

An Information Visualization System to Assist News Topics Exploration with Social Media

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ABSTRACT

With the popularity of social media, journalists often collect news materials from mass user-generated contents. However, with the outbreak of social media data, it is not easy for a journalist to see the whole picture of an event from the huge amount of data. If they only use the social media as a news source, the reported content may often become a copied view of the users, or fall into the stereotype of one-sided discussions. Aiming at improving this problem, our study uses Twitter data as an example to develop an information system to assist journalists to explore events, collect materials, and find news topics with social media. We use network analysis and natural language processing techniques to analyze the collected data and visualize the story elements. We have developed four story elements models to support different ways of exploring the data. We let the users adjust the weights on the importance of these models to retrospect the context of tweets and help users find news topics. We have designed a two-phase experiment with questionnaires to assess the appropriateness of the system. We allow the participants with various degrees of familiarity with the event to explore news topics on our system. The experimental results show that the participants have found the system to be useful and easy to use, and the journalists can explore news topics and track events in a much faster fashion.

CCS Concepts

• Networks~Social media networks • Networks~Online social networks • Information systems~Data analytics • Applied computing~Sociology

Keywords

Social media; journalism; news coverage; news topics exploring

1. INTRODUCTION

With the emerging era of big data, revolution of communication technology drastically changed the morphology of the news media. Because the power of social media is flourishing, the user-generated contents constantly provide a good source of news for the press. The journalists are changing their roles of gatekeeper [1] to gate-watcher [2] who watching for newsworthy topics. In a survey on journalism of American in 2013 [3], 53.8% of the journalists use microblogs types of social media such as Twitter at work. Regarding the purpose of using social media, 78.5% of the journalists use them to check for breaking news, 59.8% of the journalists said they used social media to find ideas for stories. In other words, social media may have redefined the mission of journalists. Given the huge amount of materials in social media, how do journalists select the news topics? How are these materi-

als organized and reported? In the same survey, about the profession of journalist, people generally agreed that it is more important for them to analyze complex problems while getting information to public are becoming relatively less important.

When a journalist would like to analyze an event, find noteworthy news topics, and dig hidden facts, the problems they may face include:

- Overwhelming amounts of content from social media

A noteworthy story usually arouses much interest in the user community. The tweets describing the story can usually incur a large amount of tweets of discussion about this topic. This makes it difficult to identify and understand the main newsworthy issues in the story.

- Repetitive process in exploring news topics

It is a repeated process for a journalist to explore news topics. There could be several stories lines developing at the same time. The journalists often need to dig deeper in each line to discover good topics about this story. This process usually repeats until the story is over or the coverage is enough.

- Collecting thoughts when exploring

When journalists are exploring new topics with social media, they usually need to handle much information at the same time. In the exploring process, journalists may have the impression of many partial facts or tips, which are too much to memorize without helps.

In summary, because of the aforementioned problems in using social media for news topic discovery, it is not easy for a journalist to analyze problems in depth for a given event. Consequently, they usually use it as a news source only and cannot take full advantage of the power of social media. Therefore, in this work, we would like to develop an information system that can help journalists deal with these problems and allow them to explore news topics more efficiently.

In order to understand how a journalist explores new topics, we have observed the behavior of journalists in performing this kind of tasks. We found that there are some patterns during the in-depth exploration. A journalist usually browses the information widely first when she is new to the event. In the browsing process, she constantly updates the information of this event and collects tips of newsworthy issues. In social media, this process usually is more complicated because of its mass amount and unstructured contents. In other words, there are typically three behaviors in news topic discovery: *exploring an event*, *collecting materials*,

and *retrospecting to exploring context*. We think that a system designed to help the journalist to discover valuable news topics from the mass of social media should provide assistance in these three aspects. This is also the design objective of our system in this study.

In the event exploration stage, we will develop functions to help a journalist explore data from four different viewpoints to quickly understand a given event. In order to help a journalist quickly grasp the whole picture of an event, we use network analysis, natural language processing, and information visualization techniques to build up story contents and collect related materials. More specifically, our system allows a journalist to find, restore, and record information sources as well as the original contents through their weights on different story elements. She can also explore tweets on one side and collect and arrange the tweets which they found relevant on the other side. Our system also allows a journalist to bookmark an exploring state to help them retrospect the context they had explored. She can return to any of these states at any time in the future.

2. RELATED WORK

The popularity of social network revolutionizes the way of collecting information and breaks the tradition of preferring experts' opinions as information sources. Mass user-generated contents such as social media become a more diverse source for a journalist to discover news topics and collect news materials. However, such a large amount of data often make journalists tend to write news without fully understanding the meaning of an event, and simply watch the reaction or emotion of social media users to decide if an event is newsworthy or not. This makes the social media become a cheap tool for competition and cannot manifest the professional role that a journalist should play. As a result, many tools have been developed to help journalists acquire more information from social media to report an event.

There have been several researches on developing tools for analyzing data in social media, and most of them focus on the Twitter platform. They usually provide dashboard-like interfaces for data acquisition and analysis. DiscoverText [4] collects data through Twitter's APIs and helps researchers archive, filter, and search. They focus on the classification of tweets and specialized in text analysis. Truthy [5] is a public social media observatory that analyzes online discourse and visualizes information diffusion on Twitter. They aimed to help researchers study how memes, a replicable unit of information such as hashtags, mentions, or links, spread on social media. Tsou et al. [6] developed an online geo-targeted search and analytics tool called SMART for monitoring tweets and tracking the diffusion of information in different cities, strongly emphasizing on the geospatial characteristics of social media data. Some other commercial social media analytics software, such as Topsy [7], Sysomos [8], Netbase [9], focus more on the use of marketing, looking for trending issues, and emphasizing on finding "top" or "influential" events, contents, and users. Marcus et al. [10] presented Twitinfo, a tool that identifies peaks in the tweeting activities to find the relation between events and sub-events with the aim of assisting a journalist to summarize an event. Diakopoulos et al. [11] presented a tool on analyzing the context of an event to help journalists identify eyewitnesses.

There are also other studies focusing on finding breaking news in real time [12][13] or tracking hot topics [14][15][16]. For example, Zubiaga developed a news-gathering tool which can be used

to classify the trending topics from Twitter official website in real time [17] with the technique of machine learning. By considering the characteristics of user diversity, re-sharing, and other social features, the system can determine whether a topic is newsworthy or not. An integrated curation system has been proposed to collect news topics from hot discussions on Twitter [18].

There are quite a few tools that are designed to analyze social media data for different kinds of users. But according to our knowledge, currently there are no systems that can help journalists analyze complex problems in depth. The demands for this kind of tools motivate us to develop a system that can assist journalists to search and browse mass data, collect related tweets, and visualize the collected data. We develop tools for visual network analysis and text analysis to help journalists visualize large data sets and customize the tool depending on the journalists' choice. We focus on retaining their thoughts throughout the exploration process to assist them in finding newsworthy topics conveniently. Our system provides useful functions such as collecting tweets and arranging materials dedicated to more complex and in-depth news coverage. Besides, our system also focuses on integrating analysis functions not only for journalists who need breaking news topics but also for those who need materials for in-depth stories from diversified viewpoints.

3. SYSTEM DESIGN

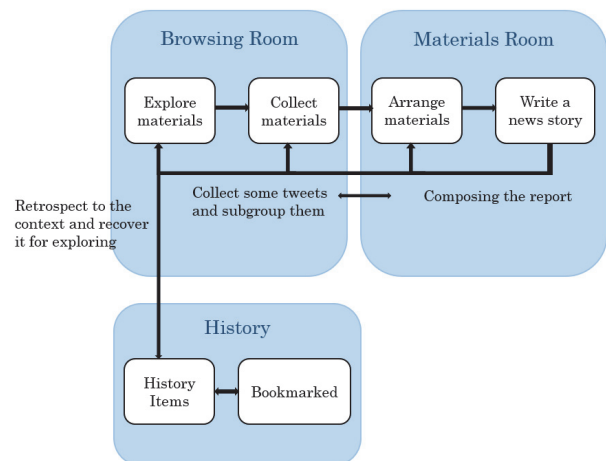


Figure 1. Three main components of our system

Our research aims at building a visualization information system to assist journalists in exploring news topics with social media. After observing the news discovery process by journalists, we divide the exploring process into three main parts, which are "exploring an event", "collecting and arranging materials" and "retrospecting to a previous exploration state." These actions correspond to the components of the system shown in Figure 1, where "exploring an event" corresponds to the Browsing Room, "collecting and arranging materials" corresponds to the Materials Room, "retrospecting to a previous exploration state" corresponds to the History page. When using the system, users explore the events and collect the tweets at the same time. They usually have an outline or draft about the directions of their news topics. Users can enter the Materials Room at any time to arrange the materials they collected. The Materials Room provides multiple groups created by the users for them to organize their thoughts for the news stories. Users can also compose their news article in this

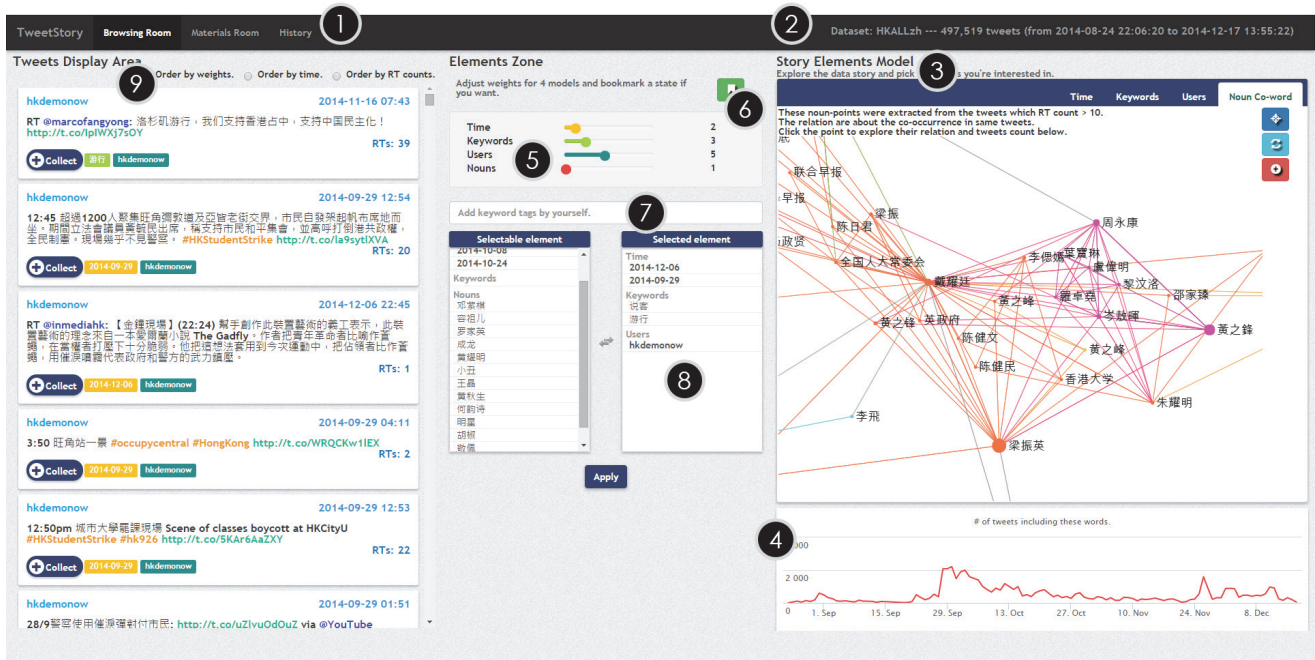


Figure 2. Interface of the Browsing Room. ① Toolbar, ② Information of datasets, ③ Story elements model, ④ Line chart of time, ⑤ Adjustment panel, ⑥ Bookmark button, ⑦ Manual input box, ⑧ Elements filter list, ⑨ Tweets display area.

area. Our system allows the users to move back and forth between the Browsing Room and the Materials Room when they feel a need to change the mode.

Exploring news topics is a progressively deepening process. When users are not familiar with an event, they can usually begin from wide open browsing and attempt to find the relations between tweets. However, it may happen that they have not found enough relevant materials in a certain direction that they have dived into. In this case, they may want to choose to go back to a certain point in the exploration process and dig into another direction. Therefore, our system provides them with the History function to allow them to retrospect to a previously explored state.

3.1 Datasets

We have used the social media data from Twitter to build and test our system. Our study used two datasets to cross test the functions of our system in the evaluation stage.

We captured tweets through the keywords about a given event under discussions from the Twitter APIs. There are two kinds of APIs to retrieve data, the Streaming APIs and the Search APIs. The main difference between these two is that the Streaming APIs does not provide historical tweets while the Search APIs can search for tweets up to a week old. However, the current Streaming APIs cannot provide filtered keywords for languages that do not separate words or phrases with spaces. As a result, we have to choose the Search APIs to collect data for our experiments. We used the acquisition function of DMI-TCAT[19] to capture data on Twitter, which is a toolset allowing one to retrieve and collect tweets and analyze them in various ways. The search APIs can search tweets published in the past 7 days for given keywords. We rewrote the mechanism of using the Search APIs in DMI-TCAT to execute the search task every two hours to continuously monitor an event. In this study, we only tracked Chinese tweets

including simplified Chinese and traditional Chinese. The number of tweets listed in Table 1 has ruled out all tweets in non-Chinese languages.

Table 1. The information of datasets

Query-bins	HKOccupyCentral	TaipeiMayorElection
Tweet count	497,519	144,572
Time period	2014-08-24 ~ 2014-12-17	2014-08-05 ~ 2014-12-17

3.2 Interface Design

In this section, we will describe the three components in our system mentioned above. First, the Browsing Room gives the users ideas and materials about an event. The interface is divided into four parts as shown in Figure 2. The top area provides the basic information about the dataset. The left area is the *Tweets Display Area*, where search results by the users' choices are shown. The right area is the *Story Elements Model*, which includes four different kinds of visualization tools to present the story elements. The last area is the middle of the interface: the *Elements Zone*, where users can adjust the weights of the elements they extracted from the story elements model for refining search.

The objective of the Browsing Room is to help journalists dig into the events. Therefore, we have designed a process consisting of three steps to facilitate the exploration task. First, when a user has no idea about a given event, she can start exploration by searching for keywords about the events from different perspectives in the Story Elements Model. When they have some ideas about the event, they can customize their search by adjusting the

weights of the elements including *Time*, *Keywords*, *Users*, and *Noun Co-Word*. Different journalists may start from different viewpoints through different story elements. For example, some-one may begin from the time when a particular event happened. Some other users may start exploration from the lead characters in the event, the discussion trends, or the active users in the social media. Therefore, one can have a good variety of ways to explore the tweets data. Except for the Time Model, the other three models allow the user to click on the elements to show the frequency of these data at the bottom time chart. More detail description of the Story Elements Model will be given in Subsection 3.3.

The middle panel is the Elements Zone. It helps users focus on the story elements they are interested in. The users collect key story elements during the interaction in the story element panel or simply type in a specific keyword in the Selectable Element area. In order to refine their search, they can select elements from the Selectable Element area and move them into the Selected Element area. According to the weights of the four element models specified by the user, the system will compute the score of each tweet and present the tweets in a sorted order. The words that the user chooses and the weights that the user adjusts can be saved as an exploration state in the History page. The purpose of the recording exploration states is to help users connect a series of thoughts through operations during exploration. The users can click on the Bookmark button provided by the system to remember a specific state that they can come back afterward.

The last part, called Tweets Display Area, is to display the tweets satisfying user constraints and sorted in a specific order. Depending on the customized weights on the story elements, the ordering of the returned tweets will be different. The users can adjust the weights at any time, press the 'Apply' button to re-calculate the scores of the tweets, and then return the highest ones. The new exploration state will be recorded as well. In the Tweets Display Area, the texts in a tweet is shown and a link to the original source is also displayed such that the users can follow the link to check out more information such as mentioned netizen, hashtags, and hyperlinks. We think it is crucial for the journalists to check the original contents to verify the sources of the news topics. All tweets also consist of a "Collect" button that allows the users to easily collect materials and keep exploring. The users can then go to the Materials Room to see the materials and arrange them.



Figure 3. Interface of the Materials Room. ① Materials Box, ②③ Arranging Area, ④ Text Editor

The goal of designing the Materials Room (see Figure 3) is to assist users in putting the tweets about a news topic together in

some order and composing the news article. The left-most panel displays the collected tweets while the middle two panels are reserved for arranging the selected tweets by dragging the tweets from the left-most panel. Users can click on the input box above the middle panels to group the tweets by the story elements. The right-most panel is the Text Editor for the users to compose a news article with the ideas from the source tweets.

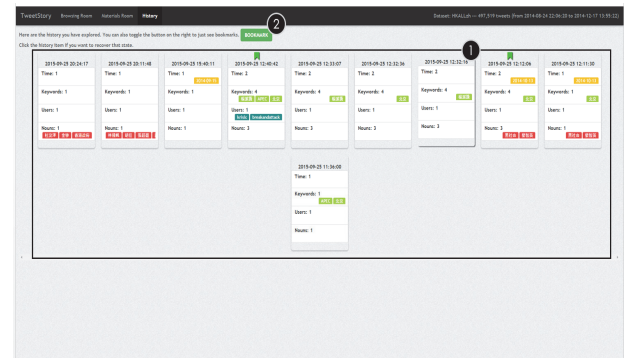


Figure 4. Interface of the History page. ① History items, ② Toggle to see Bookmarked History items

In the History page, one can examine the exploration states in the chronological order in the form of card display. An exploration state corresponds to a history item. These actions usually happen more frequently during the browsing of social media data. To make journalists concentrate on the story itself, we think the History page can string the ideas together in the composing process. After a long period of exploration, the exploration states gradually may become overwhelming; hence, the system also allows the users to press the bookmark button to retrieve only the bookmarked states.

3.3 Story Elements Model

One can analyze social media data from many aspects. For example, there are often several actors or characters in an event and many discussions among netizens. These netizens are all connected with their social networks. The easiest way to quickly understand an event from the overwhelming amount of data is by the network visualization techniques that use color or size to clearly present the roles and relations between the nodes in a social network.

In the Story Elements Model, we have provided four different ways for the users to explore data, which include *Time*, *Keywords*, *Users*, *Noun Co-Word*. These four models reflect the elements that journalists usually care most:

- I. **Trending:** Time, undoubtedly, is one of the most important elements in telling a story. When an event happens and how it evolves over time usually is the main concern of journalists.
- II. **Discussions:** Journalists usually concern the hot topics about an event and the opinions by the netizens.
- III. **Active netizens:** Who are the active users? Are there opinion leaders in a given event?
- IV. **Relations among characters, issues and discussions:** The co-occurrence of noun words in tweets can assist journalists in exploring the hidden clues and relations between them.

3.4 Determining the order of returned tweets

In the datasets, there are usually too many tweets returned by a typical query. It is often a challenging task for journalists to read through these tweets. Therefore, in the Elements Zone, we have designed an interface for the users to adjust the weights (1-10) of the four story elements described in the previous subsection to reflect their preferences of the story elements for the given event. The system will compute a normalized score for each tweet according to each story element if applicable. The overall score of each tweet is then computed according to the raw material scores and their weights associated with each story element. Then the system displays the tweets in a descending sorted order according to the scores.

4. EVALUATION

To understand how our system can assist journalists in exploring news topics, we have designed a two-phase experiment to evaluate the system. The purpose of the experiment is to verify if the journalists with different familiarities with social media datasets can explore news topics and compose news articles through the help of our system.

4.1 Experimental Design

We used two datasets in our study: “TaipeiMayorElection” and “HKOccupyCentral” for the Taipei Mayor Election event and the Hong Kong Occupies Central event, respectively. We separated the participants into two groups to explore different datasets. We observed the behaviors of the users when they used our system and assessed its usefulness in assisting the users in exploring news topics. We invited seven subjects with journalism background and some experience with social media to participate in the study. They all had written online news articles but had slight differences in the experience of news coverage and social media analysis. We took the factor of experience difference into account to assess how they used our system.

4.2 Experiment Process

Before the experiment began, we played a three-minute video about the instruction of the system such that the participants could have a preliminary understanding of how to use the system. Then, the participants would enter a four-phase procedure as shown in Figure 9: guided task, first-stage questionnaire, specific task, and second-stage questionnaire.

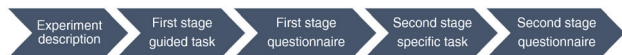


Figure 9. Experimental procedure

The purpose of first-stage guided task is to ensure that the participants have some basic familiarity with the functions of the system before the second stage of specific task. We have designed 25 small tasks to guide the participants to practice various functions provided by the system in completing a typical exploration task. In the second stage, we gave the participants a specific task of exploring news topics and composing an article by themselves for a given event. We used two different datasets in the two stages to ensure that participants are not influenced by the practice in the first stage. If a participant used the TaipeiMayorElection dataset in first stage, he will use the HKOccupyCentral dataset in second stage, vice versa.

In the design of the questionnaires, we set “ease of use” and “usefulness” as the objectives of the first and the second stage experiments, respectively. In addition to the two questionnaires, we

also used the System Usability Scale (SUS) [24] in both stages. SUS is a widely used questionnaire consisting of ten questions with five response options for respondents. SUS provides a quick and dirty, reliable tool for measuring the usability. We hoped to perceive the difference of user experience between the two stages.

In all questionnaires, we used a 5-point Likert Scaling: strongly agree, agree, ordinary, disagree, and strongly disagree. We used positive and negative cross-questioning to increase the reliability of the questionnaires. Through the questionnaires of ease of use, usefulness, and SUS in the two stages, we would like to know how the users evaluate our system and why they think so.

4.3 Analysis of Experimental Results

We evaluate the ease-of-use and usefulness of our system from the questionnaires. When the participants were doing a specific task, we recorded the user operations on the screen for further analysis of user behavior. In the following subsections, we will show and analyze the result of the questionnaires in the two stages including the SUS questionnaire. Then we assessed our system through an interview to obtain users’ feedbacks.

4.3.1 Evaluation on Ease of use

After fulfilling the guided task, the participants were asked to fill in the questionnaire about ease-of-use. We divided the user interface into five blocks for the users to assess: Story Elements Model, Elements Zone, Tweets Display Area, Materials Room, and History. In Table 2, we show the survey result on ease-of-use. The result of the questionnaire revealed that the participants generally had positive views to our system. Most of the scores were above 4. The most positive parts included the Story Elements Model and the Tweets Display Area.

Table 2. Evaluation results on ease of use

User ID	Model	Tags	Tweets	Browsing Room	Materials Room	History
A	4.50	4.25	4.80	4.52	5.00	4.33
B	4.14	3.00	4.00	3.71	4.00	4.33
C	4.43	4.25	4.40	4.36	3.67	3.67
D	4.86	4.50	4.40	4.59	4.00	4.00
E	4.71	4.00	5.00	4.57	3.67	4.67
F	3.71	3.50	4.00	3.74	3.67	3.67
G	5.00	3.75	4.80	4.52	5.00	4.67
Avg	4.48	3.89	4.49	4.29	4.14	4.19
SD	0.41	0.48	0.37	0.36	0.56	0.39

In the Story Elements Model, more than half of participants agreed that the visualization of Keywords Model was very clear and the relation of different topics was easy to understand. One of them said that the interface design for the Noun Co-word Model is useful because it allows the user to go deep into subgraph networks. Another mentioned that the interface in the Time Model was convenient because it allowed a user to zoom in or move to different periods of time by dragging the viewing window. It allowed one to quickly identify the wave of discussions at any time.

In the Tweets Display Area, most participants thought that it was convenient to have hyperlinks to the original sources since journalists all cared about news sources. They also thought that it was handy to be able to trace the tweets through their types such as retweet, mention, and hashtag. On the other hand, the feedbacks on the Elements Zone were less positive. Half of the participants did not understand the meaning of adjusting weights for the story

elements because the concept of quantitating the elements was too abstract.

The average score for the Materials Room was ranked second to the last. Three participants gave the score of 3.67 points. In our follow-up interviews, one of participants mentioned that it was not easy to arrange the tweets in a good order when the number of materials becomes large. Another two participants said that it would be useful to provide a drag-and-drop function to help the user copy the contents of a tweet to the Text Editor and add reference to it. It seemed to be crucial for the system to provide handy functions to reduce tedious repetitive actions needed in composing a news article.

From the feedbacks on ease-of-use, we could find that network analysis through visualization was useful for the users. They could find information they needed from the functions provided by the system. However, the manual adjustment of weights was not intuitive for the users and deserved further design reconsideration.

4.3.2 Evaluation on Usefulness

The questionnaire in the second stage mainly aims at assessing the usefulness of the system and investigating whether the system can bring the functionalities to users as we expected. We classified the questions into four clusters to explore the usefulness of our system, namely the Browsing Room, the Materials Room, the History page, and finally the comprehensive evaluation. In Table 3, we show the evaluation results as well as the time that each user spent on accomplishing the task.

Table 3. Result of usefulness evaluation

User ID	Total Time (min:sec)	Browsing Room	Materials Room	History	Overall
A	46:21	4.71	4.67	5.00	4.40
B	33:02	3.86	4.00	4.00	4.00
C	60:17	4.14	4.33	4.33	4.40
D	45:22	4.29	4.67	4.00	5.00
E	43:36	4.43	4.67	4.33	4.40
F	71:35	3.86	4.00	4.00	4.00
G	33:48	4.57	4.67	4.00	4.40
Avg		4.27	4.43	4.37	4.37
SD		0.31	0.29	0.34	0.31

Most participants gave positive feedbacks about the usefulness of the system. The most prominent one is the Materials Room. Most participants thought that this function was useful when they used the system on their own to explore news topics in the second stage. They were satisfied with the functions of collecting materials and arranging the tweets into different categories. One of the participants said that she liked the way of arranging tweets since she could use it to compare two-side opinions. The participants also had positive feedbacks on the usefulness of the History page. Three participants said that they thought it was not necessary to use the retrospection function in the history page in the first stage of experiment. However, when they are done with the second-stage task, they change their views about this function. They thought the function of recording the history of exploration was very useful and some of them retrospect several times. We could find that in a process of exploring new topics, going back to a previous stage to find the connections between tweets was a useful function to string clues together for finding a news story.

On evaluating the usefulness of the Browsing Room, two participants gave lower scores. In the interview, we found that one of them had done research about the event and had a clear exploration direction. The participant was the quickest one to finish writing a news article (33mins). The participant did not use much of our Story Elements Models to explore and find the keywords. Instead, he manually typed the keywords to find the tweets she needed. Nevertheless, she found something new from tweets to compare with the facts he already knew.

It is the first time for the other participant to learn about network visualization and the concept of co-word. Therefore, she was not familiar with our system. This participant spent the longest time to write a news article (71 minutes). Despite she thought that the system provided many functions for her to explore at the beginning, she found that knowledge about the event was crucial in exploration. Otherwise, it may take long time to explore. From the feedbacks, we learned that our system provided useful functions to journalists no matter what their backgrounds were on social media analysis or how they were familiar with the event. Nevertheless, there is still room for us to improve the user friendliness of the system for users with different backgrounds and knowledge about the event.

4.3.3 Analysis of SUS survey

We used SUS and interviews in both stages of the experiment to understand how the users thought about the system when they explored news stories on their own. We also compared the questionnaires obtained in both stages to find out the behavior changes.

Table 4. Results of the SUS surveys

User ID	First stage SUS score	Second stage SUS score
A	77.5	77.5
B	57.5	60.0
C	77.5	70.0
D	62.5	77.5
E	70.0	70.0
F	62.5	72.5
G	75.0	80.0
Avg	68.9	72.5
SD	7.54	6.27

The objective of SUS was to measure the subjective satisfaction on our system in a quantitative way. Bangor et al. [17] reported that SUS were most useful in evaluating web interface (41%) in nearly 273 studies and the average score obtained in these studies was 68.2 points. In order to assist researchers in interpreting the results obtained with SUS, Bangor defined four levels of scores: not acceptable (<50), marginal low (50-60), marginal high (60-70), and acceptable (>70). In our study, the average score in the first stage is slightly below 70 points, which means that it is not difficult to master our system. When the users used the system on their own to accomplish the task in the second stage, the average score went up to 72.5 points, which belonged to the acceptable level. In addition, the standard deviation in the second stage was also smaller than the one in the first stage.

Most participants gave positive feedback on using the visualization tools to perform network analysis and present the relations between story elements. The tool could help them focus on exploring events instead of handling overwhelming data. However, we found it difficult for them to use the Noun Co-word Model in

the beginning if they were not familiar with the characters in the event. On the contrary, the journalists with a basic understanding on the event thought that the Noun Co-word Model allows them to find clues for writing news articles more easily. This implies that different story element models may be used at different stages of the exploration, and the Noun Co-work Model should be more useful when the users have some basic ideas about subjects and objects in the event. Most participants considered the Keywords Model to be useful and easy to use. They thought that the keywords suggested by the system had a good representation of the main topics discussed in an event and the way of visualization was intuitive. For those participants who used to observe the trending of an event, the Time Model provided a good way for them to quickly focus on something interesting. In summary, we found that every story element model could help journalists with different background knowledge and skills to explore a news event from different exploration angles based on their needs.

The Elements Zone provided the function of filtering and ordering the overwhelming amount of tweets based on user customized settings for a given event. Although some participants may not understand how to adjust the weights in the beginning, they still can get the materials they needed after some practice. On the way of finding clues for news topics, participants usually collected tweets into the Materials Room for later digest. The participants could also make good use of the arrangement function to compare the tweets they collected.

In the specific task, we found that the participants had written two different types of news articles. One is about the topics of real events while the other is about the activities on social media. We think our system can be used for studying the issues in the real world or exploring and comparing the Online and Offline activities at the same time. We also found that the participants who reported the real world events used more often the retrospection function of the History page than other participants because they needed more assistance by the system to connect the materials they found.

5. CONCLUSIONS

Our information visualization system assists journalists in exploring, collecting, and retrospecting news topics through visualizing the contents in tweets. Users can explore datasets from variation of message volumes over time, results from the topics model, relation between active posters, and the network of nouns co-word. The users can also go deep into the texts of tweets through the elements from story models. They can collect interesting materials or tweets with newsworthy issues. They can also retrospect to a previously explored state and keep exploring and organizing until a news article is composed.

According to the experimental results, all participants successfully completed the specific task, found valuable materials and composed a news article. The survey results also showed that our system could be used to explore new topics from social media data and the usefulness and ease-of-use of the system had also been verified. Through the two stage experiments, we found that our system could be used by users with different background and various degrees of familiarity with an event.

There are several directions to improve our system in the future. First, the weight specification on the story elements in the Elements Zone did not seem to be intuitive for most users. A more intuitive feature set or interactive inquiries probably need to be developed to replace the current weighing mechanism. Second,

we hope to extend the type of datasets that we can incorporate to other social media such as facebook in the future.

6. References

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