This method assumes that the tweets retweeted by the same users have a common topic. Users retweet tweets when they want to discuss or spread them; in other words, retweeted tweets reflect the users' interests and preferences.

The method consists of three steps. First, it calculates the degree of similarity between a pair of tweets by using the multiplicity of the users who retweeted both tweets. For a tweet i and a user j, define $r_{i,j}$ as follows:

$$r_{i,j} = \begin{cases} 1 & \text{if user } j \text{ retweets tweet } i \\ 0 & \text{otherwise} \end{cases}$$

It defines a row vector $\boldsymbol{t}_i$ that corresponds to tweet i as follows (U denotes the number of the users in the dataset):

$$\boldsymbol{t}_i = \left(r_{i,0}, r_{i,1}, \dots r_{i,U}\right)$$

It calculates the degree of similarity between tweets i and j by using the following Simpson coefficient:

$$\mathrm{sim}\left(\boldsymbol{t}_i, \boldsymbol{t}_j\right) = \frac{\boldsymbol{t}_i \cdot \boldsymbol{t}_j}{\min(|\boldsymbol{t}_i|, |\boldsymbol{t}_j|)}$$

Second, it calculates the similarities of all pairs of tweets in the dataset. Then it links the N most similar pairs of tweets to construct a weighted undirected graph.

Finally, it clusters the weighted undirected graph by using the Louvain method (Blondel, Guilaume, Lambiotte, & Lefebvre, 2008), which is the clustering method based on modularity that represents degrees of connectivity among a set of clusters. It calculates a clustering in which weights between tweets in the same cluster become large while weights between tweets in different clusters become small.

4 PROPOSED METHOD

In this paper, we construct a system for analyzing tweets related to Twitter trends by combining Uchida et al.'s retweet clustering and Harve et al.'s ThemeRiver. We obtain datasets by searching for keywords of Twitter trends. Since a visualization result itself does not describe the topics of a Twitter trend, our system additionally generates legends and displays individual tweets. Legends are generated by the morphological analysis of the text of tweets in each cluster. It displays individual tweets with photos and URLs for each cluster.

4.1 Retweets Clustering

We generate multiple topics from a single Twitter trend by using Uchida et al.'s retweet clustering method, which we explained in Section 3. By applying this method to a Twitter trend, we obtain a set of clusters, each of which we regard as a distinct topic. We change the second step of the retweet clustering method; instead of processing all pairs of tweets in the dataset, we process approximately 1500 tweets that have retweets between the user-specified lower limit and the relevant upper limit. This reduces the amount of calculation, guarantees the repeatability of the clustering result, and adapts the system to user interaction.

4.2 Visualization using ThemeRiver

Our system visualizes a Twitter trend as shown in Figure 1, on the left side of which it uses ThemeRiver to visualize a clustering result. ThemeRiver is basically a stacked graph that is symmetric along a horizontal line, and visualizes a time series of multiple topics like a river flow, assigning different colors to the topics. We adopt the ThemeRiver visualization because it shows flows and strengths of topics in a simple and clear manner.

In our system, each flow in a specific color corresponds to a single topic in a Twitter trend. It uses the vertical and the horizontal axis for the numbers of tweets and the time series respectively. The system visualizes the ten highest clusters in the descending order of tweets.

4.3 Generating Legends

As shown in Figure 1, our system provides the legends of clusters on the right side of the ThemeRiver visualization, using the same colors as those of the flows in ThemeRiver. We generate the legend of each cluster by using morphological analysis and information retrieval techniques. Specifically, the system adopts three methods to generate legends. One is a word frequency method, and the other two are tf-idf and BM25 (Robertson, Walker, Jones, Hancock-Beaulieu, & Gatford, 1994). For these methods, we generate a set of documents, each of which consists of all text of tweets in a cluster except URLs and the corresponding Twitter trend keyword. This increases the number of words that are candidates of legends. We extract nouns, verbs, and adjectives as words from documents. The word frequency method simply counts the frequencies of words in each document, and extracts the five most words as legends. Tf-idf is a method for measuring how important a word is for a document, and BM25 introduces the concept of document lengths into tf-idf. The three methods for generating legends can be switched from one to another to obtain different results.

4.4 Displaying Individual Tweets

Our system displays individual tweets to allow its user to actually read and see them. It is sometimes difficult to understand topics from legends because tweets in a cluster share few words or because they mainly contain photos instead of words. The system lists tweets in each cluster together and sorts them from the newest to the oldest, in the descending order of favorites, or in the descending order of attached photos. As shown in Figure 2, the system displays tweets in the same cluster in line as Twitter's standard display method does. The system also allows its user to switch among clusters by selecting tabs. For each tweet, the system shows its user name, post time, text, photos, and links to URLs. The system first displays the ten highest tweets in the sorted result.

Figure 2: Displaying individual tweets (related to the blue cluster in Figure 1 and sorted in the order of favorites).

When the user scrolls down to the bottom of the window, the system displays the next ten highest tweets.

5 IMPLEMENTATION

Our system provides a GUI that allows changing the starting and ending points of the time series, the number of division of the time series, the lower limit of the number of retweets, and the method for generating legends. It also provides radio buttons (on the right side of the "Execute" button) that allows selecting the way to apply these changes. In the case of "Only zoom", it redraws the ThemeRiver visualization to reflect the changes, while keeping the already calculated clustering result. In the case of "Recalculation", it draws a new ThemeRiver visualization after reconstructing the internal weighted undirected graph by applying the changes and performing the clustering again.

The system is based on the concept of Visual Information Seeking Mantra (Shneiderman, 1996); it first displays a general view, and then shows necessary details according to user-specified conditions. Specifically, when the "See tweets" button is pressed, it displays individual tweets that are sorted from the newest to the oldest, in the descending order of favorites, or in the descending order of attached photos.

6 DATASETS

To experimentally evaluate our system, we collected tweets related to two Twitter trends "Hakone Ekiden" and "#NHKKohaku" (part of which were written in Chinese characters but are alphabetically written in this paper) by the Search API of Twitter. Details of the collection of the tweets are shown in Table 1. In Table 1, only the tweets that have at least one retweet are counted because our system uses *only* such tweets for its analysis. One tweet has eight attributes, a tweet ID, text, a post time, a user ID, a user name, the number of photos, and URLs.

Table 1: Characteristics of the datasets.

Twitter trend	Hakone Ekdien	#NHKKohaku
# tweets	34,894	47,187
# retweets	10,027,794	16,279,103
Data acquisition date and time	1:14, Jan. 4, 2019	16:37, Jan. 3, 2019

The trend "Hakone Ekiden" is short for the 95th Tokyo-Hakone collegiate Ekiden relay race, which was held on January 2 and 3, 2019. This race is a traditional sport event in Japan. Approximately 20 teams representing Japanese universities participated in this race. The forward path is a distance of 107 km from Tokyo to Hakone, where five runners in each team ran on January 2. The backward path is a distance of 109 km from Hakone to Tokyo, where five runners in each team ran on January 3. The rank of this race is determined by the total time for the forward and backward paths.

The trend “#NHKKohaku” is a hashtag related to “Kohaku Utagassen”, the annual contest between male and female popular singers in Japan on New Year’s Eve, sponsored and broadcasted by the NHK TV broadcasting station. This program was broadcasted from 19:15 to 23:45 on December 31, 2018, and marked the viewing rate of 41.5%.

7 EXPERIMENTS

In our experiments, we applied our system to analyze and visualize tweets in the datasets that we described in the previous section. Figures 1 and 4 visualize the trends “Hakone Ekiden” on January 3, 2019, “#NHKKohaku” on December 31, 2018 respectively. In Figure 1, the system analyzed 1580 tweets that satisfied the conditions in Table 2. It generated ten legends by using tf-idf, and their English translations are shown in Table 3. In Figures 4(a) and 4(b), the system analyzed 1733 and 2008 tweets respectively.

Table 2: Conditions of the analyzed tweets.

Visualization	Min. # retweets	Max. # retweets	Period of time series
Figures 1 and 3	8	14	6:17–17:40, Jan. 3, 2019
Figure 4(a)	10	15	19:00–23:59, Dec. 31, 2018
Figure 4(b)	30	57	19:00–23:59, Dec. 31, 2018

7.1 Hakone Ekiden

Figure 1 shows the result of applying our system to tweets related to the trend “Hakone Ekiden”. The relay race started at 8:00, and runners ran Hakone to Tokyo in five to six hours. It was broadcasted on TV. In the visualization, the number of tweets increased rapidly at 13:49, around which runners reached the goal. In this figure, different topics appear around the time when runners reached the goal, and the topics corresponding to each time period appear during the race.

Let us see further details about the topics during the race. The cluster shown in red in Figures 1 and 3 was related to a website for prompt reports of the race, while the other topics during the race were not directly related to the race itself. Therefore, we can consider that Twitter users checked and disseminated the state of the race by using this website.

The number of tweets increased at 10:03, which was caused by the increased tweets shown in blue in Figure 1. Legends of this cluster include “Freeza” and “Rilakkuma”, characters that were not related to the race, and it is difficult to know the topic of the cluster. Therefore, we display individual tweets of this cluster with the GUI, as shown in Figure 2. Here we can see photos of the characters “Freeza” and “Rilakkuma” because some people watching the race on roadsides were dressed in the costumes of “Freeza” (an enemy character who appeared in a TV animation series) and “Rilakkuma” (a teddy bear-like stuffed doll character). It should be noted that, although these tweets had a few common words in text, our system was able to classify them as the same cluster; this was because there were users interested in distinctive-looking people on roadsides. This is a typical case that our system is able to classify a topic that is difficult for text-based methods to treat.

Next, let us see more details about topics approximately between 13:00 and 14:00, i.e., for a

Table 3: Legends and the number of retweets of clusters in Figure 1.

Cluster	# tweets	Legends (tf-idf)
Red	205	map, NTV, prompt report, 95th, this
Yellow	192	Tokai Univ, Nogizaka 46, chan, 46th, go
Aqua-blue	178	Sports Hochi, firefighting, passing, fire, various place
Pink	116	next year, this year, victory,
Yellow-green	115	highlight, Haikyu, bgm, play music, soundtrack
Blue	96	Mr. Freeza, Rilakkuma, Freeza, usa, this year
Purple	91	Tokai Univ, victory, 2019, appear, record
Silver	67	Ameblo, update, Tokai Univ, image, backward
Green	66	do, century, become, run, be
Orange	55	stop, Daily Sports, earnest wish, Aoyama Univ, consecutive victory

period when runners reached the goal. We zoom in and change the number of division of this period. Figure 3 shows this result, where the color of each cluster is the same as in Figure 1, but the legends are regenerated from the document that is composed of the tweets posted during this period. In Figure 1, the clusters that correspond to purple, yellow-green, and pink increased during this period. We can read the following from the legends of these clusters: the purple cluster indicates that Tokai University became a champion; the yellow-green cluster indicates the highlight of the race; the pink cluster includes words such as this year and the next year. By zooming in this period as shown in Figure 3, the shift of major topics becomes visible. Tweets about the purple cluster increased rapidly in 13:23. Around this time, the first and the second team reached the goal on the backward path. These tweets increased around this time because the champion of the whole race was determined. In individual tweets, the pink cluster indicates impressions of the race and expectations for the next year's race. Tweets about this cluster increased around 13:50, immediately after 13:48 when the lowest team reached the goal.

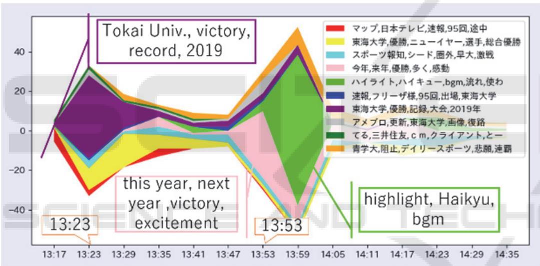
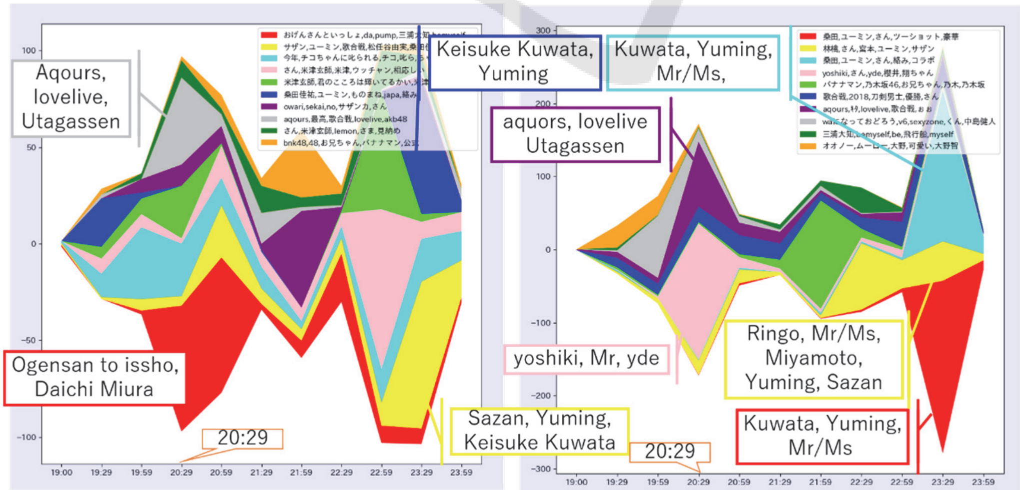


Figure 3: Zoom in the time series of Figure 1.

7.2 #NHKKohaku

We explain difference between clustering and visualization results caused by changing the lowest number of retweets. We use the trend "#NHKKohaku" and show the results in Figures 4(a) and 4(b). Both analyzed tweets between 19:00 and 23:59 on December 31, 2018. We defined the lowest numbers of retweets as 10 in Figure 4(a) and as 30 in Figure 4(b). In Figure 4(a), the highest number of retweets is 15, and there are 1733 analyzed tweets. In Figure 4(b), the highest number of retweets is 57, and there are 2008 analyzed tweets. Although the general forms of Figures 4(a) and 4(b) are similar, they include different topics.

Around 20:29, the number of tweets increased rapidly, and there are different topics as well as the same topics. The gray cluster in Figure 4(a) and the purple cluster in Figure 4(b) have the same words "aqours" and "lovelive" in legends. These two clusters have a common topic about a Japanese animation series "Love Live". Although the red cluster in Figure 4(a) and the pink cluster in Figure 4(b) increased rapidly around this time, they have different topics and appear only in one of the two results. The reason why this happened might be because of the different strengths of these topics. The legends of the red cluster include "Ogensan to issho", which is the name of a program broadcasted by NHK. The legends of the pink cluster include "yoshiki" (YOSHIKI), who is a member of a famous rock band X JAPAN. "Ogensan to issho" is a famous program, but YOSHIKI has a stronger topicality because he appeared together with other famous singers.



(a) (b)

Figure 4: Difference between the visualization results of "#NHKKohaku" with the lowest numbers of retweets set to (a) 10 and (b) 30.

Table 4: Legends extracted by applying the three methods to certain clusters in Figure 4.

Visualization	Figure 4(a)		Figure 4(b)		
Cluster	Yellow	Blue	Red	Yellow	Aqua-blue
Word frequency	Utagassen, Yuming, Sazan	Keisuke Kuwata, Yuming, Monomane, JAPA	Mr/Ms, Yuming, Kuwata, Together	Mr/Ms, Yuming, Miyamoto, Ringo	Mr/Ms, Yuming, Kuwata
Tf-idf	Sazan, Yuming, Utagassen, Yumi Matsutoya, Keisuke Kuwata	Keisuke Kuwata, Yuming, Monomane, japa, duet	Kuwata, Yuming, Mr/Ms, Together, Amazing	Ringo, Mr/Ms, Miyamoto, Yuming, Sazan	Kuwata, Yuming, Mr/Ms, duet, collaboration
BM25	Suzu, co-star, stable, proceed, earnest	Monomane, japanwww, japa, Showa, line	un, specification, live site, whole song, Amazing	Ringo, recent year, unnatural, worldview, Nagano	Was fun, raise me up, last performer, 7th day

Therefore, the pink cluster appeared not in Figure 4(a) but in Figure 4(b), which was clustered by using tweets that have more retweets.

Next, we explain difference between methods for generating legends. By using tf-idf, the system generated the same legends for the yellow and blue clusters in Figure 4(a) and for the red, yellow, and aqua-blue clusters in Figure 4(b). They have “Yuming” and “Kuwata”, “Keisuke Kuwata”, or “Sazan” in the legends. “Yuming” is the stage name of a singer Yumi Matsutoya. Keisuke Kuwata is a member of a rock band Southern All Stars, also called Sazan for short. They appeared as special guests on this program in 2018. Although these topics might look the same, there are differences. Table 4 gives a list of the legends of the five clusters in Figures 4(a) and 4(b) that were generated by using the word frequency, tf-idf, and BM25.

Although tf-idf generated only the legends related to Yuming and Kuwata for the yellow cluster in Figure 4(a), BM25 generated “Suzu”, “stable”, and “progress”. Most tweets related to the yellow cluster in Figure 4(a) mentioned their impressions about the whole program in 2018 or the presenters of this program. Suzu Hirose is one of the presenters, and the presenters progressed this program smoothly and stably. Therefore, legends generated by using BM25 were better than legends of tf-idf for this cluster.

Both the blue cluster in Figure 4(a) and the yellow cluster in Figure 4(b) have two subtopics, one of which is about Yuming and Kuwata. In the blue cluster, the other subtopic is about Monomane JAPAN, a group of five impersonators. In the yellow cluster, the other subtopic is about a duet of Ringo Sheena and Hiroji Miyamoto. In legends generated by using BM25, Monomane JAPAN and Ringo Sheena appear, but Yuming and Kuwata disappear. However, the actual topic of the two clusters were related to both subtopics. Therefore, legends generated by using tf-idf are better than legends of BM25 for these clusters.

The red and aqua-blue clusters in Figure 4(b) are similar. Tweets in these clusters mentioned how exciting the duet of Yuming and Kuwata was. This topic appeared as legends generated by using BM25. They included “amazing”, “was fun”, and “rise me up” as legends. Therefore, it is better to use legends generated by using both tf-idf and BM25 to understand these clusters.

8 DISCUSSION

The experiments showed that our system was able to analyze and visualize flows of topics in tweets related to Twitter trends. It classified tweets that had a smaller degree of textual similarity in the same cluster like the blue cluster in Figure 1 because it classified tweets based on retweets. This made it possible to find the new flows of topics by changing conditions like zooming in Figure 3. When it was difficult to understand the topics of clusters by using only the visualization, it was possible to additionally use the display of individual tweets.

On the other hand, the aqua-blue cluster in Figure 1 was a case that needed a longer time to understand its topic by using our system. We find the fire and the firefighting from legends of the aqua-blue cluster, and about half of the tweets are related to the fire that happened during the race. However, when our system displays individual tweet, there are unrelated tweets at the top such as a supporting message and an impression about the race. To solve this problem, it needs to increase kinds of methods for sorting tweets, such as first displaying tweets that include words generated as legends.

In Subsection 4.1, we explained that the number of tweets to analyze is limited to about 1500 by the number of retweets to decrease the amount of the calculation. The amount of the calculation in Section 4 is $O(n^2)$ for n tweets. Relations between numbers of tweets and execution times in the environment of our experiments (Intel Core i7-8565U with 16 GB of RAM running Windows 10) are shown in Table 5. Our method puts a higher priority on the execution time than the accuracy of the calculation, because our system assumes that a user repeats operation to change conditions in order to find topics or periods of interest.

Table 5: Execution time under each number of tweets.

# tweets to analyze	Execution time (sec)
1,034	9.71
2,120	41.00
3,026	91.03
4,057	157.82
5,123	334.29

We did not perform any formal, numeral evaluation partly because it is difficult to compare our method with existing methods. It might be possible to replace ThemeRiver with another visualizing method or to remove legends from our method and then to compare how long users need to finish analysis. However, in this case, we would also need to measure how well they perform analysis, which would be more difficult.

9 CONCLUSIONS AND FUTURE WORK

This paper presented a system for analyzing tweets related to Twitter trends by combining retweet clustering and time-series visualization to allow users to understand a topic flow of a Twitter trend in a short time. It analyzes tweets that have little textual information, visualizes a topic flow of tweets related to a Twitter trend as a chart, and finds new flows of topics by changing conditions with a GUI. It also supports understanding topics of clusters by using legends and displaying individual tweets.

This system assumes that its user finds interested flows of topics by changing conditions. It is important to reduce the execution time in order to operate smoothly when the user modifies conditions. Therefore, it is necessary to perform more efficient execution when tweets to analyze increase. Also, it is necessary to implement the function of recommending ideal conditions because a user takes time and effort to find topics of interest by modifying conditions manually. Using the modularity of the clustering result might help to solve this problem.

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