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Exploring Opinion Dynamics in Security-Related Microblog Data

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***Abstract*—Web social media has become one of the major channels for people to express their opinions, share their feelings and communicate with others. Public opinions often ebb and flow with time due to the occurrence of social events and mutual influence of people on certain topics. The dynamic change of public opinions reflects the evolvement and trend of public attitudes and can facilitate many security-related applications. In this paper, we explore the modeling and detection of opinion dynamics on a specific topic based on textual social media data. We first define three measures to provide a thorough description of opinion dynamics, and identify the key factors that influence opinion changes, namely sentiment, social influence and dynamic factors. We then develop the computational method to capture opinion dynamics in security-related data. A preliminary empirical study is conducted based on the data from Weibo, one of the most popular microblog sites in China. The experimental results show the effectiveness of our method in modeling and predicting opinion dynamics.**

Keywords—social media analytics; opinion dynamics; modeling and detection of sentiment evolvement

I. INTRODUCTION

Social media sites are growing fast and play an increasingly important role as platforms for people to share opinions, express their feelings and communicate with friends. The collective opinions in social media sites often ebb and flow with time due to the occurrence of social events and mutual influence of people on certain topics. The dynamic change of public opinions on the Web reflects the evolvement and trend of public attitudes. Modeling and detecting opinion dynamics based on social media data can help us understand and explain the dynamic changes of public attitudes toward certain social events or hot topics, and facilitate the prediction of the future trends. It is also a major indicator for many social and economic phenomena, such as public opinion polls [1], movie sales [2] and stock price [3].

The modeling and detection of opinion dynamics is of particular importance in security-related applications. It is helpful for government and enterprises to better understand security-related events from social media data, and thus can facilitate these institutions to take proper actions and respond to crisis in time. It is also helpful for them to better assess public attitudes towards security-related events, and thus can facilitate emergency management, and support policy making and evaluation as well as many other applications.

Although opinion mining and sentiment analysis is an established research and application field, its focus is mainly on the identification of opinion polarities from individual user generated text at a certain time point rather than the collective sentiments of users as a whole (on certain topics). It neither models the dynamic aspect of opinions, nor does it support the prediction of the future trends of opinion evolution. Previous related work on opinion dynamics has studied the problem in sociophysics [4, 5], albeit with the narrow focus on agent-based modeling technique and the resulting model is quite rigid. More recent work [6] has employed a feature-based method to capture several important characteristics. However, it covers only one aspect of opinion dynamics and the features selected are somehow diffused, which lower the overall performance.

In this paper, we present an approach to model and detect opinion dynamics in security-related social media data. Our work has made several contributions. To form a thorough description of opinion dynamics, we focus on the positive/negative polarity of opinions and consider three aspects of opinion dynamics, positive opinions, negative opinions and their ratio. We then identify the key factors that influence opinion changes and develop the computational method based on these factors. Besides sentiment factors, we also take people's mutual influence and dynamic factors into consideration. To verify the effectiveness of our proposed method, we conduct an empirical study to compare our method with the related work and the baseline methods using microblog data from Weibo in China.

II. RELATED WORK

Opinion dynamics has been studied in sociophysics for years, which explores opinion dynamics by examining the spread of opinion in networks using agent-based method and proposes several typical models [4, 5]. In these agent-based models, each agent contains an opinion state which can be influenced by its nearby agents and is updated by predefined rules. Opinion dynamics is emerged through iterations of agent interaction. Although agent-based method is helpful in generating the dynamic process of opinion changes from bottom-up, it is required to update agents' opinion states according to predefined rules. This is a very strong hypothesis and actually too difficult to

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satisfy in realistic situations. Besides, these models can't handle the participation of new users, a common phenomenon in social media sites. Therefore, the practical application of agent-based method is greatly limited.

To make use of the dynamic sentiment information in social media data, several work has studied the interrelation between public opinion and media data in social and economic events, such as public election polls [1], movie sales [2] or stock price [3]. However, these studies mainly focus on the discovery of correlation between opinion dynamics and social and economic phenomena, lacking deeper consideration and modeling of the factors that influence the dynamic changes of public opinion.

More recently, Nguyen et al. [6] present a feature-based method to predict opinion dynamics using twitter data. They define the ratio of positive and negative sentiment information as the sentiment measure, and propose several feature types including tweet, user, sentiment ratio and dynamics. Their work provides a good start point to study opinion dynamics using machine learning-based method. However, they only consider one measure for opinion dynamics (i.e., sentiment ratio), which could not give a complete description of opinion changes. Moreover, quite a few features used in their work are based on the simple counts of user and tweet attributes and some sentiment attributes are intuitively not very relevant to opinion dynamics based on their opinion measure. On the other hand, some factors important to the modeling and detection of opinion dynamics are missing from their work.

In this paper, we propose a feature-based approach to modeling and detecting opinion dynamics in security-related microblog data. To overcome the limitations in the related research, we clearly define three measures to represent the dynamic states of positive and negative opinions and their ratio. We choose to use different sentiment features in our work, and take social influence and dynamic features into consideration. Social influence features are used to reflect the mutual influence of users and propagation of opinions with time. Dynamic features are used to capture the dynamic patterns of sentiment changes. We employ different machine learning methods and compare our work with the related work and baseline methods using security-related microblog data from Weibo. The experimental results show the effectiveness of our method in modeling and predicting opinion dynamics.

III. PROBLEM DEFINITION

We first define the measures to represent opinion dynamics and then formulate our problem based on the defined measures. We consider the degrees of positive and negative opinions with respect to the opinions of all the tweets (including positive, negative and neutral ones), as well as the relative degree of these two opposite opinions. To capture the dynamic changes of opinions with time, we describe these measures in each unit of time, and so in each time slice, we define three measures, namely positive sentiment measure, negative sentiment measure, and positive and negative sentiment ratio measure.

We use *pos*, *neg* and *neu* to denote *positive*, *negative*, and *neutral* respectively. Let t_i ($1 \le i \le n$) be a time slice, and $tweet_i(j)$ ($1 \le j \le m$) be a piece of tweet in time slice t_i. The positive sentiment measure in time slice t_i is defined as r_i^+, that is, the proportion of positive tweets in all tweets.

$$r_i^+ = \frac{\sum_{j=1}^{m} [\![1]\!]_{polarity(tweet_i(j))=pos}}{\sum_{j=1}^{m} [\![1]\!]_{polarity(tweet_i(j))=pos\ or\ neg\ or\ neu}}$$

The negative sentiment measure in time slice t_i is defined as r_i^-, that is, the proportion of negative tweets in all tweets.

$$r_i^- = \frac{\sum_{j=1}^{m} [\![1]\!]_{polarity(tweet_i(j))=neg}}{\sum_{j=1}^{m} [\![1]\!]_{polarity(tweet_i(j))=pos\ or\ neg\ or\ neu}}$$

The positive and negative sentiment ratio measure in time slice t_i is defined as the same as that in [6].

$$r_i = \frac{\sum_{j=1}^{m} [\![1]\!]_{polarity(tweet_i(j))=pos}}{\sum_{j=1}^{m} [\![1]\!]_{polarity(tweet_i(j))=pos\ or\ neg}}$$

These three measures provide a thorough description of opinion dynamics. The dynamic changes of opinions are represented as the increase or decrease of the three sentiment measures. Assume t_c is the current time slice and t_f ($t_c<t_f$, $1 \le c,f \le n$) is a future time slice. Therefore, our problem is to build model and predict whether $r_c^+ < r_f^+$, $r_c^- < r_f^-$ and $r_c < r_f$ or not, given the information in time slices t_1, …, t_c.

IV. PROPOSED METHOD

To solve our problem, we design several types of features that cover the key factors influencing dynamic changes of opinions and develop the computational method based on lexicon-based opinion mining and machine learning techniques.

A. Feature Design

Three types of features are important in modeling opinion dynamics. One type is the sentiment information of the tweets (e.g., those described as sentiment measures). Another type is the information about users' social relationship and mutual influence (e.g., follower relations). The third type is on the dynamic aspects of sentiment and social features. We make use of different tweet types, for example, positive tweets, negative tweets and all tweets (abbreviated as "*all*"). Tweets can also be classified by their origins, for example, original tweets (abbreviated as "*origin*"), comments and reposts.

Table I lists the feature set we design in our work. We use *wtd*, *wtd_pos*, *wtd_neg* and *wtd_all* to denote *weighted*, *weighted positive*, *weighted negative* and *weighted all*,

TABLE I. FEATURE DESIGN FOR MODELING OPINION DYNAMICS

TYPES	FEATURES
Sentiment Features	1.#pos(*all*)/#all(*all*) 2.#neg(*all*)/#all(*all*) 3.#pos(*all*)/(#pos(*all*)+#neg(*all*)) 4.#pos(*origin*)/#all(*origin*) 5.#neg(*origin*)/#all(*origin*) 6.#pos(*origin*)/(#pos(*origin*)+#neg(*origin*))
Social Influence Features	7.#follower(*pos tweets*)/#follower(*all tweets*) 8.#follower(*neg tweets*)/#follower(*all tweets*) 9.#follower(*pos tweets*)/#follower(*pos+neg tweets*) 10.#comment(*pos tweets*)/#comment(*all tweets*) 11.#comment(*neg tweets*)/#comment(*all tweets*) 12.#comment(*pos tweets*)/#comment(*pos+neg tweets*) 13.#repost(*pos tweets*)/#repost(*all tweets*) 14.#repost(*neg tweets*)/#repost(*all tweets*) 15.#repost(*pos tweets*)/#repost(*pos+neg tweets*)
Sentiment/ Social Features	16.#wtd_pos(*all*)/#wtd_all(*all*) 17.#wtd_neg(*all*)/#wtd_all(*all*) 18.#wtd_pos(*all*)/(#wtd_pos(*all*)+#wtd_neg(*all*))
Dynamic Features ($t_i<t_c$)	19.#pos(all_i)/#all(all_i) 20.#neg(all_i)/#all(all_i) 21.#pos(all_i)/(#pos(all_i)+#neg(all_i)) 22.#wtd_pos(all_i)/#wtd_all(all_i) 23.#wtd_neg(all_i)/#wtd_all(all_i) 24.#wtd_pos(all_i)/(#wtd_pos(all_i)+#wtd_neg(all_i)) 25.#pos(all_c)/#all(all_c) – #pos(all_i)/#all(all_i) 26.#neg(all_c)/#all(all_c) – #neg(all_i)/#all(all_i) 27.#pos(all_c)/(#pos(all_c)+#neg(all_c)) – #pos(all_i)/ (#pos(all_i)+#neg(all_i)) 28.#wtd_pos(all_c)/#wtd_all(all_c) – #wtd_pos(all_i)/ #wtd_all(all_i) 29. #wtd_neg(all_c)/#wtd_all(all_c) – #wtd_neg(all_i)/ #wtd_all(all_i) 30. #wtd_pos(all_c)/(#wtd_pos(all_c)+#wtd_neg(all_c)) – #wtd_pos(all_i)/(#wtd_pos(all_i)+#wtd_neg(all_i))

respectively, and subscript for denoting corresponding time slice. Note that among all the 30 features listed below, only two features (the *3rd* and *21st* items in the table) are the same as those in the related work by Nguyen et al. [6]. We design most of the features on our own.

Below we briefly explain our considerations in designing these features. We take the modeling of positive opinion dynamics as an example. Features for modeling negative sentiment and sentiment ratio are similar.

1) Sentiment features: We model opinion state using the positive sentiment measure of all tweets in current time slice t_c. As original tweets reflect the users' primary sentiment state on a certain topic, we also consider the positive sentiment measure of original tweets.

2) Social influence features: We design these features to reflect the mutual influence of users and propagation of opinions. The former factor is captured using the followerrelationship between users, and the latter is captured using the counts of comments and reposts (in contrast to original tweets).

3) Sentiment/Social features: To better model sentiment information in social context, we make use of the social relationship of users and let it directly impact opinion state, by combining social influence and sentiment features.

Let $tweet_c(j)$ ($1\le j\le m$) be a piece of tweet in current time slice t_c and $follower_c(j)$ ($1\le j\le m$) be its author's follower count. We use follower information of opinion author as the weight (wt) and combine it with the sentiment feature. Sentiment/Social feature SF_c (item 16 in Table I) is defined as:

$$SF_c = \frac{\sum_{j=1}^{m} wt(follower_c(j)) \times [\![1]\!]_{polarity(tweet_c(j))=pos}}{\sum_{j=1}^{m} wt(follower_c(j)) \times [\![1]\!]_{polarity(tweet_c(j))=pos\,or\,neg\,or\,neu}}$$

4) Dynamic features: We design these features to capture the dynamic patterns of opinion changes. As sentiment measures and the weighted sentiment information are the fundamental factors for modeling opinion dynamics, we design the dynamic features based on them. In addition, to model history opinion state, We use their values in the time slices before t_c as well as the differences between their values and values in t_c.

B. Methods

1) Opinion mining method: In extracting tweets' sentiment, we combine the traditional lexicon-based method with an emoticon-based method. The lexicon-based method employs three lexicon libraries, HowNet sentiment lexicon[1], National Taiwan University's sentiment lexicon[2] and Tsinghua University's sentiment lexicon[3]. Sentiment label for each tweet is assigned based on the relative number of positive and negative sentiment words. If a tweet contains negative word, we reverse its sentiment label. As emoticons can be seen as sentiment labels with high accuracy, in our work, we collect all emoticons in Weibo (including 140 positive and 151 negative ones) for sentiment assessment.

2) Machine Learning Methods: To build the prediction model based on the features we design, we choose to use different types of representative machine learning methods. They are SVM, logistic regression, multilayer perceptron, C4.5 and random forest. The performances of these methods are tested in the next section. As the related work [6] uses SVM classification method, we also compare the performance of our method with the related work using microblog data. The results will be given in the next section.

V. EXPERIMENT

A. Dataset and Preprocessing

We evaluate our work using the data from Weibo, which is one of the most popular microblog sites in China It has gained more than 500 million users since the end of 2012 and become a key platform for topic discussions and opinion sharing. We crawled Weibo data about 2013 Beijing Capital International Airport bombing occurred on Jul. 20, 2013. No one got injured in the accident except the

[1] http://www.keenage.com/html/c_bulletin_2007.htm
[2] http://nlg18.csie.ntu.edu.tw:8080/lwku/pub1.html
[3] http://nlp.csai.tsinghua.edu.cn/site2/index.php/zh/resources

TABLE II. PREDICTION RESULTS OF OPINION DYNAMICS UNDER DIFFERENT SENTIMENT MEASURES

Sentiment Measures	**Methods**	**Time Interval (hours)**			
		12	***24***	***36***	***48***
Positive sentiment measure	ARMA	68.18%	67.27%	78.18%	74.55%
	Logistic Regression	68.18%	**74.55%**	77.27%	72.73%
	Our Method	**69.09%**	67.27%	**79.09%**	**75.45%**
Negative sentiment measure	ARMA	62.73%	**73.64%**	**74.55%**	71.82%
	Logistic Regression	61.82%	71.82%	70.00%	73.64%
	Our Method	**67.27%**	**73.64%**	71.82%	**75.45%**
Positive and negative sentiment ratio measure	ARMA	64.55%	70.91%	70.91%	75.45%
	Logistic Regression	66.36%	70.91%	70.91%	74.55%
	Nguyen et al.'s method	64.55%	71.82%	70.00%	75.45%
	Our Method	**68.18%**	**73.64%**	**72.73%**	**76.36%**

bomber, Zhongxing Ji. The bomber was a paralyzed petitioner. He claimed that he had previously been unfairly treated by the security officers which caused his paralyzation. This event brought about a controversy in major Chinese websites.

We collect the tweets related to this event in Weibo during the period from Jul. 20, 2013 to Dec. 31, 2013, with totally over 19000 tweets. We set 12 hours as the span for each time slice. The data in the first two-third time slices are used for training and the rest of data for testing.

B. Results and Discussions

We provide the prediction results of our experimental study. First, we combine our features with the representative machine learning methods and compare their performance. We then compare the performance of our method with those of the baseline methods and the related work.

The machine learning methods for test include *SVM*, *logistic regression*, *multilayer perceptron*, *C4.5* and *random forests*. We compare the accuracies of these methods, and find in general, *SVM* and *logistic regression* perform better and are more stable than other methods.

We use *SVM* to build our model and choose two baseline methods for comparison. The first method is autoregressive moving average model (ARMA), a classic time series model for predicting future values of time series. The second method we select is logistic regression using time series data, another typical method for estimating future trends from time series. Besides, we compare our method with Nguyen et al.'s method [6] (which also uses *SVM*) on the positive and negative sentiment ratio measure.

Table II gives the prediction results by our method, the related method and the baseline methods. We set four time intervals, 12 hours, 24 hours, 36 hours and 48 hours. From the table, we can see that in general, our method performs better than ARMA method and logistic regression time series method. Compared to Nguyen et al.'s method [6] on the positive and negative sentiment ratio measure, our method also achieves better performance. The experimental results illustrate that our method is relatively more effective and stable compared to the other methods.

VI. CONCLUSION

In this paper, we propose a method to model and detect opinion dynamics in security-related social media data. We define three measures to describe opinion dynamics thoroughly and develop a computational method based on the key factors that influence opinion changes. We conduct a preliminary empirical study using Weibo dataset on a specific topic, and compare our method with the related work [6] and two baseline methods. The experimental results demonstrate the effectiveness of our proposed method in modeling and detecting the dynamic changes of public opinions.

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