Retweet Reputation:
A Bias-Free Evaluation Method for Tweeted Contents

Shino Fujiki† **Hiroya Yano**† **Takashi Fukuda**† **Hayato Yamana**‡, *

†Graduate School of Fundamental Science and Engineering, Waseda University 3-4-1 Okubo, Shinjuku-ku, Tokyo, 169-8555, Japan

‡Faculty of Science and Engineering, Waseda University 3-4-1 Okubo, Shinjuku-ku, Tokyo, 169-8555, Japan

* National Institute of Informatics, 2-1-2 Hitotsubashi, Chiyoda-ku, Tokyo, 101-8430, Japan

{ fujiki, h_yano, t_fukuda, yamana }@yama.info.waseda.ac.jp

Abstract

The widespread of word of mouth using retweets on Twitter has enabled us to estimate trends in the real world. Previous research methods estimate the value of a tweeted content by calculating the number of subscribers who receive the tweet. However, we should consider the numbers of followers for both the tweeter and retweeter(s) as a greater number of followers may result in more retweets, which we call "bias." In this paper, we propose a bias-free evaluation method for tweeted contents. Experiments show that our method is successful at evaluating tweets without biases.

Introduction

In recent years, microblogging services such as Twitter have been commonly used to broadcast short messages to other subscribers in real time. Such widespread word of mouth allows us to estimate trends in the real world.

Since more than 100 million subscribers around the world use Twitter and over 50 million messages per day were broadcasted in 2010, Twitter has become a common target for researches to extract valuable messages. A Twitter message is called a "tweet" and is limited to 140 characters in length. Subscribers may register other subscribers to see their tweets. These subscribers, called "followers" are also able to quote and re-broadcast their received tweets, which is called a "retweet."

Many recent studies have demonstrated how to extract valuable information or popular authors on Twitter (Weng et al., 2010; Cha et al., 2010; Nagarajan et al., 2009; Boyd et al., 2010; Kwak et al., 2010). Moreover, other third-party services have been introduced (buzztter in 2007, and Twib, TOPSY, Retweet.com, Retweetist, and ReTweeter! in 2009).

Previous studies and current services can be classified into two groups. The first group, which includes Buzzter, Twib and TOSPY, uses term or URL frequency to extract valuable tweets. The second group, which includes Retweetist and ReTweeter!, uses the number of retweeted-tweets or number of retweet receivers. Using the frequency of words or URLs, tweeter trends can be extracted; however, we are not able to extract follower trends. The second group of services calculates the number of retweeted tweets or number of total retweet receivers to estimate how a tweet spreads to many subscribers.

In this paper, we define a valuable message as a meaningful tweet for third-person receivers who do not know the author of the tweet. We assume that such valuable messages will have the tendency to be retweeted by other subscribers who are not direct followers of the original author.

Thus, we adopt the strategy of the second group to extract valuable tweets for receivers; however, we try to avoid "bias" in which the more followers exist, the more retweets that will occur, resulting in many receivers. For example, let us assume that user-A has 1 million followers and user-B has 100 followers. In this case, the retweets from user-A have a tendency to appear to be more valuable in comparison with the retweets from user-B, as user-A has many more followers, resulting in many retweets that boost the number of total receivers regardless of how valuable the tweet are.

To extract such valuable messages, we propose a bias-free evaluation method for tweeted contents. In our method, we calculate the score of tweets based on the numbers of followers of both the original tweeter and the retweeters. The more retweets sent by subscribers who are not following the original tweeter, the higher the score given.

This paper is organized as follows. Section 2 discusses related work. Section 3 details the new bias-free evaluation method for tweets. Section 4 presents our experimental results, and shows some examples of evaluated tweets. Finally, Section 5 concludes with a description of future work.

Related Work

Previous studies and current services for extracting valuable tweets can be classified into two groups: methods based on the frequency of words or URLs, and methods based on the spreading of tweets.

Methods based on word or URL frequency

Buzztter, launched in 2007, is a real-time service that extracts phrases tweeted more frequently than usual. Nagarajan et al. developed a system called Twitris, which extracts words involved with real-world events and displays them on a world map. Twib and TOPSY, both launched in 2009, are real-time services that extract popular Web pages using frequent URLs referred to on Twitter in real time. While these services may extract tweeter trends, they are not suitable for extracting receiver trends.

Methods based on spreading of tweets

Retweet.com and Retweetist, both launched in 2009, are real-time systems that evaluate retweeted tweets based on how frequently a tweet is retweeted. Retweeter!, also launched in 2009, is a service that also evaluates retweeted tweets. It sums up the number of followers who retweet the original tweet to extract valuable tweets.

While these services extract valuable tweets by using the number of retweeted tweets or retweet receivers, they may not avoid the influence of bias that retweets from users who have many followers will boost the number of total receivers.

Bias-Free Evaluation Method

The purpose of our proposed method is to extract valuable tweets for third-person receivers who do not know the original tweeter, i.e., the original author, regardless of the popularity of the original tweeter. We assume that such valuable tweets will have the tendency to be retweeted by other subscribers who are not the followers of the original tweet. Thus, we place a high score on a tweet that is retweeted by other subscribers.

Specifically, our method calculates the score of a tweet based on both the number of followers of the original tweeter and the number of retweeters. Figure 1 shows the framework of our method.

Our method evaluates retweeted tweets using the following three steps. First, our method gathers tweets by using a Twitter streaming API, and uses these tweets to extracts retweets. Second, our method collects a list of retweeters' IDs in addition to the original tweeter's ID using a Twitter REST API. Finally, our method calculates the original tweet's score based on equation (1) below.

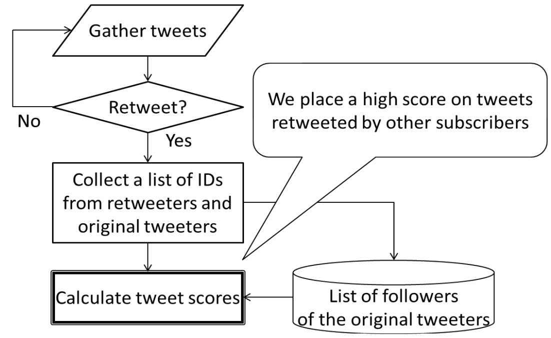

Figure 1 Framework of the proposed method method

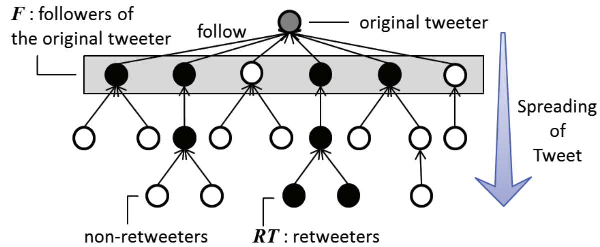

Figure 2 Relationship of each set

Retweet distinction

Tweets are classified into retweets and the other by using a regular expression '(RT|QT)(\\s)*@[a-zA-Z0-9_]+.*'. If a tweet satisfies the regular expression, it is classified into retweets. Then, from the retweets, our method extracts both the original tweet's author name and content. By comparing the original tweet's author name and content with those of the other retweets, our method identifies the set of retweets originated from the same tweets. More concretely, our method identifies both the tweets are originated from the same tweet if both the authors and the first one or more characters in their contents are the same.

Score calculation

The score of tweet is calculated using equation (1).

$$Score(t) = \frac{|RT_t \cup F_t| - |F_t|}{\sqrt{|RT_t \cap F_t|}} \cdot \frac{1}{|F_t|} \quad (1)$$

where t is a tweet, F_t is a set of followers of the original tweeter who tweets t, $|F_t|$ is the number of F_t, and RT_t is a set of subscribers who retweet t, i.e., retweeters of t. so, $|RT_t \cap F_t|$ is the number of retweeters among the followers of the original tweeter. Finally, $|RT_t \cap F_t| - |F_t|$ represents the number of retweeters who are not the followers of the original tweeter.

Here, equation (1) includes the square root in its denominator because we want to increase the score when the number of retweeters who do not follow the original tweeter increases in comparison with the number of retweeters who do follow the original tweeter.

Table 1 Tweet classification based on the reason for the retweet.

Category-1. To spread information To spread information and announce headlines. (e.g., "*Warning - Twitter goo.gl worm affecting mobile.twitter.com users: http://www....*")
Category-2. To record a favorite tweet To record a favorite tweet due to amusement, interest, or sympathy. (e.g., funny pictures, thought-provoking events that someone is going through)
Category-3. To agree or cooperate To give a reply or cooperate on questionnaires, requests, or soliciting agreement tweets. (e.g., "*RT if you have traveled by yourself.*", "*I made up my mind to buy as many hamburgers as the number of RTs.*")
Category-4. To acquire profit To obtain an advantage such as a prize. (e.g., "*Follow & RT! We'll draw 5 winners in all by lot.*")
Category-5. To interact with interesting users To interact with an interesting tweeter and/or retweeters. (e.g., "*This is going to be great! XD RT @singer The concert is beginning now! Have fun!*")

Using equation (1), we are able to place a high score on tweet t when a large number of retweeters do not follow the original tweeter.

Figure 2 shows the relationship of each set. Each circle represents a Twitter subscriber. The root circle shows the original tweeter who tweets t. The enclosed circles represent retweeters, and the circles within the rectangle are followers of the original tweeter. In other words, the number of enclosed circles within the rectangle is $|RT_t \cap F_t|$, while the number of other enclosed circles is $|RT_t \cap F_t| - |F_t|$.

Experimental Result

Data

We gathered Japanese tweets from the public timeline over the period between January 1st and 5th, 2011 by using the Twitter streaming API. The total number of gathered tweets is 8,295,634. As for the data set, we chose a total of 1,174 tweets that were retweeted by over 10 subscribers.

Evaluation Procedure

The evaluation was performed against ReTweeter!, which hereafter we call the previous method. The previous method extracts valuable retweets by calculating the total number of followers of a retweeter.

Table 2 Number of extracted valuable tweets

	previous method(P) (Retweeter!)	our method(O)	P ∩ O
Top-25 tweets	11	15	4
Top-50 tweets	31	32	6
Top-100 tweets	66	66	22

Table 3 Mean Average Precision (MAP)

	previous method (Retweeter!)	our method
Top-25 tweets	0.475	0.726
Top-50 tweets	0.532	0.673
Top-100 tweets	0.585	0.657

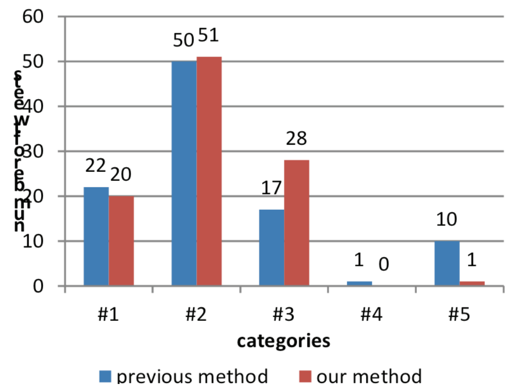

Figure 3 Results of tweet classification (Top-100 tweets)

The top-N tweets, where N is 25, 50, and 100, were extracted using both the proposed method and previous methods. We evaluated these methods from two points of view: the purpose of the retweet and the value of the tweeted contents.

First, we manually classified each top-N tweet into the five categories shown in Table 1. We determined these categories by reference to the study about why people retweet (Boyd et al., 2010). Among these five categories, the tweets in category-4 and category-5 are generally retweeted with biases. The tweets in category-4 have no general value because only retweeting subscribers receive a benefit. The tweets in category-5 will become valuable only if the receivers know the original tweeter.

Second, we evaluated each top-N tweet according to whether its content was valuable. A manual evaluation was performed by five college students, where we assumed that a tweet was valuable when over three students evaluated it as such. We then calculated the precision and mean average precision (MAP) using equations (2) and (3).

$$Precision(k) = \frac{1}{k} \sum_{1 \le i \le k} r_i \tag{2}$$

$$MAP(N) = \frac{1}{|T_v(N)|} \sum_{1 \le k \le N} r_k \cdot Precision(k) \tag{3}$$

Here, let r_i be 1 if $t_i \in T$ is valuable; otherwise, r_i is 0. $|T_v(N)|$ is the number of valuable tweets in top-N results.

Result

Figure 3 shows the classification results of the top-100 tweets. Compared with previous research, the numbers of extracted tweets categorized into category-4 and category-5, i.e., non-valuable tweets, decreased. Moreover, Table 2 and Table 3 show the effectiveness of our proposed scheme. Our method has the possibility to extract a larger number of valuable tweets than the previous method.

Below are some examples of non-valuable tweets extracted using only the previous method:

> Category-4: "*Do RT and follow @company by Jan 6. For details, go to http://www…*"
>
> Category-5: "*Happy New Year! I got married XD*"

The above tweet (#4) in Category-4 was tweeted by a company with 6,173 followers, and tweet (#5) in Category-5 was tweeted by a celebrity with 352,517 followers.

In contrast, we show the following two examples of tweets extracted using only our proposed method:

> Category-2: "*It is said that human soul weighs 21 grams. We can't confirm the truth of it. But a certain experiment revealed the same. There's a difference between the cursed doll and another one.*"
>
> Category-3: "*Please RT. My relative is missing! He went out by car. He may not be able to return home because he has dementia. … Please reply to me when you see him.*"

The above tweet (#2) in category-2 was tweeted by an ordinary subscriber with 84 followers, and (#3) in category-3 was also tweeted by an ordinary subscriber with 170 followers.

Figure 4 shows a transition in the number of retweets for the above four tweets, i.e., #4, #5, #2, and #3. The vertical axis shows the number of retweets, and the horizontal axis is the timeline. The number of retweets for tweet #3 reaches its peak immediately by retweets from non-followers. Contrary to this, tweet #2 has multiple vertices. This suggests that the original tweet spread away from the original tweeter to non-followers through retweets. Tweet #4 is greatly retweeted through a promotion. Tweet #5 is retweeted, but mostly by followers. Thus, our method places a low score on tweets #4 and #5 of which the numbers of retweets were boosted by biases with or without value, while the previous method gives them a high score.

Conclusion and Future Work

In this paper, we proposed a novel method for extracting valuable tweets that are more "hidden," but potentially interesting for more people than they reach. Our proposed method is successfully able to extract a larger number of valuable tweets than the previous method.

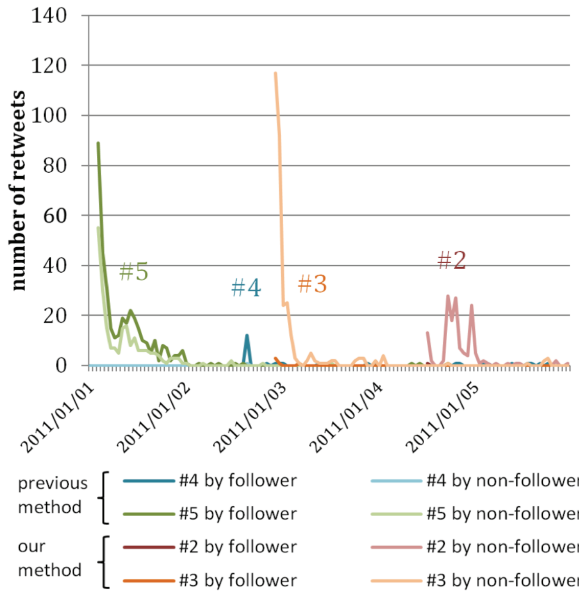

Figure 4 The transition in the number of retweets

Further studies are required to increase the precision of our proposed method in order to exclude certain non-valuable tweets in category-3, which is related to "Agreement or Cooperation."

References

Boyd, D.; Golder, S.; and Lotan, G. Tweet, Tweet, Retweet: Conversational Aspects of Retweeting on Twitter. In: *Proc. of the 43rd Hawaii Int'l Conf. on System Sciences (HICSS)*, pp.1-10, 2010 .

buzztter, http://buzztter.com (accessed 2011-01-07)

Cha, M.; Haddadi, H.; Benevenuto, F.; and Gummadi, K. P. Measuring user influence in twitter: The million follower fallacy. In: *Proc. of the 4th Int'l AAAI Conf. on Weblogs and Social Media (ICWSM)*, 2010.

Kwak, H; Lee, C.; Park, H.; Moon, S., What is twitter, a Social Network or a News Media? In: *Proc. of the Int'l World Wide Web Conf. (WWW)*, 2010.

Nagarajan, M.; Gomadam, K.; Sheth, A. P.; Ranabahu, A.; Mutharaju, R.; and Jadhav, A. Spatio-Temporal-Thematic Analysis of Citizen Sensor Data: Challenges and Experiences. In: *Proc. of the 10th Int'l Conf. on Web Information System Engineering (WISE)*, pp.539-553, 2009.

TOPSY, http://topsy.com (accessed 2011-01-07)

Twib, http://twib.jp (accessed 2011-01-07)

Retweet.com, http://www.retweet.com/ (accessed 2011-01-28)

ReTweeter!, http://retweeter.unicco.in (accessed 2011-01-07)

Retweetist, http://retweetist.com/ (accessed 2011-01-28)

TWIMPACT, http://twimpact.jp/ (accessed 2011-01-07)

Weng, J.; Lim, E.; Jiang, J.; and He, Q. TwitterRank: Finding Topic-sensitive Influential Twitterers. In: *Proc. of the 3rd ACM Int'l Conf. on WSDM*, pp.261-270, 2010.