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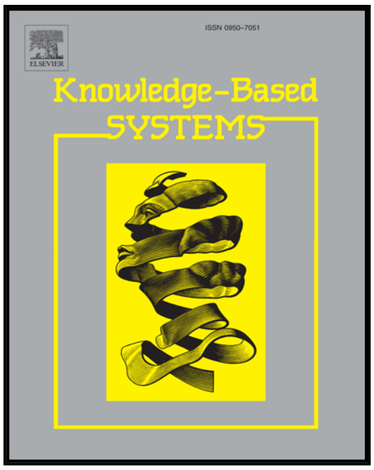

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Personality-based Refinement for Sentiment Classification in Microblog

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Abstract Microblog has become one of the most widely used social media for people to share information and express opinions. As information propagates fast in social network, understanding and analyzing public sentiment implied in user-generated content is beneficial for many fields and has been applied to applications such as social management, business and public security. Most previous work on sentiment analysis makes no distinctions of the tweets by different users and ignores the diverse word use of people. As some sentiment expressions are used by specific groups of people, the corresponding textual sentiment features are often neglected in the analysis process. On the other hand, previous psychological findings have shown that personality influences the ways people write and talk, suggesting that people with same personality traits tend to choose similar sentiment expressions. Inspired by this, in this paper we propose a method to facilitate sentiment classification in microblog based on personality traits. To this end, we first develop a rule-based method to predict users' personality traits based on the most well-studied personality model, the Big Five model. In order to leverage more effective but not widely used sentiment features, we then extract those features grouped by different personality traits and construct personality-based sentiment classifiers. Moreover, we adopt an ensemble learning strategy to integrate traditional textual feature based and our personality-based sentiment classification. Experimental studies on Chinese microblog dataset show the effectiveness of our method in refining the performance of both the traditional and state-of-the-art sentiment classifiers. Our work is among the first to explicitly explore the role of user's personality in social media analytics and its application in sentiment classification.

Keywords Sentiment classification, Social media analytics, Personality prediction, Big Five model

1 Introduction

Microblog has become one of the most popular social media for people to share information and express emotions in recent years. As information and the sentiment it carries flow fast in social media sites, it is critical for governments and public sectors to make sense of public sentiment to support decision making, policy suggestion and emergency response. It is also beneficial to monitor and analyze the sentiment implied in microblog for many business related applications.

Sentiment classification is one of the main tasks in sentiment analysis [1], with the purpose of classifying texts to certain categories according to the sentiment it carries (mostly classified as positive, negative or other specific categories). The majority of current work on sentiment classification either relies on sentiment lexicon [2-9] or applies machine learning methods [10-24]. Lexicon based methods leverage both the polarity of sentiment words in the textual content and predefined linguistic rules for sentiment classification. The key of lexicon based methods is to build high-quality sentiment lexicon, which is labor-intensive and less flexible. Thus, they are not quite applicable in open-domain environments, such as microblog. Machine learning based methods for sentiment classification usually mine textual features automatically from labeled corpora to construct sentiment classifiers. The performance of classifiers relies heavily on appropriate machine learning algorithms as well as effective textual features that are distinguishable from different classes.

Most current research on machine learning based sentiment classification treats the online texts written by different users equally and leaves out user properties in the classification process. However, the word usage in sentiment expressions by different users may vary greatly. For example, in Chinese texts, conscientious people are likely to use words or phrases like “共勉” (to encourage each other) and show positive emotions. In microblog, as the number of words in a tweet is restricted to 140 characters, users tend to use more simplified and personalized words to express their emotions in addition to common sentiment words. These words contain rich information for sentiment classification, but they may not be widely used by all the users. Taking extroverts as an example, they tend to express their emotions directly and prefer concise terms for sentiment expression [25], such as “生快” (abbreviation of Happy Birthday), which are not frequently used among other users. As traditional machine learning based methods extract the common sentiment features of online texts, they often fail to distinguish the above user-specific or personalized features, resulting in the decrease of the performance of sentiment classifiers. Therefore, it is necessary to address the above issue and develop a more fine-grained method for sentiment classification, especially for microblog data.

Previous psychological research has shown that the ways people write or talk are influenced by their personalities, and verified the associations between personality, emotion manifestations and linguistic word use [26]. Conscientious individuals talk more about work and achievements. Extroverts prefer shorter, less complex writings and more positive emotional terms [27]. These findings suggest that people with same personality traits tend to use similar words to express their sentiment. This indicates the leverage of users' personality traits for tweets grouping, and personality related sentiment words can be used as effective features to facilitate sentiment classification.

Among the personality models proposed in psychology, the Big Five model [28] is most well studied and widely adopted by computational studies on personality. The Big Five model identifies five dimensions of personality traits of people, namely agreeableness, extroversion, conscientiousness, openness, and neuroticism. A number of psychological and computational efforts have been made to predict personality based on the Big Five model, mostly utilizing user-generated content on social media sites [25, 29-48]. Inspired by the psychological findings and personality model, in this paper we propose a personality-based refinement for sentiment classification in microblog based on the Big Five model. Our goal is to leverage users' personality information to refine current sentiment classifiers. To this end, we choose Chinese microblog in our study and propose a rule-based method for personality prediction with relatively high precision. We then group tweets according to users' personality traits and train a basic sentiment classifier for each personality group. By this means, we can easily recognize and extract personality related sentiment features which are distinguishable enough within each personality group. To some extent the acquired textual features in each group reflect the commonality of sentiment word usage by people with same personality traits. In addition, we adopt an ensemble learning strategy to make full use of both general and personality-based sentiment classification.

Our work has made several contributions. We first propose a personality-based refinement for sentiment classification in microblog based on the Big Five model. To gain higher precision of personality prediction, we develop a rule-based method by analyzing the textual and microblog usage information in tweets. On the basis of this, we extract textual features for each personality group and employ ensemble learning for effective sentiment classification. Experimental studies show the effectiveness of our proposed method for refining sentiment classification compared with both the traditional and state-of-the-art sentiment classifiers. To the best of our knowledge, our work is among the first to explicitly explore the role of user's personality in social media analytics, and we choose sentiment classification as an exemplar field for our investigation.

The rest of the paper is organized as follows. Section 2 introduces related work on sentiment classification and personality prediction. Section 3 describes our proposed method in detail. In section 4, we conduct experimental studies and analyze the results for personality prediction and sentiment classification. Section 5 concludes the paper and raises some future considerations.

2 Related work

2.1 Sentiment classification

Sentiment classification is one of the main tasks in sentiment analysis, which has gained increasing attraction in recent years [49]. It aims to classify the polarity of a text into positive, negative or neutral. Sentiment classification can be performed at word level [50], sentence level [13] and document level [51]. Most current approaches to sentiment classification fall into two main categories: lexicon based methods and machine learning based methods.

Lexicon based methods make use of both the existing sentiment lexicons (e.g., the MPQA subjectivity lexicon [52], SentiWordNet [53]) and linguistic rules for sentiment classification. The performance of lexicon based methods strongly relies on the quality of sentiment lexicons, which usually consist of sentiment expressions as well as their sentiment polarities and strength. The early work by Turney et al. [2] takes the average of the polarities of sentiment expressions in a review as its overall sentiment polarity. Meanwhile, a lot of work investigates the impact of negation words, intensification words and diminishing words etc. on the sentiment polarity of whole sentence [3-5]. There is also work using hand-crafted linguistic rules that consider the syntactic structure of sentences for sentiment classification [6-8]. Hogenboom et al. [8] apply Rhetorical Structure Theory to recognize the important parts in a text in terms of their contribution to the overall sentiment. Emoticons are used together with sentiment words for polarity classification as well, and it was found that the sentiment carried by emoticons tends to dominate that conveyed by textual cues [9]. In lexicon based methods, it is often costly to build sentiment lexicons manually. Thus much research work has focused on the automatic construction of sentiment lexicons [54-61]. Some studies leverage the synonymous and antonymous relations in thesauruses or semantic lexicons such as WordNet to expand sentiment lexicons [57, 58]. On the other hand, based on the Web corpus, Turney et al. [55] propose a method to determine the polarities of candidate terms through their point-wised mutual information (PMI) with the predefined seed words. Besides word-level information, some linguistic rules (e.g. conjunction rules) have also been exploited to determine the polarities of words [56, 61]. More recently, some research has investigated the issues of domain-specific [59] and cross-domain [54, 60] sentiment lexicons construction.

Machine learning based methods often treat sentiment classification as a traditional problem of text categorization, for which a fundamental issue is to extract effective textual features from corpus. Applying supervised learning, Pang et al. [13] compare the performance of Naïve Bayes, Support Vector Machine (SVM) and Maximum Entropy, and find that SVM achieves the best result with bag-of-word features. Conditional random fields (CRFs) have also been applied to take into account the context of a sentence in the document for classifying the sentiment polarity of the sentence [12]. Recently, researchers find that the combination of word features, part-of-speech features, sentiment lexicon features and hashtag features contributes to improving the classification performance significantly [14-17]. Besides, Gao et al. [18] investigate the influence of user leniency and product popularity on sentiment classification, and develop approximated decoding algorithms to collectively classify the sentiments of product reviews. Some other work employs semi-supervised and ensemble learning methods for sentiment classification. Based on small set of labeled data, Gao et al. [10] employ a semi-supervised learning strategy to iteratively train the sentiment classifier. Melville et al. [11] combine lexicon based method with sentiment classifier, and employ ensemble learning to integrate the classification results. In recent years, researchers focus more on exploiting deep learning based models for sentiment classification, such as recursive neural network (RNN) [19, 20] and convolutional neural network (CNN) [20, 21]. These models learn word embeddings from corpus and make use of them for the representation of sentences or documents. Satos et al. [21] propose a deep convolutional neural network to extract sentiment features from the character level up to the sentence level, which can handle words and sentences of arbitrary size. Xu et al. [19] introduce a cache mechanism to Long Short-Term Memory neural network to help the recurrent units keep sentiment information more effectively. For sentiment classification of short texts, Wang et al. [20] combine CNN and RNN to make use of both the coarse-grained local features and the long-distance dependencies. These deep learning based models usually need extra and large corpora for the pre-training of word embedding, and the process of model training is often quite time-consuming. Other machine learning based methods consider issues such as domain adaptation [22], and the incorporation of topic information [23, 24].

In recent years, concept-level sentiment analysis has drawn much attention among the researchers [62], which aims to extract and leverage multi-word concepts for sentiment analysis. To this end, some knowledge bases that capture the sentic and semantic information of concepts are constructed [63]. On the basis of this, a lot of work represents each text as bag of concepts and performs sentiment classification [64, 65]. While current concept-level sentic knowledge bases are oriented to English, such knowledge bases for other languages (e.g. Chinese) are still missing.

Sentiment classification in microblog is similar to traditional sentiment classification task except for the handling of short text. For microblog, there are a great number of informal words in tweets, making traditional sentiment lexicons unsuitable for microblog. As new sentiment words emerge constantly in microblog, it is difficult to recognize these new words and construct sentiment lexicons. Therefore, machine learning based methods are more applicable to sentiment classification in microblog.

2.2 Personality prediction

Many personality models have been proposed in psychology, such as the Big Five model [28] and MBTI model [66]. Among psychological personality models, the Big Five model is the well-founded definitive model of personality [34] and has been widely adopted in both psychological and computational studies [25, 29-48, 67]. The Big Five model describes the personality of people from five dimensions, namely openness, conscientiousness, extroversion, agreeableness and neuroticism. People with high openness are imaginative, creative and intellectually curious. They have great interest in learning and exploring new things. Conscientiousness reflects the extent to which a person is self-disciplined and well-prepared for opportunities. People with high conscientiousness are enthusiastic about work and yearn for achievements. High scores on extroversion indicate the preference for interacting with people. Extroverts enjoy social life while introverts prefer being alone. Agreeable individuals are generous, trustworthy and always willing to help others. They seek for social harmony. Neuroticism reflects the emotional stability of people. The higher score a person gets on neuroticism, the more easily he or she may get stuck in negative emotions.

Based on the Big Five model, both psychological and computational work has been carried out on the prediction of personality. Many psychological studies have explored the relationships between people's language use and personality traits in Big Five model [25, 29-33]. Among these studies, the "Linguistic Inquiry and Word Count" (LIWC) program [68] is commonly used for extracting linguistic features. It calculates the term frequencies of different psychological word categories (e.g. social processes, perceptual processes, affective processes) in given texts. On the basis of this, most research utilizes the Pearson correlation coefficient or Spearman's rank correlation coefficient to measure the strength of correlations and identifies significant linguistic cues associated with different personality traits in user-generated contents (e.g. self-narratives [25, 29], blogs [31], tweets [33]). For example, extraversion has been found to associate with words about humans, social processes, and family [29]. Conscientious individuals tend to write more achievement and work-related words [25]. People with high agreeableness express empathy and interpersonal concerns frequently [31]. In addition to linguistic features, researchers have also studied users' footprints on social media sites (e.g., Facebook Likes, status updates) to identify significant factors that reflect users' personality traits [30, 32]. These psychological research and findings indicate the potential of utilizing user-generated contents and user behavior for personality prediction.

Over the past few years, computational efforts have been made to predict users' personality traits in the Big Five model using social media [34-48], focusing on the application of machine learning techniques. Based on the YouTube dataset, some work [36-39] extracts emotional, psycholinguistic and other features and applies machine learning algorithms to predict the values under each personality dimension. The achieved F1-measures on different personality dimensions range from 50% to 80%. Several work has been done on microblog platforms [34, 35, 40, 43]. Golbeck et al. [34] extract twitter usage features, structural features and linguistic features, and apply two regression algorithms to predict users' personality traits. Adali et al. [35] investigate three types of behavioral features, such as network bandwidth and reciprocity of actions for personality prediction. They find that behavioral features are equivalently effective to the prediction as text features. Bai et al. [40] propose to predict the personality of SinaWeibo (weibo.com) users from their online behaviors through multi-task regression and incremental regression. In the above work on microblog platforms, the achieved Mean Absolute Error (MAE) ranges from 0.1 to 0.2. Besides, Nowson et al. [43] apply machine translation models to address the multilingual issue in text-based personality prediction, and the achieved Root Mean Square Error (RMSE) ranges from 0.08 to 0.25. Other work for personality prediction has been done on Facebook [30, 41, 42, 44, 45]. Bachrach et al. [30] employ multivariate linear regression with users' Facebook profiles as features for prediction and get the results of RMSE ranging from 0.27 to 0.29. Affective and egocentric network features have also been leveraged for personality prediction on Facebook [44]. As Facebook corpus is relatively limited in size and channel, Farnadi et al. [41] make use of additional corpora and apply cross-domain learning to predict personality. Similarly, Verhoeven et al. [45] take the outputs of the personality classifiers trained on an additional essay dataset as meta-features to predict the personality traits of Facebook users.

More recently, deep learning techniques have also been employed for personality prediction, mainly based on the Big Five model [46-48, 67]. In the literature, different deep neural networks are trained to learn word, sentence and document embeddings for text-based personality prediction. For example, Liu and Zhu [46] utilize stacked auto-encoders to extract linguistic representation feature vectors of texts and use them for personality prediction in microblog. Liu et al. [47] infer users' personality traits based on the hierarchical, vectorial word and sentence representations trained by a bi-directional recurrent neutral network. Majumder et al. [67] train a convolutional neural network to acquire sentence and document vectors based on the pretrained word embeddings, and use them to classify users' Big Five personality traits. Besides, for cross-modal personality prediction, Xianyu et al. [48] propose a heterogeneity entropy neural network to extract the common information between modalities and map it to users' personality traits. Deep learning based methods usually need large corpora to achieve good performance, and large numbers of annotated personality labels for model training are quite difficult to collect.

Previous literature has stated that personality influences the ways people express their emotions, in this paper, we propose a method to facilitate sentiment classification in microblog based on the Big Five model. To predict users' personality traits, we develop a rule-based personality prediction method with high precision, by considering the factors used in the related work as well as the new factors we identify. Based on the predicted personality traits of different users, we group tweets and extract textual features for each personality group respectively. By this means, our personality-based refinement for sentiment classification can leverage effective features that reflect the diverse word use of people with different personality traits.

3 Proposed Method

We propose a personality-based method to refine sentiment classification (called *PbSC*) in microblog. As the tweets posted by the users with same personality trait tend to contain similar sentiment related features, to capture these features, we first allocate tweets to different groups according to the personality traits of their users. In doing so, a tweet may belong to several personality groups. For the tweets in each group, we then extract textual features and train a basic sentiment classifier. Finally, to integrate the results of all the personality-based and the general sentiment classifiers, we employ ensemble learning and construct a meta-classifier. When classifying a tweet, each classifier generates an output, which is then used as an input for the meta-classifier to yield the final classification result. The personality-based refinement process for sentiment classification is given in Fig. 1, where *HE*, *HA*, *HC*, *LE* and *LA* refer to three personality dimensions (*Extroversion*, *Agreeableness* and *Conscientiousness*) and their values (*High* and *Low*).

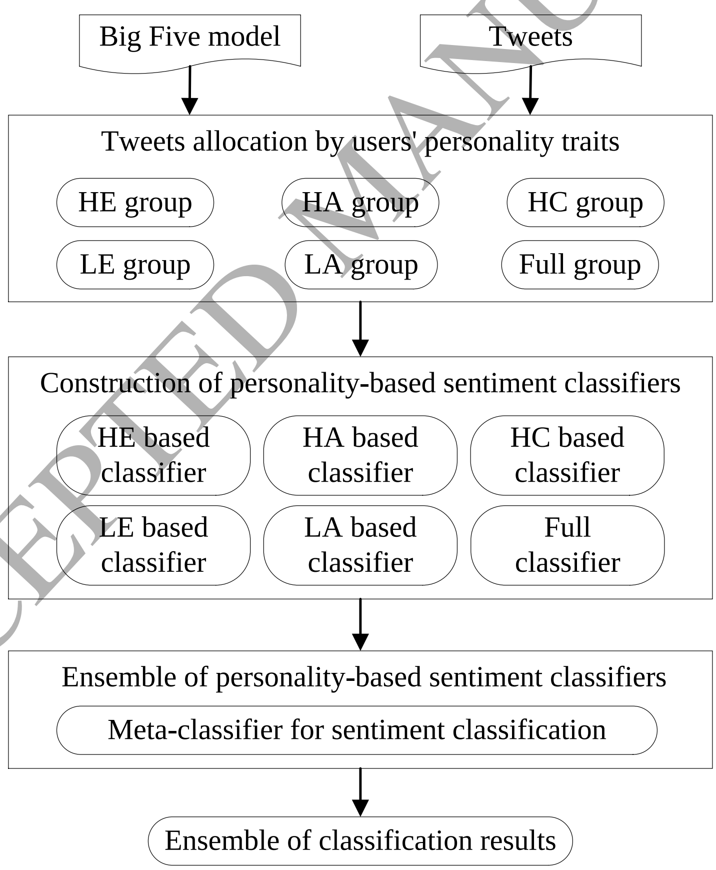

Figure 1. Personality-based refinement process for sentiment classification

3.1 Tweets allocation by users' personality traits

To accurately allocate tweets to different groups, the personality traits of users should be predicted with high precision. Currently, we consider three dimensions of personality traits in the Big Five model, extroversion (*E*), agreeableness (*A*) and conscientiousness (*C*). The other two dimensions, openness and neuroticism, are relatively difficult to make prediction based on the previous research [33, 35, 40]. The problem of personality prediction is defined as follows. Given a list of tweets posted by a user *u*, generate the vector of *u*'s personality traits (E_u, A_u, C_u), where E_u, A_u and C_u represent the corresponding personality dimensions of the user, and their values can be high, low or medium.

To tackle the personality prediction problem, we propose a rule-based method to achieve more accurate prediction results than those using machine learning based methods. We design several groups of rules to determine the user's personality dimension values as high or low. For each personality dimension, if there exists no matching rules or more than one contradictory rule, the dimension value is set to medium.

After personality prediction, we allocate users' tweets to different personality groups according to their personality dimension values. We classify tweets into six different groups, namely high conscientiousness (*HC*) group, high extroversion (*HE*) group, low extroversion (*LE*) group, high agreeableness (*HA*) group, low agreeableness (*LA*) group, and *Full* group. As users with low conscientiousness are rarely found in our annotated microblog dataset, currently we ignore this group. Besides, all the tweets are allocated to the *Full* group, which is used to extract commonly used textual features and train a general sentiment classifier.

As the leveraged information in microblog contains textual information and microblog usage information, our rule-based method considers these two kinds of information. The personality prediction rules can be divided into two categories: text based rules and microblog based rules. Below we discuss them in detail.

3.1.1 Text based prediction rules

We exploit the linguistic cues users leave in their tweets to construct text based rules for personality prediction. The textual information we use to predict personality dimension values is given in Table 1 (corresponding rules are given in the brackets). We did not use traditional psychological dictionaries (such as LIWC) because there is no directly mapping between the words in LIWC and personality dimension values. In constructing text based prediction rules, we summarize the expressions (including words, phrases, emoticons, etc.) that indicate different personality traits of microblog users.

Table 1. Textual information used for personality prediction

Personality dimensions	**Values**	**Textual information**
Conscientiousness	High	word/phrase indicating high conscientiousness (*HC1-HC3*)
		emoticon indicating high conscientiousness (*HC1-HC3*)
	Low	word/phrase indicating low conscientiousness (*HC1-HC3*)
		emoticon indicating low conscientiousness (*HC1-HC3*)
Extroversion	High	word/phrase indicating high extroversion (*HE1*)
	Low	word/phrase indicating low extroversion (*LE1*)
Agreeableness	High	word/phrase indicating high agreeableness (*HA1*)
		emoticon indicating high agreeableness (*HA2*)
		tweet with praising word/phrase (*HA3*)
		tweet with positive word and without negative words (*HA4*)
		tweet with exclamation mark and with only positive words (*HA5*)
	Low	word/phrase indicating low agreeableness (*LA1*)
		emoticon indicating low agreeableness (*LA2*)
		tweet with abusing word/phrase (*LA3*)
		tweet with negative word and without positive words (*LA4*)
		tweet with exclamation mark and without positive words (*LA5*)
		tweet with question mark and exclamation mark (*LA6*)

Our text based rules infer a user's personality dimension as high or low based on the textual information in Table 1. Each rule is composed of the numbers or the ratios of tweets with personality related textual information. Below we explain the rules we design to predict conscientiousness, extroversion and agreeableness in detail.

Conscientiousness prediction rules mainly make use of personality related information. As people with high conscientiousness are self-disciplined and in pursuit of achievement, they thus frequently use words associated with work (e.g. "学习" (study), "很忙" (very busy)) and goals (e.g. "坚持" (insist), "决心" (determination)). They also enjoy encouraging themselves by publishing contents containing expressions like "努力工作" (work hard). On the contrary, people with low conscientiousness often indulge themselves, resulting in the frequent use of words like "无聊" (boring), "酒" (alcohol) and emoticons like "困" ([Sleepy]) (Note that [] is used to represent emoticons). If the number or ratio of tweets with *HC* expressions and emoticons (#*HC_tweet* or *Ratio*(*HC_tweet*)) a user *u* posts is relatively *high* and those with *LC* expressions and emoticons (#*LC_tweet* or *Ratio*(*LC_tweet*)) is relatively *low*, infer that the value of his/her conscientiousness dimension (C_u) is *high* (*Rule HC1-HC3*). The ratios here refer to the proportions of the corresponding tweets in all the original tweets. Take *Rule HC1* as an example (p_1, p_2, q_1 and q_2 are the thresholds used by the rule).

Rule HC1:
IF $\#HC\_tweet \geq p_1 \wedge \#LC\_tweet \leq p_2 \wedge Ratio(HC\_tweet) \geq q_1 \wedge Ratio(LC\_tweet) \leq q_2$
THEN $C_u = high$

Similar to the prediction of conscientiousness, extroversion prediction rules are based on personality related information. As extroverts like to get involved in activities and interact with others, the expressions like “团队” (team), “伙伴们” (guys) and “出发” (set out) appear in their tweets with high frequency. In contrast, introverts prefer staying alone rather than hanging out with others. They often show less interest in social activities by using words like “宅” (stay at home) in their tweets. If the number of tweets with *HE* expressions a user posts is relatively *high*, infer that the value of his/her extroversion dimension is *high* (*Rule HE1*). The prediction rule for *LE* (*Rule LE1*) is similar. Other extroversion prediction rules are based on microblog usage information, which will be introduced later.

Agreeableness prediction rules consider sentiment words and punctuations as well as personality related information. Agreeable individuals usually get along well with others, and the expressions and emoticons that express praise, gratefulness and trust are good indicators of high agreeableness, such as “真棒” (wonderful), “感激” (appreciate) and “[鼓掌]” ([Applause]). In contrast, people with low agreeableness often show unfriendliness, question, criticism, abuse or aggressiveness. They vent negative attitudes in microblog through expressions like “讨厌” (hate) and “滚粗” (get out) and emoticons like “[别烦我]” ([Do not bother me]) and “[怒]” ([Angry]). We employ a traditional sentiment lexicon to recognize positive and negative words in tweets and help determine users’ agreeableness dimension value. To capture users’ strong tendency of agreeableness in tweets, we also consider the combinations of sentiment words and exclamation mark, and those of question mark and exclamation mark.

The text based rules leverage the above information to predict user’s dimension value of agreeableness. The predictions of high and low agreeableness are similar to each other. We take the prediction of low agreeableness as an example. For a user *u*, the value of agreeableness dimension A_u is inferred as *low*, if the ratio of his/her tweets with *LA* expressions is relatively *high (Rule LA1*), or the ratio of his/her tweets with *LA* emoticons is *high* and he/she has posted *adequate* tweets with emoticons (*Rule LA2*), or the number of his/her tweets with abusing words is *high* (*Rule LA3*). Furthermore, we infer the value of a user’s agreeableness dimension as *low*, if the ratio of his/her tweets with negative words and without positive words is relatively *high* (*Rule LA4*), or the ratio of his/her tweets with exclamation marks but without any positive words is relatively *high* (*Rule LA5*), or the ratio of his/her tweets with both the question mark and the exclamation mark is relatively *high* (*Rule LA6*).

Below we give an example rule, where *Ratio*(*LA_emoticon_tweet*) refers to the proportion of the tweets with *LA* emoticons in all the tweets with emoticons, and *#Emoticon_tweet* refers to the number of all the tweets with emoticons, and q_{15} and p_{16} are the thresholds used by the rule.

Rule LA2:
IF $Ratio(LA\_emoction\_tweet) \geq q_{15} \wedge \#Emoticon\_tweet \geq p_{16}$
THEN $A_u = low$

3.1.2 Microblog based prediction rules

We incorporate some microblog usage information for the prediction of extroversion. In addition to publishing plain texts in microblog, users could also publish tweets with locations or mentions (i.e. @), upload photos or videos, and retweet or comment on others' tweets. Given that extroverts enjoy participating in activities and sharing their experiences with others, they post a lot of tweets with photos, selfie videos, and locations. They often receive many comments from others as well. Besides, extroverts interact frequently with their friends while introverts are accustomed to staying on their own. Thus extroverts tend to mention others in their tweets, while introverts seldom get comments from others or get retweeted.

For a user *u*, the value of extroversion dimension (E_u) is inferred as *high*, if the number and ratio of his/her tweets with photos and comments are all relatively *high* (*Rule HE2*), or the number of his/her tweets with selfie videos or locations is relatively *high* (*Rules HE3& HE4*). Furthermore, we infer the value of a user's extroversion dimension as *high*, if the ratio of his/her tweets that mention others is relatively *high* (*Rule HE5*), or the total number of friends he/she has mentioned is relatively *high* (*Rule HE6*). On the other hand, if the ratio of a user's original tweets without comments and retweets is very *high*, we infer that the value of his/her extroversion dimension is *low* (*Rule LE2*).

We give two example rules. In *Rule HE2*, *#Photo_Comment_tweet* refers to the number of tweets with photos and comments, and *Ratio(Photo_Comment_tweet)* refers to the ratio of tweets with photos and comments in all the original tweets. In *Rule LE2*, *#Origin_tweet* and *Ratio(Origin_tweet)* refer to the number and ratio of original tweets in all the tweets, and *Ratio(¬Comment_Retweet_tweet)* refers to the ratio of tweets without comments and retweets in all the original tweets. Below p_8, p_{13}, q_6, q_8 and q_9 are the thresholds used by these two rules.

Rule HE2:
IF $\#Photo\_Comment\_tweet \geq p_8 \wedge Ratio(Photo\_Comment\_tweet) \geq q_6$
THEN $E_u = high$

Rule LE2:
IF $Ratio(\neg Comment\_Retweet\_tweet) \geq q_8 \wedge \#Origin\_tweet \geq p_{13} \wedge Ratio(Origin\_tweet) \geq q_9$
THEN $E_u = low$

3.2 Construction of personality-based sentiment classifiers

We extract personality related sentiment features and construct a basic sentiment classifier for each personality group. As bag-of-word features have proven quite effective in sentiment classification in previous research [13], we first utilize a word feature based sentiment classifier for our investigation. For the word feature based sentiment classifiers, in addition to word unigrams, we also take emoticons as features because they usually convey specific sentiments. After feature extraction, each tweet is represented as a vector, in which the value of each item equals to the term frequency of the corresponding textual feature. Our personality-based method provides the refinement mechanism to enhance the performance of existing sentiment classification methods, and thus can be combined with the typical classification algorithms as well as the state-of-the-art sentiment classifiers [14-16].

Table 2 illustrates some examples of the textual features extracted in each personality group using the word feature based sentiment classification. These textual features are those words which appear much more frequently in the corresponding personality groups than in the *Full* group, and our personality-based method helps the effective extraction of more distinguishable sentiment features than only using traditional sentiment classification methods.

Table 2. Examples of frequent textual features in each personality group

Personality group	Examples of selected textual features
HC group	成了(Done), 努力(Effort), 支持(Support), 终于(Finally), 失败(Failure)
HE group	哈哈哈哈(Ha-ha), [耶(Yeah)] , [握手(Handshake)], 崩溃(Breakdown), 可怕(Horrible)
LE group	真心(Sincerity), 不开心(Unhappy), 难受(Feel bad), 失眠(insomnia), [失望](Disappointed)
HA group	爱你(Love you), [赞啊(Awesome)], [好爱哦(Love a lot)], [蜡烛(Candle)], [悲伤(Sad)]
LA group	罪责(Guilt), 逃避(Escape), 勾结(Collision), 凶残(Ferocious), 傻逼(Fool)

From Table 2, we can see that the textual features in each personality group reflect the commonality of the corresponding users' sentiment expressions. Conscientious people often express sentiments about achievements (e.g. effort and failure). Extroverts like to directly express positive (e.g. [Handshake]) or negative (e.g. [Horrible]) sentiments towards others, while introverts tend to express positive (e.g. sincerity) or negative (e.g. unhappy or feel bad) feelings about themselves. For agreeable individuals, their positive sentiment expressions are often related to love and praise (e.g. love you, awesome), while their negative sentiment expressions concern more with sympathy (e.g. candle and sad). In contrast, people with low agreeableness usually express negative sentiments by blaming or abusing others (e.g. guilt and fool).

3.3 Ensemble of personality-based sentiment classifiers

A tweet may be associated with several personality traits of the user, and thus belongs to more than one personality group. To integrate the classification results of different personality groups, we employ ensemble learning and build an integration model. One consideration is to merge all the textual features from different groups to build one sentiment classifier. To train a whole sentiment classifier, those personality related features which are less frequently used may not take effect when mixing up with other more commonly used features. Therefore, we choose to integrate the classification results of different basic classifiers instead.

To this end, we build a meta-classifier based on the outputs of all six basic classifiers. By doing so, we take into account both personality-based and general sentiment classification. Another advantage of our method is that it is able to classify a new subjective tweet as positive or negative without acquiring its personality information in advance, and meanwhile makes full use of each personality-based classifier.

The ensemble process of basic sentiment classifiers is given in Fig. 2. Given a set of training tweets t_1, t_2, …, t_m, we employ the six basic classifiers to generate the output (p_{ij}^{+}, p_{ij}^{-}) for each tweet t_i, where p_{ij}^{+} and p_{ij}^{-} denote the probabilities of tweet t_i being positive and negative respectively, calculated by the jth classifier. Based on the outputs of each basic classifier, We represent t_i as a six-dimensional vector $\boldsymbol{v_i} = (v_{\mathrm{i}1}, v_{\mathrm{i}2}, \ldots, v_{\mathrm{i}6})$. The value of each item v_{ij} in $\boldsymbol{v_i}$ equals to the difference of p_{ij}^{+} and p_{ij}^{-}, the absolute value of which indicates the confidence of the classification result. After representing each tweet as such a vector, we apply the existing classification algorithms to construct a meta-classifier which integrates the classification results of the six basic classifiers.

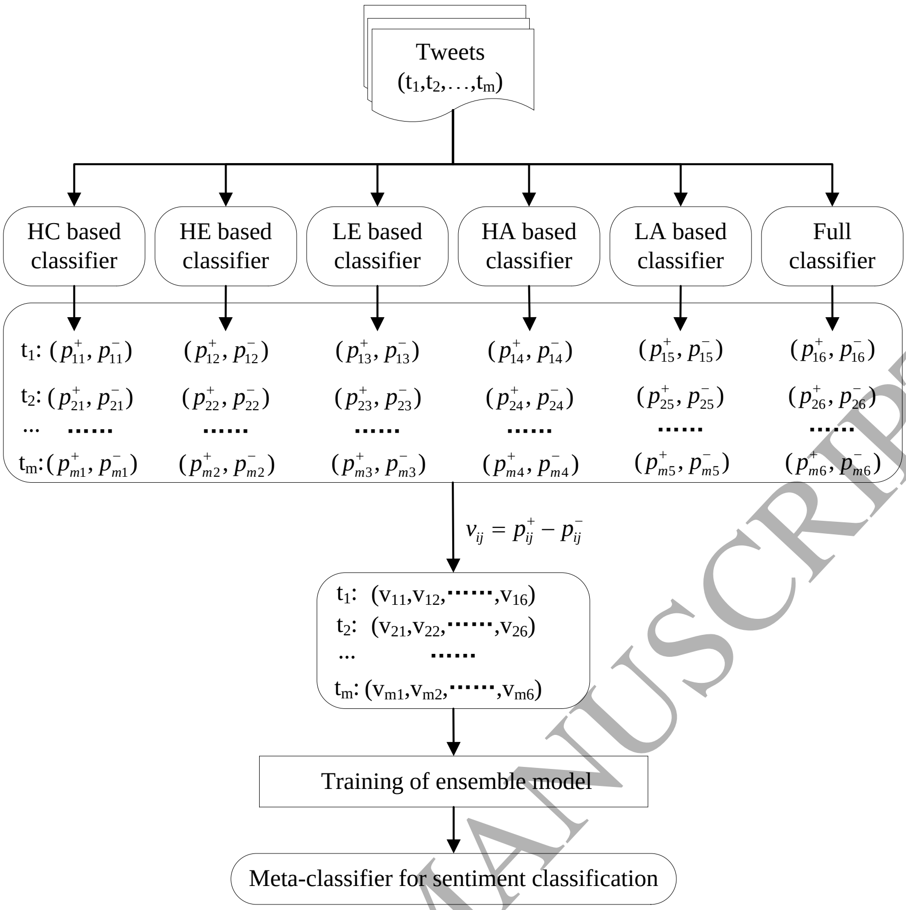

Figure 2. Ensemble process of basic sentiment classifiers

4 Experiments

4.1 Dataset

As there is not publicly available microblog dataset with personality information of users, to collect data for our study, we crawl 968854 tweets from SinaWeibo, the most famous microblog site in China. We adopt a breadth-first strategy in the data crawling process, and collect tweet information as well as user information. For each tweet, we collect its content along with its author information and original tweet (if it retweets another tweet). We neglect the users who do not post any original tweets. All the crawled tweets are posted during the period from Oct. 21, 2009 to Dec. 15, 2014. The whole dataset consists of the latest 450 tweets posted by each user (maybe less), which covers a variety of topics, including daily life, current events and many others.

4.2 Experiment 1: Personality prediction

In order to evaluate our rule-based personality prediction method, we compare its prediction results with human judgements. In preparing the test data, we randomly choose 200 users from our dataset and use the collected tweets of them for our experiment. We then invite two raters to annotate each user's personality traits based on the tweets they post. Both of the two raters were given the description of the Big Five model in Wikipedia [69] for reference. In order to acquire users' personality information with high precision, the raters were told to label the data only when the evidence in the tweets clearly showed corresponding personality dimensions in the Big Five model. To ensure high quality of the test data, we only keep the consistent judgments annotated by both raters. Here we did not use typical "questionnaire" to acquire users' personality information as in many psychological studies, because we focus on the personality traits that users exhibit through their online tweet interactions instead of exploring their true personalities in real life.

We compare the performance of our rule-based method with a series of typical machine learning based methods, including Naïve Bayes (NB), Support Vector Machine (SVM), Logistic Regression (LR) and Decision Tree (DT). In our method, we choose the widely used lexicon "DUTIR-EmotionWord" [70] as the traditional sentiment lexicon. The machine learning based methods take all the information we use in our method as features, including both the textual information and the microblog usage information. For each machine learning based method, we construct five classifiers for the prediction of *HC, HE, LE, HA* and *LA* respectively, and apply 10-fold cross validation to evaluate the performance. Since our method leverages the results of personality prediction to facilitate personality-based sentiment classification, our purpose is to recognize tweets with clear personality traits as precise as possible so as to come up with better tweets allocation based on users' personality traits for the extraction of personality related sentiment features. Thus we focus on "precision" metric for the comparison of our rule-based method and the typical machine learning based methods. The personality prediction results by different methods are given in Table 3.

Table 3. Precisions of personality prediction by different methods

Methods	***HC***	***HE***	***LE***	***HA***	***LA***
NB	43.8%	77.9%	34.7%	46.2%	52.6%
SVM	—	83.1%	71.4%	—	—
LR	—	80.9%	63.6%	65.4%	80%
DT	35.7%	75%	68.4%	42.4%	16.7%
Rule-based	**84.6%**	**86.5%**	**86.7%**	**76.2%**	**83.3%**

From the experimental results, we can see that our method achieves higher precision than the comparative machine learning based methods in each personality dimension value group. Among the machine learning based methods, NB performs best in the prediction of *HC*, SVM achieves the highest precision in the prediction of *HE* and *LE*, and LR achieves the highest precision in the prediction of *HA* and *LA*. Due to the class imbalance problem in several groups, SVM for *HC*, *HA* and *LA* groups and LR for *HC* group fail to achieve reasonable performance, while our rule-based method achieves fairly good performance under all these circumstances. Machine learning based methods usually perform better in terms of “recall” metric, but our rule based method is more advantageous on recognizing adequate personality-related tweets with relatively high precision to facilitate further personality-based sentiment classification.

4.3 Experiment 2: Sentiment classification

To evaluate our personality-based refinement for sentiment classification, we invite two senior graduate students from Chinese Academy of Science majored in AI and Social Media Analysis for data annotation. They label the sentiment polarities of all the tweets posted by the 200 users (the same as those in the personality prediction experiment). It takes the two raters 77 and 96 hours for annotation. The number of the annotated positive and negative tweets is 7444 and 2911 respectively. After personality prediction by our method, the number of these tweets in *HC*, *HE*, *LE*, *HA* and *LA* groups is 1081, 3692, 622, 1697 and 296 respectively.

4.3.1 Comparative methods

To test the effectiveness of our personality-based refinement method, we choose a few representative sentiment classification methods and build the basic sentiment classifiers for comparison. These comparative methods include the traditional word feature based sentiment classifiers together with five widely used classification algorithms, namely Decision Tree (DT), Random Forest (RF), Logistic Regression (LR), Support Vector Machine (SVM) and Naïve Bayes (NB). In addition, we include three notable state-of-the-art methods proposed recently in the comparative methods. They are NRC_Canada [14], TeamX [15] and Webis [16], which rank *first* in the Twitter sentiment classification task of SemEval 2013, SemEval 2014 and SemEval 2015 respectively.

The state-of-the-art sentiment classification methods, NRC_Canada, TeamX and Webis are all based on the textual features. NRC_Canada [14] trains an SVM with linear kernel using features such as word and character n-grams, punctuation marks and negation etc. TeamX [15] uses similar but fewer features than NRC_Canada, and chooses LR as the sentiment classifier. Webis [16] combines NRC_Canada, TeamX and another two existing sentiment classifiers (i.e. GU-MLT-LT [71] and KLUE [72]) in an ensemble and employs weighted voting for sentiment classification. The weights are measured by the classification confidence of each classifier. As these methods were originally developed for English tweets, we keep all those features that can be applied to Chinese microblogs. For the word feature based sentiment classifiers, to reduce noise, we only extract word unigrams and emoticons that appear in at least three tweets as features. In our *PbSC* method, we choose LR as the classification algorithm for the meta-classifier because of its relatively good performance in sentiment classification.

To examine whether our personality-based refinement can boost the basic sentiment classifiers (including the word feature based classifiers and the above three state-of-the-art classifiers), we compare the performance of basic sentiment classifiers with and without our *PbSC* method. In addition, to further compare the performance of ensemble learning alone and our personality-based refinement, we choose to use the personality-independent variance of *PbSC* (abbreviated as *PbSC*(random)) by allocating tweets to the six groups randomly. The number of tweets and the distribution of positive and negative tweets in each group of *PbSC*(random) are the same as those in the personality groups of *PbSC*.

4.3.2 Experimental results and analysis

Next we first compare our *PbSC* method with the traditional word feature based sentiment classifiers. We then check whether *PbSC* can boost the state-of-the-art sentiment classifiers. Finally, we conduct computational complexity analysis to investigate the efficiency of our method. For quantitive analysis, we use the macro average of F1 value as the evaluation measure, as it balances the precision and recall of classifiers. We randomly select 66% of the tweets in our dataset for training and use the left for testing.

4.3.2.1 Comparison with traditional sentiment classifiers

Sentiment classification results of the traditional word feature based sentiment classifiers and our *PbSC* refinement are given in Table 4, where "Pure" refers to the original sentiment classifiers without our *PbSC* method.

Table 4. F1 values of the word feature based sentiment classifiers and personality-based refinement

Methods	DT	RF	LR	SVM	NB
Pure	82.40%	87.86%	90.76%	91.33%	92.30%
***PbSC*(random)**	83.02%	87.97%	91.10%	91.39%	92.66%
PbSC	**83.28%**	**88.26%**	**91.32%**	**91.45%**	**92.85%**

From Table 4, we can see that among different classification algorithms, Naïve Bayes gains the best performance. By taking these word feature based classifiers as basic sentiment classifiers, our *PbSC* refinement always outperforms the corresponding original classifiers. Comparing *PbSC* with *PbSC*(random), it can be found that *PbSC* always achieves higher F1 values, which demonstrates the effectiveness of personality-based tweets grouping and sentiment classification. It can also be found from Table 4 that *PbSC*(random) always achieves better performance than the corresponding original classifiers, demonstrating the effectiveness of ensemble learning module of *PbSC*.

To further investigate the contribution of each personality group to sentiment classification, we remove one personality group and the corresponding basic sentiment classifier from *PbSC* and compare its performance with the original *PbSC* method. Table 5 gives the F1 values of our *PbSC* method trained without one personality group, where $PBSC_{-HC}$, $PBSC_{-HE}$, $PBSC_{-LE}$, $PBSC_{-HA}$ and $PBSC_{-LA}$ refer to the *PbSC* method trained without *HC*, *HE*, *LE*, *HA* or *LA* group respectively.

Table 5. F1 values of the *PbSC* method trained without one personality group

Methods	*PbSC*	$PbSC_{-HC}$	$PbSC_{-HE}$	$PbSC_{-LE}$	$PbSC_{-HA}$	$PbSC_{-LA}$
DT	83.28%	**82.85%**	82.94%	83.27%	**82.85%**	83.24%
RF	88.26%	**87.84%**	88.21%	87.97%	87.89%	87.86%
LR	91.32%	**91.06%**	91.18%	91.16%	91.09%	91.18%
SVM	91.45%	91.39%	91.24%	**91.20%**	91.64%	91.56%
NB	92.85%	**92.29%**	92.34%	92.33%	92.74%	**92.29%**

It can be seen from Table 5 that the original *PbSC* method achieves the highest F1 values almost in all the cases, suggesting that each personality group contributes to the refinement of sentiment classification, and our ensemble strategy can make full use of all the personality-based classifiers. Comparing the *PbSC* methods trained without different personality groups, we can find that removing *HC* group decreases the F1 values most than removing other personality groups, indicating that *HC* group may contribute most to the refinement.

4.3.2.2 Comparison with the state-of-the-art sentiment classifiers

We further evaluate our *PbSC* refinement with the state-of-the-art methods proposed in SemEval. Sentiment classification results of NRC_Canada, TeamX, Webis and our *PbSC* refinement are given in Table 6, where “Pure” refers to the original sentiment classifiers without our *PbSC* method.

Table 6. F1 values of the No.1 sentiment classifiers by SemEval and personality-based refinement

Methods	NRC_Canada	TeamX	Webis
Pure	91.63%	93.37%	93.81%
***PbSC*(random)**	91.73%	93.51%	93.79%
PbSC	**92.27%**	**93.63%**	**94.05%**

We can see from Table 6 that TeamX outperforms NRC_Canada and Webis outperforms TeamX. It can also be seen that the performance improvement of *PbSC*(random) with NRC_Canada over the original NRC_Canada are relatively small. *PbSC*(random) with Webis even performs worse than the original Webis. One possible reason for this is that Webis is indeed the ensemble of four existing sentiment classifiers, thus it is hard to further improve its performance by ensemble learning. Our personality-based refinement *PbSC* yields higher F1 values than the corresponding original methods and *PbSC*(random). It shows the effectiveness of our *PbSC* method in boosting the state-of-the-art sentiment classifiers. The experimental results generally verify the effectiveness of our proposed *PbSC* refinement for sentiment classification.

4.3.2.3 Computational complexity analysis

Our personality-based refinement for sentiment classification consists of three parts: user-based tweets allocation, personality-based sentiment classification and ensemble of sentiment classifiers. Although user-based tweets allocation is an important first step, the computational complexity of our method mainly depends on the construction of basic sentiment classifiers and classifier ensemble.

To test time complexity, we record the time costs of different parts in *PbSC* during the training process, including the construction of *HC, HE*, *LE, HA*, *LA*, *Full* classifiers and the meta-classifier. The construction of each classifier includes both feature extraction and classifier training. We run *PbSC* for five times and report the average time costs, which are given in Table 7. Each column in Table 7 corresponds to one of the comparative methods which are used as the basic sentiment classifier in *PbSC*.

Table 7. Time costs of different parts in *PbSC*

Classifiers	DT	RF	LR	SVM	NB	NRC_Canada	TeamX	Webis
***HC* classifier**	0.29s	0.49s	0.26s	0.35s	0.27s	4.68s	0.61s	16.69s
***HE* classifier**	2.15s	4.60s	1.17s	3.74s	1.09s	21.69s	2.75s	115.66s
***LE* classifier**	0.20s	0.31s	0.19s	0.21s	0.20s	23.21s	0.38s	50.43s
***HA* classifier**	0.46s	0.83s	0.39s	0.64s	0.37s	10.47s	0.93s	31.76s
***LA* classifier**	0.18s	0.26s	0.18s	0.19s	0.19s	9.72s	0.45s	18.40s
***Full* classifier**	19.53s	40.33s	7.57s	53.34s	7.00s	95.89s	16.10s	642.78s
meta-classifier	16.84s	211.35s	16.12s	67.25s	17.31s	964.15s	58.93s	969.97s
Total	39.64s	258.18s	25.89s	125.92s	26.42s	1029.81s	80.15s	1845.68s

It can be seen from Table 7 that compared with the original sentiment classifiers (i.e. the *Full* classifiers), the time cost by the construction of the personality-based classifiers is almost negligible. This is because the proportion of personality-based tweets in the whole dataset is relatively small. Besides, in most cases, the construction of the meta-classifier is the most time-consuming. One possible reason is that in the ensemble learning process, our method has to use all the personality-based classifiers and the *Full* classifier to generate the confidence scores of all the training data. However, this process can be easily parallelized as the personality-based and the *Full* classifiers are independent of each other.

4.3.3 Illustrations and discussions

To illustrate the effectiveness of *PbSC*, we select and analyze some tweets in our dataset which are correctly classified by our personality-based sentiment classifiers in *PbSC* but wrongly classified by Webis. Here we choose Webis for comparison because it achieves the best performance in all the comparative methods. Table 8 gives some examples of such tweets grouping by different personality-based sentiment classifiers.

Table 8. Example tweets which are correctly classified by *PbSC* but wrongly classified by Webis

Classifiers	**Example tweets**	
	content	**polarity**
***HC* classifier**	责任与放纵的博弈。我能行的！为了家人！加油！…… (The game of responsibility and indulging. I can do it! For my family! Go for it!)	positive
	云南鲁甸加油！！！灾难无情人有情，全国人民都紧张着你们！！！ (Hold on Ludian, Yunnan!!! The disasters are merciless but we are together with you. The people all over the country are caring about you!!!)	positive
	法律面前人人平等??百姓,平民,冤案,错案一大堆!中国的司法公正体现在哪里?? (Equality before the law?? For the common people, the ordinary people, there are lots of injustices and misjudged cases! Where is the judicial justice in China??)	negative
***HE* classifier**	这辈子没这么爽过 (I have never felt so good in my life)	positive
	太给力了，是不是？ (It is quite awesome, isn't it?)	positive
	中秋假期一帮球友踢几场太爽了。 (It is so liberating to playing soccer with friends in the mid-autumn vacation.)	positive
***LE* classifier**	又在催了，身心俱疲。。。 (Being pushed again, I feel so exhausted…)	negative
	我好难过，比我小时候丢了我最心爱的玩具还要疼！ (I feel so sad, much sadder than the moment I lost my favorite toy in my childhood!)	negative
	我怎么会蠢到觉得他会一心一意对我呢 (How can I be so silly to believe that he will treat me heart and soul)	negative
***HA* classifier**	跟老妈讲电话神马的最窝心啦… (It is the sweetest to have a phone conversation with my mother…)	positive
	逗比一枚，专业卖萌二十年！不谢[爱你] (A cute guy who has majored in acting cute for twenty years! Welcome [love you])	positive
	无法拒绝的日本料理[好喜欢] (Undeniable Japanese cuisine [like very much])	positive

***LA* classifier**	哪个说这家海底捞好吃？哪个说服务好？完全反对 (Who says the hot pot in this Haidilao restaurant is delicious? Who says the service is good? I totally disagree)	negative
	这就是中国特色。她就是中国傻逼的代言人。 (This is the Chinese characteristic. She is the representative of the fools in China.)	negative
	滚！啊啊啊！ (Get out! Aaaaa!)	negative

From Table 8, we can see that these example tweets contain the sentiment features which clearly reflect users' personality traits. As people with high conscientiousness often encourage themselves or others to pursue achievements, words such as "加油(go for it, or hold on)" and "责任(responsibility)" are effective features of their positive sentiment. Besides, they like to comment on current affairs, making words such as "冤案(injustice)" and "错案(misjudged cases)" also being effective sentiment features. For the extroversion dimension, extroverts tend to use direct and simplified sentiment expressions frequently, thus the *HE* classifier extracts words like "爽(feel so good, or liberating)" and "给力(awesome)" as sentiment features to make correct judgements. For the introverts, as they often express their inner feelings, the words such as "身心俱疲(exhausted)" and "难过(sad)" are distinguishable features of negative sentiment for the *LE* classifier. In the microblogging sites, people with high agreeableness are inclined to use emoticons to praise others. Conversely, people with low agreeableness are accustomed to venting negative sentiments by abusing others. Therefore, the *HA* classifier takes words like "窝心(sweet)" and emoticons like "[爱你]([love you])" and "[好喜欢]([like very much])" as useful features for positive sentiment. In contrast, the *LA* classifier takes abusing words such as "傻逼(fool)" and "滚(get out)" as useful features for negative sentiment. In summary, by grouping tweets according to users' personality traits, our *PbSC* method can extract and leverage distinguishable personality related sentiment features, which makes it more effective than purely using the original sentiment classifiers.

5 Conclusion and Future Work

Microblog has become one of the major social media platforms for people to express their opinions. It is both beneficial and critical for many applications to understand the sentiments implied in user-generated contents. Most previous work on sentiment classification makes no distinctions of the texts published by different users. Thus personalized sentiment information is often neglected in the analysis process. Inspired by the psychological findings that personality influences the ways people write and talk, this paper proposes a personality-based refinement method *PbSC* to extract personalized features for sentiment classification in microblog based on the Big Five model. We first develop a rule-based method to predict user' personality traits with relatively high precision, which considers both the textual information and the microblog usage information. In order to leverage more personalized textual features, we group tweets according to the predicted personality traits, and then extract sentiment features and train basic classifiers for each personality group. On the basis of this, we employ ensemble learning and build a meta-classifier to make full use of both the personality-based and general sentiment classifiers. Experimental studies using SinaWeibo dataset show the effectiveness of our proposed method in refining the performances of both the traditional and state-of-the-art sentiment classifiers.

Our work is among the first to explore the role of user's personality in social media analytics, and we choose sentiment classification as an exemplar field for our investigation. In the future, we shall make several further improvements for our work. First, we shall explore the usage of other personality dimensions in sentiment classification. As we mainly use bag-of-words model to represent tweets, we shall also apply personality information to other textual models, such as deep learning based model. The third direction is to extend *PbSC* for more fine-grained emotion classification. Finally, as *PbSC* involves an ensemble learning process, we can apply parallel computing to accelerate this process.

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