Stance Influences Your Thoughts: Psychology-inspired Social Media Analytics

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Abstract. There are abundant user posts in social media which contain valuable information. Lots of previous studies focus on social media analytics, such as topic detection, sentiment prediction, and event trend analysis. According to psychological theories, namely ***affective forecasting***, ***endowment effect***, and ***negativity bias***, user stance (one's role in a specific social event, e.g. involvement) results in biased sentiment and attitude in real scenarios. However, user stance has not been taken into consideration in previous work. In most cases, user stance is a visible factor, so we argue that it should not be ignored. In this paper, we introduce user stance into two real scenarios (sentiment analysis and attitude prediction). Firstly, analyses on two real scenarios indicate that user stance does matter and provides more useful information for event analyses. Different user stance groups have significantly distinct sentiments and attitudes on an event (or a topic). By taking the differences into consideration, it is easy to get better mining results. Secondly, experimental results show that taking user stance information into account improves prediction results. Instead of designing a new algorithm, we propose that different algorithms should incorporate users stance information in online social event analysis. To the best of our knowledge, this is the first work which integrates psychological theories of user stance bias on understanding social events in the online environment.

Keywords: Social Media Analytic · Event Mining · Topic Analysis

1 Introduction

In recent years, users are used to browsing news and expressing their opinions on social media (such as Twitter and Facebook), especially when there are some

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special events or news. A huge number of posts are generated by users towards various topics, and the posts also contain abundant information for data mining and analysis. Due to the necessity of understanding user feedback/opinions and its potential applications, many studies are conducted on social media analysis, including online topic detection, event tracking, and sentiment/attitude prediction. For example, companies are willing to listen to users feedback about their products, and governments look forward to learning more about citizens opinion towards a certain event for further decisions. Existing studies [1, 21, 23, 25] mainly make use of obviously features, such as the number & content of posts.

On the other line of research, some well-established psychological theories, namely, ***affective forecasting*** [20], ***endowment effect*** [9], and ***negativity bias*** [10], show that user stance will impact on user's sentiments and attitudes expression. Thus, previous studies, which take all data into account directly and ignore the influences of user stance, may result in biased estimation of user sentiments and attitudes. A simple way to define user stance types in a scenario is to distinguish related users and unrelated bystanders. For example, in "Samsung Note7 explosion" event (Samsung Galaxy Note7 explosion events after launching), the owners of Note7 are event-related users and others are bystanders.

Thus, in this paper, we argue that user stance, which contains valuable information for analysis, should be taken into account too. To verify whether user stance does matter in user sentiment and attitude prediction, event analysis is conducted on two real scenarios in distinct languages (Chinese and English) and different social media (Weibo and Twitter). The results confirm our suggestion that user stance feature attributes to event analysis and mining. Besides, note that user stance is a visible factor in many conditions, it can be introduced into sentiment/attitude prediction studies. So we conduct sentiment and attitude prediction experiments on real scenarios with various algorithms. The performances of multiple algorithms are improved by adding user stance feature.

Our main contributions are listed as follows:

- Inspired by psychological theories, we propose to take user stance into consideration in social event mining. To the best of our knowledge, this is the first work which integrates psychological theories of user stance bias on understanding users in the online environment.
- We conduct detailed analyses on two real scenarios to explore user stance's impacts on attitude, sentiment for model specification, and the results show that it does matter in users' attitude and sentiment expression.
- The experiments on various datasets indicate that user stance is a useful feature in sentiment and attitude prediction, which contributes to better online event analysis results and user understanding.

2 Related Work

There are several topics related to our work: social event studies in social media and social psychology studies.

2.1 Social Event Studies in Social Media

Event analysis is concerned with developing & evaluating informatics tools and frameworks to collect, monitor, analyze, summarize, and visualize social media data to extract effective patterns and intelligence about certain events [4]. Some previous studies are concentrated on how to detect new events or hot topics in social media. Many real-time detection algorithms are proposed, such as [22]. Some studies consider not only event or topic detection but also further analysis of people's feedback: Sayyadi et al. focus on event tracking in social information streams [18]. Other conducted studies on social media related to certain social events or topics (e.g. E-commence and politics) [19]. A vital part of social media analysis is to understand the users sentiment/attitude towards an event or topic based on the posts users published in social media. Sentiment prediction is very useful to mine users feelings about some products or events. For example, Mostafa et al. adopt user tweets to predict users brand sentiments [15]. Then, multiple well-designed algorithms are proposed for sentiment prediction in social media, such as emoticon based method [21, 8] and dynamic analysis [25]. In analyzing politic related events, attitude prediction is more helpful to understand peoples opinions (support or opposite). Gayo et al. propose a meta-analysis of electoral prediction from Twitter data [5].

However, most previous studies are conducted on the entire collected dataset (user posts) without consideration in user stance. In this paper, user stance is introduced into social media analytics for the first time. And our study focuses on event mining and user sentiment/attitude prediction tasks.

2.2 Social Psychology Studies

Social psychology is the scientific study of how people's thoughts, feelings, and behaviors are influenced by the actual, imagined, or implied the presence of others [2]. There are several psychological theories about people's attitudes, sentiments, and stances in events.

Affective forecasting theory is originally mentioned in [6], which refers to that people are usually leading to higher inaccuracy when they respond to complex social events, often overestimates the degree in which they have not encountered [20]. ***Endowment effect*** theory states that the ownership creates a psychological association between the object and the owner. People will ascribe more value to their ownership [9]. ***Negativity bias*** theory [10] shows that bad things have a stronger influence than good things in peoples feeling [3]. In summary, these studies show that ones stance has great impacts on his/her attitude and sentiment. Moreover, there were a few social media studies that have taken psychological theories into consideration. The effects of users' experiences on their actions are investigated in [14]. Kosinski et al. conduct user's psychological personality prediction study based on user's action in Facebook [13]. They extend their studies and find that there are opportunities and challenges in the areas of psychological assessment, marketing, and privacy [24]. The correlation between users' activities in Facebook and their mood is discussed in [17], which is related to ***affective forecasting*** theory.

There are some attempts on introducing psychological theories into social media studies and the attempts are successful in improving the mining results. Our work is inspired by the psychological theories mentioned before, and we intend to apply these theories to better understanding user sentiments and attitudes.

3 User Stance and Psychology theories

In this section, user stance, attitude, and sentiment are defined as follows:

- **Stance**: User's role in a specific scenarios. e.g. involved in or not, related user or bystander. A simple way to define user stance types in a scenario is to distinguish related users and unrelated bystanders.
- **Attitude**: User's predisposed state of mind regarding a value, which is precipitated through a responsive expression towards an event [16], e.g. agreement.
- **Sentiment**: Users emotional response towards a social event/products, e.g. happy, sad. Note that attitude and sentiment are two distinct factors. For example, there are two users support a basketball team (attitude), if this team lost a game, one may feel angry and the other may feel sad (different sentiments).

The related psychological theories and their potential effects in sentiment/attitude prediction are as follows:

- ***Affective forecasting*** theory shows that the user's responses to complex social events will cause certainty bias if they are related users. This is the basic theory shows that user's stance will influence his/her attitude and may change his/her sentiment.
- ***Endowment effect*** theory indicates that related users may show more positive sentiments.
- ***Negativity bias*** theory suggests that bystanders will show more negative sentiments on an event/item.

According to these theories, we think that related users who have known the target will tend to show more positive sentiment than bystanders in event analysis scenarios.

4 Does User's Stance really Matter? Empirical Studies

To investigate the impact of user stance on real scenarios, we conduct model specification on social event analysis with two real-world datasets.

4.1 "Samsung Note7 Explosion" event in Weibo.

Users often show their sentiments towards social events on social media, and we are going to verify if the sentiments are affected by user stances. "Samsung Note7 Explosion" is a big event in 2016 and has been widely discussed, which is caused by the new published Samsung Galaxy Note7 may result in explosion when charging.

Dataset. This dataset is crawled by Weibo[1] search API from Aug. 1 to Oct. 31, 2016 with the query "Samsung Note7". 21,343 posts from 13,277 users are collected. For each post, its post content, user id, user nickname, the device from which the post is sent (e.g. iPhone 6s, Samsung Note7), and publish time are recorded. The posts in this dataset are in Chinese.

Stance Specification. As Samsung Note7, a type of mobile phone, is the key in this event, so user's stance is the mobile phone type he/she used here. Samsung users, especially Note7 users, are event-related users. Other device holders are bystanders. To better understand the influence in group sentiment caused by user's stance, users are divide into three groups with their devices recorded by Weibo (users who use unknown devices are ignored here.):

- **Group A**: Samsung Galaxy Note7 users (534 users).
- **Group B**: Other Samsung devices users (630 users).
- **Group C**: Other devices users (5,245 users).

Analysis. Firstly, sentiment analysis is an important part of previous events tracking approaches. The algorithm applied here is [7], which has good performance on sentiment prediction in Weibo posts. In this algorithm, the input is the content of a single user post, and the output is a 3-dimension vector which records the positive, neutral, and negative scores (S_+, S_0, and S_-, and we have $S_+ + S_0 + S = 1.0$). The sentimental label of each post is decided by the scores. Due to the fact that most of the words get higher neutral score than other sentimental scores, S_0 is always the major sentiment component of a post. Following the setting in the paper, each post is tagged with a sentiment label according to its scores:

- **Positive**: $S_+ > S_-$ and $S_+ > \delta$.
- **Negative**: $S_- > S_+$ and $S_- > \delta$.
- **Neutral**: Other conditions.

The value of δ is decided by pilot hand labeling by two experts, and δ is set as is set as 0.33.

The average sentiment scores of the posts posted by each user group are shown in Table 1. From the table, distinct user groups show various sentiment distributions, indicating that user sentiments are highly affected by their stances based on ***Affective forecasting***. Influenced by ***endowment effect***, Samsung users show more positive sentiment towards the Note7 explosion, especially Galaxy Note7 users. Other users show more negative sentiment caused by ***negativity bias***.

To check if user stance matters user sentiment, significance tests are conducted to see whether there are differences between the sentiment distributions

[1] www.weibo.com

Table 1. The average sentiment scores of each group

Group	S_+	S_0	S_-
A	0.138	0.614	0.248
B	0.131	0.613	0.256
C	0.113	0.632	0.255

Table 2. The two-sided t-test results between user groups.(* means p-value < 0.01, ** means p-value < 0.001)

Group	**A**	**B**	**C**
A	-	0.4352	0.0001**
B	0.4352	-	0.0013*
C	0.0001**	0.0013*	-

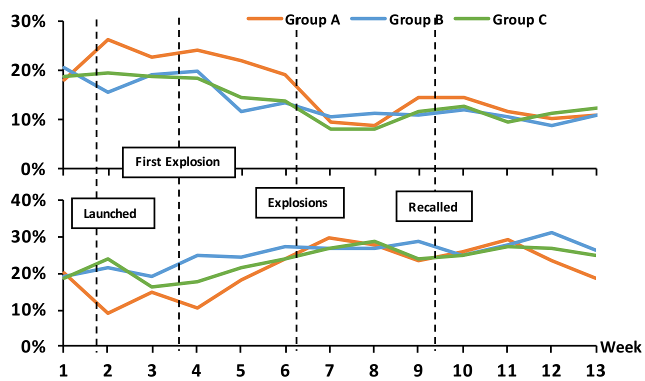

Fig. 1. Sentiment changes with time-varying in each week (from August to October). The upper/bottom figure records the percentage change of positive/negative sentiment in posts. Important dates are marked.

of user groups in a different stance (group A, B, and C). If there are significant differences, it means stance is correlated with user sentiment. We use two-sided t-test between the tweet sentiment scores of the groups and present the results in Table 2. From the table, it is apparent that the sentiment distributions of group A&C and B&C are significantly diverse. There is no significant difference between Note7 users (group A) and other Samsung users (group B), because users in group A and B are both event related people. Non-Samsung users (group C) are affected by ***negativity bias*** theory and hence express more negative sentiment. Figure 1 shows the sentiment changes with time-varying in each week on distinct user groups, and the most famous topics in each month are "launch" (August), "explosion" (September), and "recall" (October). Affected by ***affective forecasting***, users in different stances show various feedbacks. Note that Galaxy Note7 users show different sentiment towards Note7 in August and September. Since these users already have Note7, even though it may cause an explosion, they have more positive sentiment towards Note7. This is influenced by ***endowment effect***.

The analysis results in this section show that stance does have a certain impact on sentiment.

4.2 "Brexit" event in Twitter

Not only user sentiments, but also user attitudes can be seen in social media. So we try to verify if the attitudes are influenced by user stances too.

Dataset. "Brexit" (British exiting from the European Union) is taken as another social event for model specification analysis. This dataset is collected from Twitter[2] from Jun. 1 to July. 15, 2017 with the query "Brexit". Limited by the search policy of Twitter, we get more than 1,500 posts from over 500 users at last. For each post, post content, user id, user nickname, use location, and publish time are recorded. The posts in this dataset are in English.

Stance Specification. This is a politics event related to British and European people, so the user's stances are related to the country where he/she is from. European users, especially British users, are event-related users. Other users are bystanders. Users are divided into three groups according to their location recorded by Twitter, including British group (Group A), European group (Group B), and others group (Group C). Different from the former event, our analysis is focused on stance to attitude here.

Analysis. Many previous studies attempt to find users' attitude towards different events. To get the ground truth of user attitude in each post, we conduct hand labeling here. Each post is labeled by three people (master students in computer science and technology department) and the label of each post is depended on the majority opinions. If the labels of a post given by the three annotators are totally different, they will have a discussion to achieve a final agreement. Three types of attitude are used here: support, neutral, and oppose. The attitude ratio of each user group is shown in Table 3.

Table 3. The attitude ratio of each group

Group	Support	Neutral	Oppose
A	0.222	0.382	0.396
B	0.038	0.850	0.111
C	0.103	0.627	0.270

As we can see from the table, influenced by ***affective forecasting***, British users show more polarized attitudes towards this event. Most group B and C users hold neutral attitudes, especially European. ***Endowment effect*** and ***negativity bias*** will result in sentiment bias, so user attitudes are less influenced

[2] www.twitter.com

by them. We conduct t-test to verify if there are significant differences between different groups. Referring to table 4, it is apparent that there are significant differences between every two groups. The results verify that users' stances do influence their attitudes too.

In the next Section, we will conduct several experiments to apply user stance information to sentiment and attitude prediction.

Table 4. The two-sided t-test results between user groups(** means p-value < 0.001).

Group	A	B	C
A	-	0.0001**	0.0006**
B	0.0001**	-	0.0005**
C	0.0006**	0.0004**	-

5 User Stance Enhanced Algorithms

Based on the analysis in Section 4, we believe that user stance should be an valuable information in social event analysis. Thus, several user stance enhanced algorithms are designed to improve the performances in these tasks, and the performance of these methods will show that if user stance is a valuable feature.

In this section, we will introduce the Enhanced-CNN model for sentiment and attitude prediction. This model is based on a CNN model and we combine user stance features with the primary model.

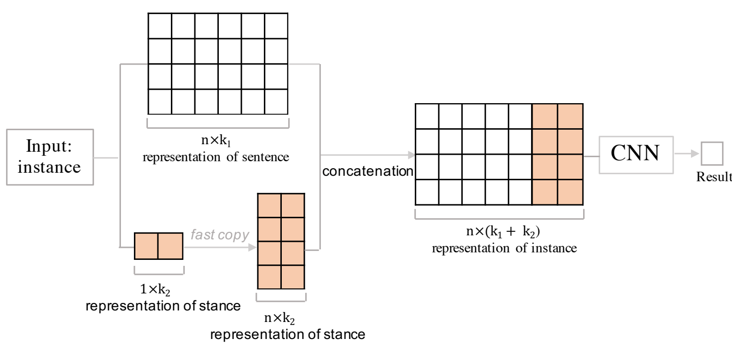

Fig. 2. Enhanced-CNN with stance feature.

The basic CNN model shown in Figure 2 is a slight variant of a sentence classification CNN model [11]. We choose this model because it performs well with little tuning of hyperparameters. It is suitable for verifying that stance features do influence users' attitude and sentiment. We get enhanced-CNN by modifying this CNN model in the embedding layer. Firstly, the representation of a sentence is concatenated by the word2vec embedding of each word, which is noted as $x_{1:n}$.

$$x_{1:n} = x_1 \oplus x_2 \oplus x_3 ... \oplus x_n \tag{1}$$

where $\oplus$ represents the concatenation operator. Then we get the stance embedding vector v_1. Corresponding to the sentence length n, we get the stance representation by fast copy

$$v_1 :_n = v_1 \oplus v_1 \oplus v_1 ... \oplus v_1 \tag{2}$$

Finally, we concatenate $x_1 :_n$ and $v_1 :_n$ to get the final instance representation $S_1 :_n$ before we put it into the CNN convolutional layer. So every filter in the convolutional layer will get the stance feature, In this way, the model performence will get improvement.

$$S_{1:n} = x_{1:n} \oplus v_{1:n} \tag{3}$$

We use cross-entropy loss in our model, which is defined as:

$$Loss = - \sum_{1 \leq i \leq n} y_i log(p_i(x)) \tag{4}$$

where n denotes the number of classes, y_i is the ground truth of labels, and $p_i(x)$ is the probability distribution of labels.

Note that this model is not only able to conduct sentiment prediction, but also able to predict attitude. As the input of the two tasks is a post and the output of them is a label. In next section, we will introduce the implementation details in dealing with the two tasks.

6 Experimental Results and Analysis

User stance has already been shown to be an essential factor in social events mining and it does have an influence on user' attitude and sentiment. Here, we will verify if it is useful in sentiment classification and attitude prediction. Besides the basic CNN and Enhanced-CNN, we use Naïve Bayes, Adaboost, Linear SVM, and Random Forest to verify if the stance features contributes to the predictions (for these methods, we only add user stance features in the input feature vector).

6.1 From Stance to Sentiment

Firstly, sentiment prediction experiments are conducted. The dataset is introduced in Section 4.1. Each post is vectorized with these features: **a) Word2vec feature**, 200-dimension, averaged by the vectorized representation of each word (trained with over 40,000,000 posts). **b) Content feature**, 3-dimension, including the publish time of this post, whether contains a hashtag (e.g. #Note7#), whether contains URL. **c) User's stance feature**. 1-dimension, the device from which the post is published. The prediction target is the sentiment of this post:

positive, neutral, or negative. Moreover, our aim is to examine if the stance features are helpful. Thus, we only consider whether there are improvements by adding stance features into the prediction.

For CNN and Enhanced-CNN, a pre-trained Chinese word2vec vectors[3] with dimension of 300 is used, which is trained on a 0.73G posts data from Weibo. One channel, 3 sizes filters(3,4,5), and max pooling strategy are adopted for CNN model. We use Adam [12] with a learning rate of 0.001 by optimizing the cross-entropy loss.

Table 5. The results of posts sentiment prediction.

Algorithm	No stance Feature		All Features	
	Accu	F1	Accu	F1
Naïve Bayes	52.23%	0.541	**53.55%**	**0.554**
Adaboost	68.56%	0.558	**68.83%**	**0.564**
Linear SVM	70.08%	**0.672**	**71.26%**	0.668
Random Forest	71.14%	0.681	**72.06%**	**0.690**
Enhanced-CNN	79.10%	0.687	**79.80%**	0.687

The results with 10-fold cross-validation are recorded in Table 5 (Enhanced-CNN with no stance feature is the basic CNN model). The prediction performances of all algorithms perform better with the extra stance feature. Enhanced-CNN with stance features achieves the best performance. The results show that user stance is helpful to sentiment prediction.

6.2 From Stance to Attitude

Table 6. The results of posts attitude prediction.

Algorithm	No stance Feature		All Features	
	Accu	F1	Accu	F1
Naïve Bayes	53.48%	0.511	**56.12%**	**0.544**
Adaboost	57.44%	0.399	**57.66%**	**0.549**
Linear SVM	59.15%	0.584	**60.48%**	**0.597**
Random Forest	57.97%	0.554	**62.92%**	**0.598**
Enhanced-CNN	68.40%	0.579	**70.88%**	**0.600**

We are going to apply stance feature to attitude prediction here. The dataset used here is illustrated in Section 4.2. Each post is vectorized with these features: **a) bag-of-words feature**, 500-dimension, words appear more than 3 times are taken into consideration. (as the corpus is smaller here, so bag-of-words is enough) **b) Content feature**, 2-dimension, including the publish time of this post, whether the post contains URL. **c) User's stance**. 1-dimension, the location where the publisher from. Especially, for CNN model, Glove[4] which is trained on Wikipedia is used to initialize word vector, the dimension of vector

[3] https://github.com/Embedding/Chinese-Word-Vectors
[4] http://nlp.stanford.edu/projects/glove/

we use is 300. Other settings are same as Subsection 6.1. Our consider is that whether there are improvements by adding stance features for attitude prediction.

The attitude prediction results with 10-fold cross-validation are shown in Table 6. All algorithms get improvements, and Naïve Bayes and Random Forest get larger improvements. The results indicate that user stance feature is effective on attitude prediction, so we can apply it to real scenarios.

7 Conclusions and Future Work

Inspired by psychological theories, namely ***affective forecasting***, ***endowment effect***, and ***negativity bias***. User stance is introduced as an unneglectable factor in social event mining in this study. Two datasets collected from different platforms (Weibo and Twitter) in distinct languages (Chinese and English) about several real scenarios ("Samsung Note7 Explosion" and "Brexit") are analyzed. Traditional tracking methods and stance based analysis are conducted. The results show that users stance has significant influences on his/her sentiment and attitude, indicating that it can be applied to social events analyzing. More conclusions are drawn when we employ user stance feature in mining. Furthermore, the experimental results demonstrate that user stance Enhanced-CNN attributes to the prediction of user sentiment and attitude. Finally, we have some discussions about the application of this finding. To the best of our knowledge, this is the first work that takes psychological theories into consideration on improving the performance of social event analysis. The experimental results show that our proposal is validated. Users stance is an essential factor in mining. We suggest that further social events analyzing works should adopt this idea.

Our future work contains two parts: 1) We will try to find an automatic way to distinguish the stances in a new social event, which will contribute to social event mining. 2) We want to go further in the interdisciplinary area of psychology and social media to achieve better event mining and understanding.

References

1. Predicting and interpolating state-level polls using twitter textual data. American Journal of Political Science
2. Allport, G.: The historical background of social psychology. Handbook of social psychology pp. 1–46 (1985)
3. Baumeister, R.F., Bratslavsky, E., Finkenauer, C., Vohs, K.D.: Bad is stronger than good. Review of General Psychology **5**(4), 477–509 (2001)
4. Fan, W., Gordon, M.D.: The power of social media analytics. Communications of the Acm **57**(6), 74–81 (2014)
5. Gayo-Avello, D.: A meta-analysis of state-of-the-art electoral prediction from twitter data. Social Science Computer Review **31**(6), 649–679 (2013)
6. Gilbert, D.T., Pinel, E.C., Wilson, T.D., Blumberg, S.J., Wheatley, T.P.: Immune neglect: a source of durability bias in affective forecasting. Journal of personality and social psychology **75**(3), 617 (1998)

7. Jiang, F., Cui, A., Liu, Y., Zhang, M., Ma, S.: Every term has sentiment:learning from emoticon evidences for chinese microblog sentiment analysis. In: second ccf conference,nlpcc2013. pp. 224–235 (2013)
8. Jiang, F., Liu, Y.Q., Luan, H.B., Sun, J.S., Zhu, X., Zhang, M., Ma, S.P.: Microblog sentiment analysis with emoticon space model. Journal of Computer Science and Technology **30**(5), 1120–1129 (2015)
9. Johnson, E.J., Hubl, G., Keinan, A.: Aspects of endowment: a query theory of value construction. Journal of Experimental Psychology Learning Memory Cognition **33**(3), 461 (2007)
10. Kanouse, D.E., Hanson Jr, L.R.: Negativity in evaluations. In: Preparation of this paper grew out of a workshop on attribution theory held at University of California, Los Angeles, Aug 1969. Lawrence Erlbaum Associates, Inc (1987)
11. Kim, Y.: Convolutional neural networks for sentence classification. arXiv preprint arXiv:1408.5882 (2014)
12. Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980 (2014)
13. Kosinski, M., Stillwell, D., Graepel, T.: Private traits and attributes are predictable from digital records of human behavior. Proceedings of the National Academy of Sciences **110**(15), 5802–5805 (2013)
14. Mills, J.S., Polivy, J., Herman, C.P., Tiggemann, M.: Effects of exposure to thin media images: Evidence of self-enhancement among restrained eaters. Personality and Social Psychology Bulletin **28**(12), 1687–1699 (2002)
15. Mostafa, M.M.: More than words: Social networks text mining for consumer brand sentiments. Expert Systems with Applications **40**(10), 4241–4251 (2013)
16. Perloff, R.M.: The dynamics of persuasion: communication and attitudes in the twenty-first century. Routledge (2010)
17. Sagioglou, C., Greitemeyer, T.: Facebooks emotional consequences: Why facebook causes a decrease in mood and why people still use it. Computers in Human Behavior **35**, 359–363 (2014)
18. Sayyadi, H., Hurst, M., Maykov, A.: Event detection and tracking in social streams. In: Icwsm (2009)
19. Sridhar, S.: Social influence effects in online product ratings. Journal of Marketing **76**(5), 70–88 (2012)
20. Wilson, T.D., Gilbert, D.T.: Affective forecasting: Knowing what to want. Current Directions in Psychological Science **14**(3), 131–134 (2010)
21. Xie, W., Zhu, F., Jiang, J., Lim, E.P., Wang, K.: Topicsketch: Real-time bursty topic detection from twitter. In: IEEE International Conference on Data Mining (2013)
22. Xie, W., Zhu, F., Jiang, J., Lim, E.P., Wang, K.: Topicsketch: Real-time bursty topic detection from twitter. IEEE Transactions on Knowledge and Data Engineering **28**(8), 2216–2229 (2016)
23. Xu, Z., Liu, Y., Zhang, H., Luo, X., Lin, M., Hu, C.: Building the multi-modal storytelling of urban emergency events based on crowdsensing of social media analytics. Mobile Networks Applications **22**(2), 218–227 (2017)
24. Youyou, W., Kosinski, M., Stillwell, D.: Computer-based personality judgments are more accurate than those made by humans. Proceedings of the National Academy of Sciences **112**(4), 1036–1040 (2015)
25. Zhu, L., Galstyan, A., Cheng, J., Lerman, K.: Tripartite graph clustering for dynamic sentiment analysis on social media. In: Proceedings of the 2014 ACM SIGMOD international conference on Management of data. pp. 1531–1542. ACM (2014)