# Detecting Microblogger's Attitude towards Bursty Events: a Text Chain Model

Lina Liu[a], Jihong Shen[b], Qianghua Zhu[c]
[a] College of automation, Harbin Engineering University, Harbin 150001, Heilongjiang, China
Email: 294184604@qq.com
[b] College of Science, Harbin Engineering University, Harbin 150001, Heilongjiang, China
Email: jhshen@163.com
[c] College of electronic engineering, Naval University of Engineering, Wuhan 430033, Hubei, China
Email: qhzhu@gmail.com

***Abstract*—With the booming of social media, microblog attracts more and more people to discuss public issues and share their views and opinions. In this paper, we focus on the sentiment analysis in Chinese microblog from the aspect of users. We aim to detect microbloger's attitude on bursty events by proposing a novel text chain model. We firstly formulate the problem of user sentiment analysis. By leveraging the link symbols in contents, we generate micrblog units and prune to user text chains which will be regarded as a whole in the follow-up process. Then, we use MaxEnt-LDA model to extract target events and opinion words, and use a lexicon-based model to detect user's orientation towards a certain atomistic event. Experimental results show that our model could detect user's attitudes effectively.**

***Keywords*-Sentiment analysis, microblogger, text chain**

## I. Introduction

With the rapid development of Internet and communication technologies, people become more and more willing to share their views and opinions through Internet. Microblog, as a typical application of Web2.0, attracts increasing more users to discuss current issues. Many such social networks like Twitter, SINA-Weibo are extremely rich in content and have become valuable sources of public opinions. It is said that there were 31 million related tweets on the day of U.S. presidential election in November 2012, and the victory messages by Barack Obama was reposted 766,620 times. Table I shows top10 issues in a survey conducted by China Internet Public Opinion Analysis Report in 2012[1]. As shown in the table, there are much more messages in microblog than in other platforms, and microblog has become a new media platform for users to express their opinions.

Sentiment analysis or opinion mining refers to the application of natural language processing, computational linguistics, and text analytics to identify and extract subjective information in source materials. There has been rich research in text sentiment analysis due to its great potential value and applications in economy, marking, politics and many other areas. Traditional text sentiment analysis methods classify sentiment into three types: positive, neutral, and negative. Most of the methods just focus on the sentiment classification from the text level. In fact, we sometimes need to perform the analysis in user level, detecting microblogger's attitude towards certain issues in order to analyze the orientation distribution to make more precise decision.

In this paper, we just focus on sentiment analysis in user-level. We aim to detect user's orientation towards certain events. More specifically, given a certain user and bursty events in microblog, we consider the time elements combining with text elements. The main contributions of this paper are as follows.

1. We define the problem of user level sentiment analysis formally, comprehensive considering time dimension and text space dimension.

2. We propose a new text chain model to integrate user's microblog according to the link relationships. The text chains are then regarded as a whole in the process of atomistic event detection and user sentiment analysis. We use MaxEnt-LDA model to detection atomistic events and the corresponding sentiment words. Then we use a lexicon-based model to detect user's orientation towards a certain atomistic event.

3. We collected 4.8 million real microblog data about the *2012 London Olympic Games* in SINA-Weibo to perform experimental evaluation. The results show our model could effectively present user level sentiment analysis.

Note that all our methods are based on Chinese Microblog, yet the technical is also available in any other languages. The rest of this paper is organized as follows. Section 2 discusses related prior works. In Section 3, we present our approach in detail. Experiments and evaluations are described in Section 4 and we conclude our work in Section 5.

## II. Related Work

### A. Sentiment Analysis

There have been a large number of research papers in this area. B.Pang did a very good survey about the techniques and approaches which promise to directly enable

Manuscript received August 10, 2011; revised January 2, 2012; accepted April 16, 2012. 
This work was supported in part by NSFC (No. 11601063); NSFHLJ (No. F200931).
[1]http://yuqing.people.com.cn/n/2012/1221/c210123-19974822-2.html


doi:10.4304/jsw.9.5.1163-1169

TABLE I
TOP 10 ISSUES DISCUSSED IN DIFFERENT PLATFORMS IN CHINA, 2012

| Events | Tian Ya Community | Kai Di Community | Renren | Sina Microblog | Tencent Microblog | Total |
|---|---|---|---|---|---|---|
| Diaoyu Island | 2,240,000 | 206,000 | 740,000 | 68,463,301 | 52,958,600 | 124,607,901 |
| London Olympics | 445,000 | 26,400 | 393,000 | 55,562,228 | 12,868,900 | 69,295,528 |
| Shenzhou 9 spacecraft | 121,000 | 7,340 | 72,700 | 35,157,797 | 3,422,700 | 38,781,537 |
| Huanyan Island | 2,240,000 | 143,000 | 579,000 | 10,007,209 | 5,532,000 | 18,501,209 |
| A Bite of China | 42,300 | 1,360 | 71,700 | 10,747,662 | 371,200 | 11,234,222 |

opinion-oriented information-seeking systems [1]. B.Liu (2012) reviews the existing approaches from document level, sentence level, and aspect level. The main research approaches are usually based on two aspects, supervised learning and unsupervised learning [2].

Supervised learning methods, such as naive Bayes or Support Vector Machines（SVM），were firstly taken to sentiment analysis in Pang et al. (2002) [3]. They used supervised learning to classify movie reviews into two classes, positive and negative, and showed that using unigrams as features in classification performed quite well with either naive Bayes or SVM. A large number of papers have been published in the literature since then [4]–[10]. Typically, In Pang(2004), a machine-learning method that applies text-categorization techniques to just the subjective portions of the document is used to help sentiment analysis [4]. In Liu(2005), an opinion observer was proposed to analyze and compare opinions on the Web [5]. In Bespalov et al.(2011), sentiment classification was performed based on supervised latent n-gram analysis [6] and Pak studied the problem of sentiment analysis on Twitter [7].

As for unsupervised learning, sentiment words and phrases are used for sentiment classification. Turney(2002) is a typical method of this technique [11]. It performs classification based on some fixed syntactic patterns that are likely to be used to express opinions. Given a review, the algorithm computers the average sentiment orientation (SO) of all phrased in the review based on point-wise mutual information measures, and classified the review as positive if the average SO is positive and negative otherwise. In addition, lexicon-based method, like [12]–[14], which uses a dictionary of sentiment words and phrases with their associated orientations and strength, and incorporates intensification and negation to compute a sentiment score for each document, is also widely used. Liu et al [15] combined domain-specific sentiment lexicon with hownet for Chinese sentiment analysis. Wang et al [16] proposed a fuzzy domain sentiment ontology based opinion mining approach for Chinese online product reviews. Huang et al [17] proposed appraisal expression recognition based on generalized mutual information.

### B. topic detection

Unlike many other studies on products or services, our study objects are public events or topics. Topic detection has been widely studied duo to its important application in long reviews. Basically, there are two models for topic representation: vector space model (VSM) and generative probability model.

As for VSM, it use vector to represent a document, each keyword or feature of the document is regarded as one dimension in the vector space. The similarity of two documents is measured according to the distance in space. There are many methods to represent the feature weight like *tf*idf*, which stands for term frequency－inverse document frequency. It is a numerical statistic which reflects how important a word is to a document in a collection or corpus, and is often used as a weighting factor in information retrieval and text mining. Most methods use clustering algorithms to detection topics in this model [18].

For generative probability model, the most common models currently in use is Probabilistic latent semantic analysis(PLSA) [19] and Latent Dirichlet Allocation(LDA) [20].PLSA, also known as probabilistic latent semantic indexing (PLSI, especially in information retrieval circles), uses a mixture decomposition derived from a latent class model to perform probabilistic latent semantic analysis. LDA was proposed in 2003 by David Blei et. al. Each document is viewed as a mixture of various topics, and each topic consists many words. Many improved models such as [21]–[23] are generally extensions on LDA.

In this paper, we focus on user level sentiment analysis towards microblog bursty events, and we propose a text chain model to aggravate user's text according to link symbols. We now detail our models and methods in the following section.

## III. MODELS AND APPROACH

### A. Problem Formulation

*Definition 1 (Microblog Stream):* Microblog stream is defined as $D = \{d^{t_1}, d^{t_2}, d^{t_3}, \cdots\}$, where $d^{t_i} = \{w_1, w_2, \cdots\}$ is a microblog message, $t_i$ is the post time of message $d_i^{t_i}$, and $w^j$ is the feature item after segmentation and removing stop words. $D^T = \{d^t | t \in T\}$ represents the messages set during time window $T$.

Like text opinion proposed in [12], [24], we define a user opinion towards a certain events as follows.

*Definition 2 (User opinion):* A user opinion towards an event is a trituple *h:(e,s,tp)*, where *h* is the opinion holder, *e* is the event or the topic, *s* is the sentiment orientation of the user, and *tp* is the time period of the opinion.

Note that in our definition, *h* is the author of the microblog, and sentiment orientation *s* may change according to time period *tp*.

So the problem can be formulated as: Given a user *h* and his microblogs, we aim to detect what orientation *s* of the user towards the events *e* expressed in the text during *tp*. Mostly, *tp* is less than or equation to the duration time of *e*. If we set *tp* so small that there is only one single message in *tp*, it will transform into the message level sentiment analysis.

In order to fully implement the process, we need to conquer several challenges, including:

1. How to organize the user's microblog during *tp*;
2. How to detect the target events *e*;
3. How to analyze the orientation of the text.

We propose a text chain model to integrate the microblogs according to link relationship, use MaxEnt-LDA model to detect the atomistic events and lexicon-based model to detect user's orientation. Our model and methods are as follows.

### B. Text Chain Model

Text chain model is used to integrate user's microblogs. Unlike traditional long reviews, microblog allows users to reply or repost one message many times. So the opinion of user is not only implied in the original messages, but also exists in the comments. By leveraging rich link relationship, we use text chain model to organize user's messages.

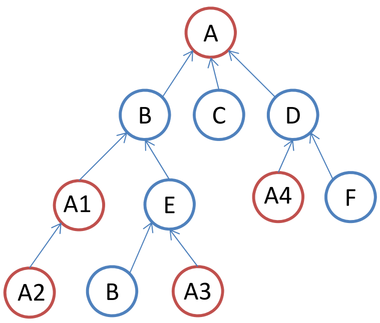


Fig. 1. An example of microblog unit

We define a *microblog unit* as *one original messages followed by many comments by different users*. Figure 1 shows an example of this *microblog unit*. The circle represents user, and the arrow means the comment or repost relationship. More specifically, user *A* posted an original message and user *B,C,D* reply or repost this message. Then, user *A* and *E* replied to *B*. User *A* then made a complement to the prior comment of user *B*. What's more, user *A,B* commented on user *E*, and user *A,F* make a comment on user *D*. The red circles *A1,A2,A3,A4* mean comments posted by A.

We can see from figure 1 that original message and the following comments all contains the opinion of user *A*. So when conducting sentiment analysis, just using the original message is incomplete. We use a text chain model to organ the original messages and comments. In SINA-Weibo, when user *B* reply to user *A*, there will be a link prefix "reply to A: " to mark that it is a comment. And if *B* reposts a message of user *A*, there will be *"repost A:"* before the message. By leveraging those symbols, we use regular expression to generate the structure of *microblog unit*. We use tree structure to store *microblog unit*. For each message collected by API, if it is an original message, it must the root node of the tree. If the message contains link information like *"reply to"* or *"repost to"*, there must be a path from the leave node to a certain node. Note that the end point of the path may be not the root node, because the length limitation of microblog is only 140. For each tree node, we save the user information and the text content besides the link information. The *microblog units* generative algorithm from data streams is shown in algorithm 1.

**Algorithm 1** Generating Microblog Units from Data Steams.

**Input:**
The microblog stream, $D$;
Regular expression of symbols, $R$

**Output:**
Microblog units set, $MU$;

**for** each message $d \in D$ **do**
  detecting whether $d$ contains symbols according to $R$;
  **if** $d$ contains no $R$ **then**
    generate a new microblog unit $mu_i$;
    $d \rightarrow$ the root of $mu_i$;
    add $mu_i$ to $MU$;
  **else**
    separate $d$ into several part by $R$;
    generate a node path $p$;
    detecting whether the end node $en$ exists in $MU$;
    **if** $en \in MU \wedge en \in mu_j$ **then**
      add $p$ into $mu_j$;
    **else**
      generate a new microblog unit $mu_k$;
      $p \rightarrow mu_k$;
      add $mu_k$ to $MU$;
    **end if**
  **end if**
**end for**
**return** $MU$;

In fact, there are three types of links in the *microblog unit*: *comment, repost with comments, repost without comments*. We conduct different strategies for these three types while generating the text chain.

1) *comments and repost with comments*: we extract the content before the symbols, as it is what the user *B* write personally.

2) *repost without comments*: we regard the message of prior user *A* as the content of *B*. Here, we think that if user *B* just reposted what user *A* wrote without any comment, he (or she) should agree with what user *A* said and they had similar opinions. In this case, we can see from the generating process that the text content of node *B* in microblog unit should be null.

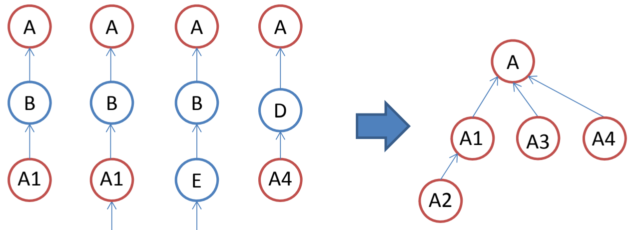


Fig. 2. Five typical dimensions of emotional vector overtime

Using above rules, we could prune *microblog unit* to create text chain. Algorithm 2 is the generative algorithm of text chain from microblog unit using depth-first search(DFS).

*A* is the root of microblog unit, and it is also the root of text chain. For the comments of reposts *A1,A2,A3,A4*, we detect their corresponding path to root *A*.

1. For the path from node *A1* to root *A:* $A1 \rightarrow B \rightarrow A$, as node *B* is posted by other user, so we remove node from the path such that *A1* is the first child of *A*.

2. For *A2*, the path $A2 \rightarrow A1 \rightarrow B \rightarrow A$ covers the path of *A1*, so *A2* is a child of *A1*.

3. For the path $A3 \rightarrow E \rightarrow B \rightarrow A$ of *A3*, node *B* and *E* are from other users, so *A3* is a child of *A*.

4. The situation of *A4* is similar to *A3* and *A4* is a child of *A*.

The process is shown in figure 2. In the follow-up modules, the text chain of user *A* will be regarded as a whole.

**Algorithm 2** Generating Text Chain by DFS.

**Input:**

A certain microblog unit , $mu$;

**Output:**

Text chain of the root node, $tc$;

root node $r$, $visited[r] = 1$;
$w = r.child()$;
**while** w.exist() **do**
  **if** $visted[w] = 0$ **then**
    Recursive implementation the algorithm:
    **if** $(w.user == tc) \wedge (w.content! = null)$ **then**
      put node $w$ into $tc$;
    **else**
      $w_i$ = the least ancestor of $w$ with content;
      put $w_i$ into $tc$;
    **end if**
    w=r.nextchild();
  **end if**
**end while**
**return** $tc$;

### C. Detecting Target Events

As our opinion targets are public events or hot topics in microblog, we use MaxEnt-LDA topic model proposed in [23] to extract the target events(aspects) and opinions. The LDA(Latent Dirichlet Allocation) topic model is an unsurprised learning model that assumes each document consists of a mixture of various topics and each topic is a probability distribution over words. The generation model is widely used in topic detection, and MaxEnt-LDA is a variant of traditional LDA, which extracts not only the targets aspects, but also the aspect-specific opinion. The plate notation of MaxEnt-LDA is shown in figure 3.

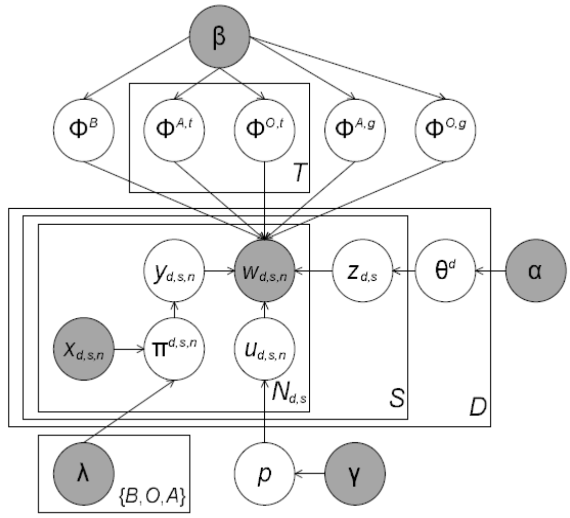


Fig. 3. Five typical dimensions of emotional vector overtime

In this model, $\alpha$ is the parameter of the Dirichlet prior on the per-document topic distribution, and $\beta$ is the parameter of Dirihlet prior on the per-topic word distribution. For each document $d$, topic distribution $\theta^d \sim Dir(\alpha)$, and $z_{d,s} \sim Multi(\theta^d)$ is topic for word in document as in standard LDA. There are five word distributions from a symmetric Dirichlet prior with parameter $\beta$: a background model $\phi^B$, a general aspect model $\phi^{A,g}$, a general opinion model$\phi^{O,g}$, $T$ aspect models $\{\phi^{A,t}\}_{t=1}^{T}$and $T$ aspect-specific opinion models$\{\phi^{O,t}\}_{t=1}^{T}$. Parameter $y_{d,s,n}$ indicates whether a word is a background word, aspect word, or opinion word, and parameter $u_{d,s,n}$ indicates the word is general or aspect-specific. Maximum Entropy model is used to training a model to determine the value of $\pi^{d,s,n}$ and $x^{d,s,n}$ associated with $y_{d,s,n}$ using training set. The distribution of $w_{d,s,n}$ meets the following distribution.

$$w(d,s,n) \sim \begin{cases} \text{Multi}(\phi^B) & \text{if } y_{d,s,n} = 0 \\ \text{Multi}(\phi^{A,z_{d,s}}) & \text{if } y_{d,s,n} = 1, u_{d,s,n} = 0 \\ \text{Multi}(\phi^{A,g}) & \text{if } y_{d,s,n} = 1, u_{d,s,n} = 1 \\ \text{Multi}(\phi^{O,z_{d,s}}) & \text{if } y_{d,s,n} = 2, u_{d,s,n} = 0 \\ \text{Multi}(\phi^{O,g}) & \text{if } y_{d,s,n} = 2, u_{d,s,n} = 1 \end{cases} \quad (1)$$

The generative process of MaxEnt-LDA model is shown in algorithm 3. Note that in our model, the document $d$ is a text chain but not a single message.

**Algorithm 3** Generative process of MaxEnt-LDA

**for** each message $d \in D$ **do**
  choose $\theta^d \sim \text{Dir}(\alpha)$;
  **for** each sentence $S \in d$ **do**
    choose $z_{d,s} \sim \text{Multi}(\theta^d)$;
    **for** each word $w_{d,s,n} \in S$ **do**
      setting $\pi_{d,s,n}$ with Maximum Entropy Model;
      choose parameter $y_{d,s,n} \sim \text{Multi}(\pi_{d,s,n})$ over $\{0, 1, 2\}$;
      choose $u_{d,s,n} \sim \text{Bernoulli}(p)$ over $\{0, 1\}$;
      choose $\phi \in \{\phi^B, \phi^{A,z_{d,s}}, \phi^{A,g}, \phi^{O,z_{d,s}}, \phi^{O,g}\}$ and $\phi$ ~;Dir($\beta$) according to equation 1 parameterized by $y_{d,s,n}$ and $u_{d,s,n}$;
      choose a word $w_{d,s,n}$ ~Multi($\phi$);
    **end for**
  **end for**
**end for**

### D. Lexicon-based user orientation detection

After the process of MaxEnt-LDA, we got the aspects (target events in our situation) and sentiment words. In this section, we aim to detect user's orientation towards target events by using a lexicon-based model.

We use Hownet [2] as our basic lexicon which contains twelve classes: Minus Attribution, Plus Attribution, Plus Entity, Minus Entity, Minus Event, Plus Event, Minus Feeling, Plus Feeling, Minus Sentiment, Plus Sentiment. It contains 11,888 Chinese words and 105,027 English words.

For a given event $e_j$ and time period *tp* , we integrate all the sentiment words generated by III-C during time *tp*. Let $W = \{w_{ij1}, w_{ij2} \cdots w_{ijn}\}$ is the sentiment words of user $u_i$ towards $e_j$, where $w_{ijk}$ is the $k$th sentiment word. $H$ is the Hownet lexicon, and $f = f(w_{ijk})$ is the sentiment score of $w_{ijk}$. We follow the below rules to calculate the orientation of user $u_i$.

1) if $w_{ijk} \in H$. The sentiment score of $w_{ijk}$ depends on the orientation types of lexicon. More specifically,

$$f(w_{ijk}) = \begin{cases} 1 & \text{if } w_{ijk} \in \text{Plus lexicons} \\ -1 & \text{if } w_{ijk} \in \text{Minus lexicons} \end{cases}$$

2) if $w_{ijk} \notin H$. For each $w_p \in H$, we calculate the semantical distance dis$(w_p, w_{ijk})$ between $w_p$ and $w_{ijk}$ and choose the most similar $\hat{w}$ such that

$$\hat{w} = \arg \min_{w_p \in H} \text{dis}(w_p, w_{ijk})$$

and set

$$f(w_{ijk}) = f(\hat{w})$$

Besides, we consider the sentiment shifters and degree adverbs. Most sentiment shifters are negative words like *not, none, never* and so on. If there is a sentiment shifter before $w_{ijk}$, we set the final sentiment score as $-f(w_{ijk})$. If there is a degree adverb like *too, more, extreme*, we double the sentiment score. The domain of $f$ is {-2, -1, 0, 1, 2} which the polarity represents positive or negative, and value represents strength of sentiment words.

The sentiment score of $W$ is calculated by the average score of each word according to the following equation.

$$f(W) = \frac{1}{n} \sum_{k=1}^{n} f(w_{ijk})$$

## IV. Experimental Study

### A. Data Set

The data set we used in our experiment contains 4,823,281 messages posted by 2,182,298 microbloggers, ranged from 28th, June to 13th, June 2012 about *London Olympic Games*. All messages were collected by SINA-Weibo API by search the keyword *Olympic*. Figure 4 is log-log distribution of the messages number per user. The $x$ axis represent the message number, and $y$ axis is the number of users posting the corresponding number of messages.

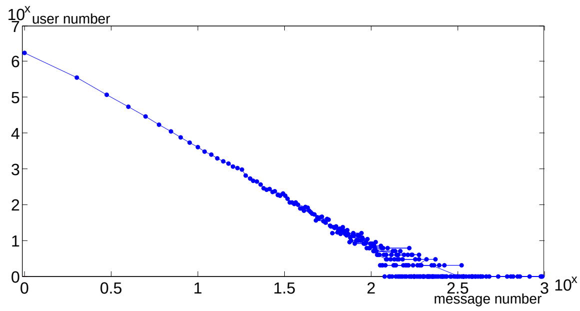


Fig. 4. Five typical dimensions of emotional vector overtime

As shown in the figure, the number of messages posted by per user follows power-law distribution, which means most user conduct few messages while a small number of user post large amount of microblogs. According to the data set, there are 1,716,749 users posted only one message, and only 1 people post 388 messages about the games which is the largest number in our data set.

### B. Experiment and Results

We set parameters $\alpha = 0.1$ and $\beta = 0.1$, set the topic number $k = 420$ which according to the news reports. As for the time period, firstly we set *tp=17 days* which is the whole period time of *London Olympic Games*. In this case, we aimed to analyze the user orientation distribution towards the overall event. Figure 5 shows the message orientation distribution and user orientation distribution.

We can see from the figure 5, there are 53.2% positive messages and 46.8% negative messages for the overall games. When it comes to the user level, positive users made up only 48.6%, which is less than 50% while negative users accounts for 51.4%. By analyzing the date set, we found that users who tent to post few messages are more negative, and those who post many messages about the games tent to post more positive messages.

[2] http://www.keenage.com/html/e_index.html

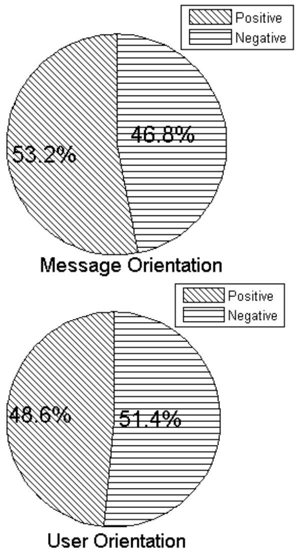


Fig. 5. Message Orientation and User Orientation

We now set *tp=1* day, and analyzed users sentiment by day. Figure 6 shows the orientation distribution in user level over time. At the beginning and end of the *Games*, most users are positive, which reflects that people are pleased with the opening and closing ceremonies. During the *Olympic Games*, the orientation of users varies accompany with different events. The highest point of negative sentiment appears in 7th June, when Chinese famous athlete *Liu Xiang* failed in the 110 meter hurdles.

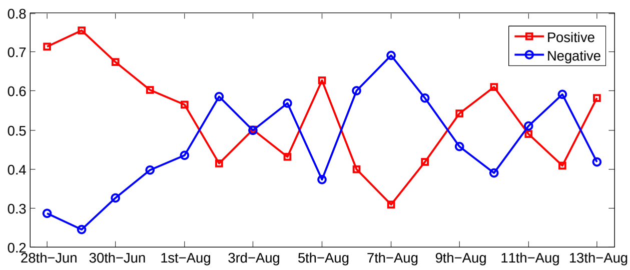


Fig. 6. Five typical dimensions of emotional vector overtime

For the text chain model, we compared our algorithm with sentiment analysis using the original messages only(SAOM). We use precision to evaluate our model. As the corpus contains so many messages, we chose 100 users randomly to detect their attitudes towards bursty events. The average precision of our model is 74.3%, while for SAOM, the average precision is only 65.8%, which reflects the effectiveness of our model.

## V. CONCLUSION AND FUTURE WORK

In this paper, we focus on the sentiment analysis in Chinese microblog from the aspect of users. We aim to detect microbloger's attitude on bursty events by proposing a text chain model. We firstly formulate the problem of user sentiment analysis. By leveraging the link symbols in contents, we generate micrblog units and prune to user text chains which will be regarded as a whole in the follow-up process. Then, we use MaxEnt-LDA model to extract target events and opinion words, and use a lexicon-based model to detect user's orientation towards a certain atomistic event. Experimental results show that our model could detect user's attitudes effectively.

## REFERENCES


[1] B. Pang and L. Lee, "Opinion mining and sentiment analysis," *Foundations and Trends in Information Retrieval*, vol. 2, no. 1-2, pp. 1–135, 2008.

[2] B. Liu, "Sentiment analysis and opinion mining," *Synthesis Lectures on Human Language Technologies*, vol. 5, no. 1, pp. 1–167, 2012.

[3] B. Pang, L. Lee, and S. Vaithyanathan, "Thumbs up?: sentiment classification using machine learning techniques," in *Proceedings of the ACL-02 conference on Empirical methods in natural language processing*, vol. 10, 2002, pp. 79–86.

[4] B. Pang and L. Lee, "A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts," in *Proceedings of the 42nd annual meeting on Association for Computational Linguistics*. Association for Computational Linguistics, 2004, p. 271.

[5] B. Liu, M. Hu, and J. Cheng, "Opinion observer: analyzing and comparing opinions on the web," in *Proceedings of the 14th international conference on World Wide Web*. ACM, 2005, pp. 342–351.

[6] D. Bespalov, B. Bai, Y. Qi, and A. Shokoufandeh, "Sentiment classification based on supervised latent n-gram analysis," in *Proceedings of the 20th ACM international conference on Information and knowledge management*. ACM, 2011, pp. 375–382.

[7] A. Pak and P. Paroubek, "Twitter as a corpus for sentiment analysis and opinion mining," in *Proceedings of the Seventh International Conference on Language Resources and Evaluation (LREC'10)*, Valletta, Malta, 2010, pp. 1320–1326.

[8] X. Wang, F. Wei, X. Liu, M. Zhou, and M. Zhang, "Topic sentiment analysis in twitter: a graph-based hashtag sentiment classification approach," in *Proceedings of the 20th ACM international conference on Information and knowledge management*. ACM, 2011, pp. 1031–1040.

[9] T. Wilson, J. Wiebe, and P. Hoffmann, "Recognizing contextual polarity: An exploration of features for phrase-level sentiment analysis," *Computational linguistics*, vol. 35, no. 3, pp. 399–433, 2009.

[10] G. Qiu, B. Liu, J. Bu, and C. Chen, "Expanding domain sentiment lexicon through double propagation." in *IJCAI*, vol. 9, 2009, pp. 1199–1204.

[11] P. D. Turney, "Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews," in *Proceedings of the 40th annual meeting on association for computational linguistics*. Association for Computational Linguistics, 2002, pp. 417–424.

[12] M. Hu and B. Liu, "Mining and summarizing customer reviews," in *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 2004, pp. 168–177.

[13] S.-M. Kim and E. Hovy, "Automatic detection of opinion bearing words and sentences," in *Companion Volume to the Proceedings of the International Joint Conference on Natural Language Processing (IJCNLP)*, 2005, pp. 61–66.

[14] L. Zhang, Y. Jia, B. Zhou, and Y. Han, "Microblogging sentiment analysis using emotional vector," in *Cloud and Green Computing (CGC), 2012 Second International Conference on*. IEEE, 2012, pp. 430–433.

[15] L. Liu, M. Lei, and H. Wang, "Combining domain-specific sentiment lexicon with hownet for chinese sentiment analysis," *Journal of Computers*, vol. 8, no. 4, pp. 878–883, 2013.

[16] H. Wang, X. Nie, L. Liu, and J. Lu, "A fuzzy domain sentiment ontology based opinion mining approach for chinese online product reviews," *Journal of Computers*, vol. 8, no. 9, pp. 2225–2231, 2013.

[17] H. Huang, Q. Liu, and T. Huang, "Appraisal expression recognition based on generalized mutual information," *Journal of Computers*, vol. 8, no. 7, pp. 1715–1721, 2013.

[18] L. Zhang, J. Yan, B. Zhou, and Y. Han, "Detecting real-time burst topics in microblog streams: how sentiment can help," in *Proceedings of the 22nd international conference on World Wide Web companion*. International World Wide Web Conferences Steering Committee, 2013, pp. 781–782.

[19] T. Hofmann, "Probabilistic latent semantic indexing," in *Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval*. ACM, 1999, pp. 50–57.

[20] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent dirichlet allocation," *the Journal of machine Learning research*, vol. 3, pp. 993–1022, 2003.

[21] M. Hoffman, F. R. Bach, and D. M. Blei, "Online learning for latent dirichlet allocation," in *advances in neural information processing systems*, 2010, pp. 856–864.

[22] Z. Ding, Y. Jia, B. Zhou, J. Zhang, Y. Han, and C. Yu, "An influence strength measurement via time-aware probabilistic generative model for microblogs," in *Web Technologies and Applications*. Springer, 2013, pp. 372–383.

[23] W. X. Zhao, J. Jiang, H. Yan, and X. Li, "Jointly modeling aspects and opinions with a maxent-lda hybrid," in *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 2010, pp. 56–65.

[24] B. Liu, *Web data mining: exploring hyperlinks, contents, and usage data*. Springer, 2007.