# A Personality-Based Weibo Sentiment Analysis Model: PLSTM (Postprint)

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## Abstract

Users with different personalities exhibit distinct linguistic expression patterns. Existing sentiment analysis research seldom considers user personality. To address this problem, we propose a personality-based sentiment analysis model for Weibo, termed PLSTM. The model first utilizes personality identification rules to partition Weibo texts into five personality-specific collections and one general collection. Subsequently, it trains a separate sentiment classifier for each personality text collection. Finally, it fuses the six base sentiment classifiers to derive the final sentiment polarity. Experimental results demonstrate that the PLSTM method achieves an F1-score of 96.95%, indicating substantial improvements in accuracy, recall, and F1-score over previously commonly used baseline sentiment analysis models.

## Full Text

## Preamble

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### A Personality-Based Microblog Sentiment Analysis Model: PLSTM

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**Abstract:** Users with different personalities exhibit distinct language expression patterns. Existing sentiment analysis research seldom considers user personality. To address this limitation, this paper proposes a personality-based microblog sentiment analysis model called PLSTM. The model first employs personality recognition rules to divide microblog texts into five personality-specific sets and one universal set. It then trains a dedicated sentiment classifier for each personality text collection. Finally, it fuses the six base classifiers to determine the ultimate sentiment polarity. Experimental results demonstrate that the PLSTM method achieves an F1-score of 96.95%, indicating substantial improvements in accuracy, recall, and F1-score compared to previously common baseline sentiment analysis models.

**Keywords:** sentiment analysis; personality; word2vec; long short-term memory network; classifier fusion

## 0 Introduction

In recent years, with the rapid development and maturation of Internet technology, social networking platforms have gained widespread adoption. Emerging platforms such as Weibo and WeChat enable convenient publishing of text, images, and videos, facilitating information exchange and opinion expression, which has made them immensely popular among users.

Microblogs serve not only as a medium for interpersonal communication but also as a means for individuals to express personal emotions in both professional and daily life. People can follow trending events, share their viewpoints, and understand others' perspectives through microblogs. While expressing opinions, disseminating ideas, and articulating personal feelings, users generate substantial amounts of information with subjective emotional characteristics. This information contains various sentiment orientations that may reflect users' preferences and interests or exert significant influence on the propagation of online public opinion. Consequently, sentiment analysis of microblog discourse can measure user preferences and political stances, understand public perspectives on real-life hot topics, and predict future trends. When microblog discourse contains content detrimental to ethnic unity, timely control and guidance can redirect public opinion toward positive directions.

The term "sentiment analysis" was first introduced by Nasukawa et al. [**?**] in 2003, while "opinion mining" was first used by Dave et al. [**?**] in the same year. Early text mining research [**?**, **?**] focused primarily on extracting factual information from texts. Recent attention has shifted toward opinion mining, also known as sentiment analysis. This transformation is driven by the proliferation of review, blog, microblog, and social media texts that contain abundant subjective sentiments. Traditional methods such as Support Vector Machines (SVM), Naive Bayes (NB), and Maximum Entropy have been employed to determine sentiment polarity in review texts, yet they overlook the fact that users with different personalities exhibit varying commenting styles. Yu et al. [**?**] utilized sentence similarity and Naive Bayes classifiers for subjective text classification, based on the assumption that subjective sentences exhibit greater similarity among themselves than with objective sentences. Wei et al. [?] surveyed sentiment analysis research progress from perspectives of text granularity and text type, introducing existing resources but without detailed examination of specific methods. Yang et al. [?] reviewed text sentiment analysis literature from five aspects: sentiment word extraction, corpus and sentiment dictionary construction, analysis of evaluation objects and opinion holders, document-level sentiment analysis, and practical applications, providing necessary commentary. Zhang et al. [?] proposed a feature selection method based on short-comment co-occurrence, using short-comment features to supplement long-comment features, but did not consider incorporating user personality as a feature component. Poria et al. [?] employed multimodal cues combining audio, video, and text for sentiment analysis. Liu et al. [?] utilized convolutional neural networks for feature extraction, ultimately training an internet short-text sentiment classification model based on deep convolutional neural networks. Li et al. [?] proposed using Long Short-Term Memory (LSTM) language models for sentiment analysis. Chen et al. [?] employed both BiLSTM and CNN neural network methods to improve sentiment analysis effectiveness.

Regarding microblog sentiment analysis, He et al. [?] proposed a sentiment semantics-enhanced deep learning model. This approach first used word vector representation techniques to construct an emotional space feature representation matrix for commonly used emoticons in microblogs, then performed matrix-vector multiplication to map word meanings into the emotional space, and fed the mapping results into an MCNN (multi-channel convolution neural network) model to train a microblog sentiment classifier. However, this method did not consider that personality influences user expression patterns, with different personality types using distinct words or emoticons. Sun et al. [?] adopted deep neural networks with convolutional extension features for Chinese microblog sentiment analysis, demonstrating that under appropriate architecture and parameter configurations, the proposed deep belief network outperformed SVM and NB in sentiment classification performance.

In personality prediction, numerous psychological and computational studies have explored relationships between language use and personality traits within the Big Five model [?]. Most research employs Pearson correlation coefficients or Spearman' s rank correlation coefficients to measure correlation strength and identify significant linguistic cues associated with different personality traits in user-generated content [?]. Machine learning techniques have also been applied to predict user personality characteristics in social media [?]. Golbeck et al. [?] extracted Twitter usage features, structural features, and linguistic features, applying two regression algorithms to predict user personality traits. Bai et al. [?] proposed using multi-task regression and incremental regression to predict user personality through online behavior on Sina Weibo. Nowson et al. [?] applied machine translation models to address multilingual issues in text-based personality prediction.

The aforementioned sentiment analysis and personality prediction efforts largely represent distinct research domains. Sentiment analysis has not considered that users with different personalities express emotions differently, nor has it explored integration approaches combining sentiment and personality analysis. Psychological research indicates that personality influences writing and speaking styles, with individuals sharing similar personalities tending to select comparable emotional expressions. To address this issue, this paper proposes a personality-based microblog sentiment analysis model called PLSTM (Personality Long Short-Term Memory network).

## 1.1 Personality Model

Psychology has proposed several personality models, such as the Big Five model [?] and the MBTI model [?]. Among these, the Big Five model represents a more authoritative framework [?] and has been widely adopted in psychology and artificial intelligence [?]. The Big Five model describes human personality across five dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism. Individuals high in openness are imaginative, creative, and curious. Conscientiousness reflects the degree of self-discipline and preparation for opportunities. Highly conscientious individuals are passionate about work and eager to achieve. High extraversion indicates a preference for social interaction, while introverts prefer solitude. Agreeable individuals are generous, trustworthy, and always willing to help others. Neuroticism reflects emotional instability.

## 1.2 Word2vec Overview

Word2vec is a tool developed by Google for training word vector models, primarily employing two language models: CBOW (continuous bag-of-words) and skip-gram. Word2vec can digitize text representation, converting text into a form that computers can recognize, understand, and process. As a neural network, it preprocesses text before applying deep learning algorithms. Although Word2vec itself does not implement deep learning, it transforms text into vector forms comprehensible to deep learning [?]. Through training, Word2vec simplifies text processing to vector operations in K-dimensional vector space, where semantic similarity can be represented through vector space similarity. Consequently, word vectors trained by Word2vec can be utilized in numerous NLP-related tasks, such as part-of-speech analysis, clustering, and synonym identification. Word2vec enables efficient additive composition operations on word vectors, with Mikolov' s optimized single-machine version capable of training hundreds of billions of words per day [?].

## 1.3 LSTM Overview

In text sentiment analysis research, the sequential relationship between words is crucial. Mikolov [?] proposed a language model known as Recurrent Neural Networks (RNN), widely recognized as highly suitable for processing text sequence data. Theoretically, RNN language models can capture temporal sequential structures across entire documents and handle long-term dependency issues. In practice, however, RNNs may fail to successfully learn relevant knowledge. When the interval between contextual information and the current prediction position increases, backpropagation through time (BPTT) with excessive backward propagation layers leads to loss of historical information and gradient vanishing or explosion [?]. To overcome this difficulty, Hochreiter et al. [?] proposed Long Short-Term Memory (LSTM) networks, which achieve favorable results in certain application scenarios. LSTM is specifically designed to avoid long-term dependency problems, with remembering long-term information being its default behavior. Currently, LSTM networks are the most widely applied variant, replacing RNN nodes in hidden layers with LSTM units to preserve text historical information. LSTM employs three gates to control the utilization and updating of text historical information: the input gate, forget gate, and output gate. The memory cell and three-gate design enable LSTM to read, preserve, and update remote historical information. [Figure 1: see original paper] illustrates the LSTM structure.

## 2 Personality-Based Microblog Sentiment Analysis Model

To further enhance sentiment analysis effectiveness, this paper proposes a personality-based microblog sentiment analysis model. Since microblog texts posted by users with similar personalities often contain comparable emotional features, the model first categorizes microblog texts into different personality sets based on personality traits. For each dataset, Word2vec obtains vector representations of words in the text, generating a word vector matrix that serves as input to LSTM for training a sentiment classifier. Finally, to integrate results from all personality-specific and general sentiment classifiers, ensemble learning constructs an integrated classifier. During microblog text classification, each classifier generates outputs that serve as inputs to the integrated classifier for producing final classification results. The personality-based sentiment classification model framework is shown in [Figure 2: see original paper], where C, A, and E refer to the three dimensions of extraversion, agreeableness, and conscientiousness, respectively, while H and L indicate high and low personality values (e.g., HA represents high agreeableness, LA represents low agreeableness).

### 2.1 Personality Classification

To accurately assign microblog texts to different sets, the model must precisely predict the personality characteristics of texts. Current personality prediction primarily considers three dimensions from the Big Five model: extraversion, agreeableness, and conscientiousness. The remaining two dimensions—openness and neuroticism—present greater prediction difficulty based on previous research [?, ?] and are therefore not considered in this work. Each personality is further divided into high and low dimensions based on score values, resulting in five dimensions: high conscientiousness, high agreeableness, low agreeableness, high extraversion, and low extraversion. Due to insufficient low conscientiousness texts in microblogs, low conscientiousness is temporarily excluded from this study.

This paper adopts a rule-based personality classification method to predict the three personality dimensions of extraversion, agreeableness, and conscientiousness. For each personality, a personality dictionary is constructed containing commonly used words under that personality. These dictionaries determine whether a text exhibits certain personality expressions. presents example words from each personality dictionary.

Each personality group' s text features reflect commonalities in corresponding emotional expressions. As shown in , conscientiousness expressions often involve perspectives on achievement (e.g., effort, failure). Agreeableness expressions typically relate to love and praise (e.g., "love you," "awesome" ), expressing more sympathy (e.g., "sad" ). In contrast, low agreeableness expressions usually include accusations or insults directed at others (e.g., "it's all your fault,""stupid" ). Extraversion expressions favor direct articulation of positive (e.g., "happy" ) or negative (e.g., "sad" ) emotions.

For a given text X, if the number of high conscientiousness (HC) expression words (HC_Cword) or emoticons (HC_Cemoction) is relatively high, the text is inferred to have high conscientiousness. presents the primary text features for personality prediction. Although document-level sentiment analysis has achieved promising results, most documents contain more than one sentiment type, making sentence-level sentiment analysis more effective than document-level analysis.

shows the personality determination rules (where p1, p2, ···, p10 are thresholds determined experimentally). Texts satisfying any personality determination rule are assigned to the corresponding personality set. Since a text may conform to multiple rules, it can simultaneously belong to multiple personality sets.

### 2.2 Sentiment Classifier Result Fusion

Labeled datasets construct the base sentiment classifiers for each personality set. As microblog texts are sequence data with word-level units exhibiting long-range dependencies—particularly for words reflecting sentiment and personality—LSTM is employed as a sequence model capable of addressing long-term dependency issues.

Generic sentiment classifiers may render infrequently used personality-related features ineffective when mixed with other common features during training. Therefore, this paper fuses classification results from different base classifiers. Since a user may exhibit multiple personalities, a microblog text may belong to multiple personality sets.

First, LSTM trains a sentiment classifier for each personality dataset. During prediction, each sentiment classifier independently predicts the sentiment orientation of microblog texts. Subsequently, result fusion integrates outputs from all six base classifiers. The sentiment classifier fusion process is illustrated in [Figure 3: see original paper]. Given a set of microblog texts, six LSTM base sentiment classifiers generate outputs for each text, where and represent the positive and negative probabilities computed by the j-th classifier, respectively.

Based on each base sentiment classifier's output, fusion methods combine results to obtain final sentiment polarity. This paper considers three fusion methods: sum, weighted sum, and median. The formulas for the three fusion methods are as follows:

where: represents the final sentiment polarity; is the number of sentiment categories ( =1,2,3···C), with C=2 in this paper (positive and negative); are the output probability scores from the six classifiers; and are the weights of each base classifier.

## 3 Microblog Sentiment Analysis Experiments

To validate the feasibility of the proposed method, the following experiments were designed. The experimental environment: operating system Win7, processor Intel Core i5, 8 GB memory, CPU 2.5 GHz, development tool PyCharm Community Edition 3.3.

### 3.1 Experimental Data

The training data originates from literature [?], comprising texts posted by Sina Weibo users from October 21, 2009, to December 15, 2014. The dataset includes microblog content and basic author information but excludes forwarded texts. It contains 10,474 texts, each annotated with sentiment polarity: 7,562 positive and 2,912 negative.

The test data comes from the Chinese microblog sentiment analysis evaluation dataset provided at the 2012 CCF Natural Language Processing and Chinese Computing Conference, totaling 1,100 texts (500 positive, 600 negative).

### 3.2 Basic Sentiment Classifier Comparison

This experiment validates the classification accuracy of each base sentiment classifier, including five personality-based classifiers and one universal classifier. The training data includes: universal set (10,474 texts), high conscientiousness set (HC, 3,151 texts), high agreeableness set (HA, 3,188 texts), low agreeableness set (LA, 3,204 texts), high extraversion set (HE, 5,585 texts), and low extraversion set (LE, 3,154 texts). Results are presented in .

As shown in , among the five personality-based classifiers, HA and HC achieve higher F1-scores than the ALL classifier, demonstrating that sentiment classification tailored to different personality sets is effective.

The test data contains the most texts with HA and HC personalities and the fewest with LA personality. Comparison results reveal that HA and HC classifiers achieve higher F1-scores, while the LA classifier has the lowest F1-score, indicating that personality-specific classifiers are more effective when sufficient texts of that personality exist. This confirms the significance of targeted sentiment classification for different personality sets.

To further investigate each personality' s impact on final sentiment classification results, experiments removed one personality set' s sentiment classification results during fusion and compared performance with the full PLSTM method. presents the comparison, where PLSTM-HC, PLSTM-HA, PLSTM-LA, PLSTM-HE, and PLSTM-LE represent personality-based sentiment classification models trained without the HC, HA, LA, HE, or LE personality text sets, respectively.

Results in show that PLSTM achieves the highest F1-score in all cases, indicating that removing any personality text set degrades sentiment polarity classification performance. This demonstrates that each personality text set contributes to final classification accuracy, and training personality-based sentiment classifiers should fully utilize various personality text sets to achieve optimal integrated classifier performance.

### 3.3 Fusion Method Comparison

This experiment validates and selects fusion methods for different base classifiers, focusing on sum, weighted sum, and median approaches. The sum method assigns equal weights to all classifiers ( ). The weighted sum method determines weights for each personality set through cross-validation, with the primary criterion being maximal accuracy. Two datasets were used: Dataset 1 (1,100 texts from the 2012 CCF conference, 500 positive, 600 negative) and Dataset 2 (1,500 texts crawled from Weibo, 750 positive, 750 negative).

Since calculating optimal weights for each base sentiment classifier requires excessive computation, thirty experimental runs were conducted, selecting the weight combination yielding the best accuracy as the approximate optimal result. The final weights for each personality set were . compares accuracy under partial weight configurations.

Dataset 2, crawled from Weibo and manually annotated after preprocessing, contains certain errors and subjectivity, resulting in significantly lower experimental results than Dataset 1.

results show that in both datasets, highest accuracy occurs when HC has the highest weight. presents experimental results for the three fusion methods.

As shown in , the weighted sum method achieves the highest F1-score. The sum method assumes all classifiers have equal importance, but in practice, different classifiers have varying significance and should possess different weights, making it less effective than weighted sum. The median method sorts several classifier results and selects the middle value, which also proves less effective than weighted sum in this context. Therefore, this paper selects the weighted sum method as the final fusion approach.

### 3.4 Comparative Experiments

To validate the effectiveness of the proposed PLSTM model, comparative experiments were conducted against baseline sentiment classification models including SVM, LSTM, and Kim' s [**?**] CNN-rand, CNN-static, and CNN-non-static, evaluating accuracy, recall, and F1-score. Results are presented in .

Experimental results in demonstrate that the proposed method achieves higher accuracy than all baseline methods, confirming its effectiveness. Since users with similar personalities exhibit consistent expression patterns, sentiment classifiers trained for each personality text set are more targeted than generic classifiers. Additionally, ensemble learning fuses results from each personality-specific classifier and a universal classifier, enabling less frequently used personality-related features to contribute effectively. Consequently, the proposed method outperforms other baseline sentiment classifiers.

## 4 Conclusion

This paper addresses the issue that existing sentiment analysis rarely considers how users with different personalities have varying language expression patterns, proposing a personality-based microblog sentiment analysis model called PLSTM. The article analyzes current status and challenges in sentiment and personality analysis, presents the overall PLSTM architecture, and validates the model' s effectiveness through experiments.

PLSTM currently employs only LSTM-based classifiers for sentiment classifier training. Future work will consider alternative deep neural network models such as Bidirectional LSTM (BiLSTM) and Deep Belief Networks (DBN) to potentially achieve better results. Additionally, incorporating the remaining two personality dimensions—openness and neuroticism—may further enhance the personality-based sentiment analysis model' s performance.

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*Note: Figure translations are in progress. See original paper for figures.*