# Polarity Classification of Tweets Considering the Poster's Emotional Change by a Combination of Naive Bayes and LSTM

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**Abstract.** Twitter, as a popular social networking service, is used all over the world, with which users post tweets for various purposes. When users post tweets, an emotion may be behind the messages. As the emotion changes over time, we should better consider their emotional changes and states when analyzing the tweets. In this study, we improve polarity classification by considering the poster's emotional state. Firstly, we analyze the sentence structure of a tweet and calculate emotion scores for each category by Naive Bayes. Then, the poster's emotion state is estimated by the emotion scores, and a prediction model of emotional state is created by Long Short Term Memory (LSTM). Based on the predicted emotional state, weights are added to the scores. Finally, polarity classification is performed based on the weighted emotion scores for each category. In our experiments, our approach showed better accuracy than other related studies.

**Keywords:** Twitter · Polarity classification · Naive Bayes · Deep learning

## 1 Introduction

On Twitter, users can post tweets in real time, and many users express their opinions and feelings when interacting with other users. There are many studies that investigate the emotions in tweets.

Our emotions change over time. We can regard them as a series of flows. For example, if something happy happens, we will feel better for a certain period. Conversely, if something unpleasant happens, our feelings get worse and the remarks will be negative. It means that the emotional state of a poster may change at a different time. Therefore, we should consider the poster's emotional state behind the posted tweets when analyzing them.

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Until now, many studies have focused on the emotional tweets themselves, and few studies take into account the emotional state of the posters. The accuracy of polarity classification has been improved by machine learning. However, how to estimate the emotional state behind the tweets is not well discussed. Hulliyah et al. [7] surveyed emotion recognition methods for sentiment analysis, but the emotional state was not considered.

In this study, we propose a polarity classification approach that takes into account the poster's emotional state. In our approach, emotion classification by Naive Bayes is combined with Long Short Term Memory (LSTM). LSTM is a kind of deep learning, and it can create a time series model. We estimate the emotional state from emotion scores obtained by Naive Bayes, and predict the poster's emotional change with LSTM. By using predicted emotions for weighting scores, we can classify tweets based on not only emotional words but also the poster's emotion changes. By this mean, our approach is more user-centric.

The rest of this paper is organized as follows. In Sect. 2, we overview related research on emotion analysis and polarity classification on Twitter. In Sect. 3, we describe and explain our proposed approach. We show our experiments and discuss the results in Sect. 4. Finally, a summary of this study and future works are described in Sect. 5.

## 2 Related Work

### 2.1 Emotion Analysis for Social Media

A user's emotional state changes along the time axis. A tweet is a text posted by a human user, and emotion may be behind the tweet. As Braunstein et al. [2] suggested, a human mind should be considered not only from the explicit aspect but also the implicit aspect. In addition, to analyze and classify tweets more accurately, it would be necessary to analyze both the tweets and their posters.

Beasley and Mason [1] investigated the relationship between emotional expression in social media and subjective emotion using questionnaires. Kramer [8] analyzed Facebook posts and revealed differences between an emotion trend of holidays and that of weekdays. Nguyen et al. [9] created a model to predict emotion changes in a group based on machine learnings. Fujita et al. [4] investigated whether emotional tweets affect others' posts. They revealed that positive tweets affect others while negative tweets are hard to spread.

### 2.2 Emotion Detection and Classification

Polarity analysis is a typical theme of natural language processing, and recently machine learning such as deep learning is used. In order to take into account the appearance order and context of sentences, Recurrent Neural Network (RNN) and LSTM are applied. Vateekul and Koomsubha [14] performed emotion classification for Thai tweets data using LSTM. In their experiments, LSTM showed

higher accuracy in emotion classification than SVM and Naive Bayes. Su et al. [11] showed that word2vec and LSTM can be combined to improve the emotion classification. Maulidiah and Sarno [3] showed that their approach can classify tweets with an accuracy of 74% by weighting emoticons.

In order to evaluate emotion, multiple datasets are prepared [10,15]. As a typical dataset, there is Sentiment140 [5]. This dataset is used to classify positive and negative. Uysal and Murphey [13] used multiple datasets including Sentiment140 and verified the classification accuracy by the characteristic selection of words. Huang et al. [6] proposed an emotion evaluation model using random forest and clarified emotional tendency by places. They also used Sentiment140 to evaluate their model.

### 2.3 Position of This Study

When analyzing tweets, the emotional state of the poster was rarely taken into account. Beasley [1] evaluated the relationship between the emotional state of the user and emotional tweets. Their results showed that there was no significant correlation. However, there is a gap between subjective emotion and objective emotion. Therefore, even though the poster him/herself is not aware, potential emotions may appear in the tweets.

In this paper, we propose a polarity classification approach considering the emotional state in chronological order. Naive Bayes, which is a statistical method, is adopted for calculating emotion scores. Moreover, we adopt LSTM, which is mainly used for time series analysis. Using LSTM, we consider the poster's emotional state as time series data and predict the emotional state.

## 3 Polarity Classification Considering Emotional States

The overview of our approach is shown in Fig. 1. Firstly, tweets posted by a user are collected. Secondly, dependency analysis is performed on the relationships between words. Thirdly, a score for a positive and negative category is calculated by Naive Bayes. Thereafter, emotional states are estimated by LSTM, and category scores are weighted based on the estimated state. Finally, using the weighted category scores, the polarity of tweets is judged.

### 3.1 Dependency Analysis

Dependency analysis is a method to analyze the structure of a sentence. The words such as "very" and "little" have a function to change the meanings of related words. By understanding the relationship between words, we can evaluate the polarity more effectively. Dependency analysis is used to adjust the category score attached by Naive Bayes.

To perform dependency analysis, various tools such as Cabocha and MST-Parser are provided. In this study, we use Syntaxnet[1]. This is the neural network framework released by Google in 2016.

[1] https://github.com/tensorflow/models/tree/master/research/syntaxnet.

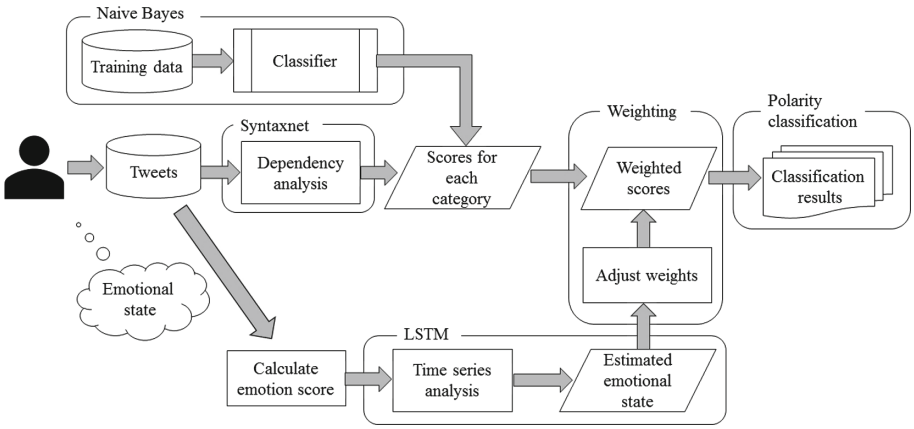



**Fig. 1.** Our proposed approach

### 3.2 Calculating Category Scores by Naive Bayes

After performing dependency analysis, positive and negative emotion category scores are calculated by Naive Bayes. Naive Bayes is a kind of supervised learning and classifies tweets based on the probability that a word appears in each category. Based on the probability, the score for each category is calculated for the word. In this method, it is assumed that words appear independently.

### 3.3 Estimating Emotional State by LSTM

Using Naive Bayes, the scores of positive category and negative category for tweets are calculated separately. Based on the method proposed in our previous study [12], the total score is calculated for each category. The total positive score of the tweet ($TPST$) can be expressed in Eq. (1).

$$TPST = \sum_{i=1}^{n} PES_i \tag{1}$$

where $n$ represents the number of words in the tweet. $PES_i$ represents the positive emotion score of a word. The positive emotion score is calculated by Naive Bayes based on the probability that a word appears in the positive category.

The total negative score of the tweet ($TNST$) can be calculated in Eq. (2).

$$TNST = \sum_{i=1}^{n} NES_i \tag{2}$$

where $n$ represents the number of words in the tweet. $NES_i$ represents the negative emotion score of a word. The negative emotion score is calculated by Naive Bayes in the same way as the positive score.

Estimation of emotional state is carried out by time series analysis. Nguyen et al. [9] defined the ratio of positive tweet count as an emotion tendency, and we referred to their approach. As a poster's emotional state, we use the positive emotion ratio to measure the emotional state ($EST$) for a tweet. $EST$ is defined as follows:

$$EST = \frac{TPST}{TPST + TNST} \tag{3}$$

where $TPST$ is the score of the positive category of the tweet, and $TNST$ is the score of the negative category. The range of $EST$ is from 0 to 1. Since $EST$ represents the ratio of positive emotion ratio, it can be regarded as a positive tendency if it is larger than 0.5, and negative if it is smaller than 0.5.

### 3.4 Weighting Category Score Based on Predicted *EST*

To predict $EST$, LSTM, which is a kind of deep learning, is used. LSTM is an extension of RNN. It is composed of a cell, an input gate, an output gate, and a forget gate. By using the forget gate, LSTM can store not only short-term but also long-term memory. Therefore, the time series can be predicted more accurately.

We estimate $EST$ by creating a time series model for each poster. If the poster is in a state of pleasure, it has a high likelihood to post a positive tweet next time. Based on the predicted $EST$ ($PEST$), $TPST$ and $TNST$ are weighted. The detail will be described in Sect. 4.3.

### 3.5 Polarity Classification Based on Weighted Category Scores

Based on weighted category scores, the tweet is classified. The tweet has a weighted score for each category: $TPST$ and $TNST$. If $TPST$ is higher than $TNST$, the tweet is regarded as positive. Otherwise, the tweet is regarded as negative.

## 4 Experiments and Discussion

### 4.1 Dataset and Preparation

We used the Sentiment140 dataset collected by Go et al. [5]. This dataset is used for polarity analysis and consists of positive 800,000 tweets and negative 800,000 tweets. We randomly selected 100,000 tweets (positive 50,000 tweets and negative 50,000 tweets) as training data. As described in [5], tweets of each category were collected based on emoticons. They collected not only tweets but also usernames and tweet dates as well.

In this experiment, we arranged users in descending order by the number of tweets and selected users with more tweets. We excluded accounts for advertisements and users who posted only positive or negative tweets.

As a result, three users, "mcraddictal", "SallytheShizzle" and "VioletsCRUK", were selected. "mcraddictal" has 66 positive tweets and 209 negative tweets. "SallytheShizzle" has 97 positive tweets and 182 negative tweets. "VioletsCRUK" has 217 positive tweets and 61 negative tweets.

### 4.2 Dependency Analysis and Category Scoring by Naive Bayes

To analyze the structure of sentences, we used Syntaxnet. After dependency analysis, we calculated category scores for a tweet by Naive Bayes. As described above, we trained Naive Bayes with 100,000 tweets.

Based on the relation of the words obtained by dependency analysis, we adjusted to the score of the related word. For example, the tweet "I'm very happy" is emphasized by the meaning of "very", and "It's little better" is weakened by the meaning of "little". In addition, the tweet "I'm not happy" is reversed the meaning of "I'm happy". Therefore, referred to our previous study [12], we set weighted magnification as 1.5 times for "very" and 76 synonyms, 0.5 times for "little" and 96 synonyms, and $-1$ times for "not" and nine synonyms. Based on the result of the dependency analysis, we weighted scores of related words. The total score of the categories for a tweet is calculated and expressed as $TPST$ and $TNST$.

### 4.3 Estimating Emotional States and Weighting Scores

After calculating the score for each category, a user's emotional state was estimated. We calculated $EST$ for each tweet. We used $EST$ to measure emotional states, and modeled them with LSTM. For each user, we used their first 200 tweets as training data, and the rest as test data. We ran LSTM on Python and set hyper-parameters as follows:

- Hidden layer: 5
- Epoch: 100
- Timewindow: 3

Vateekul et al. [14] investigated the hyper-parameters of LSTM for polarity classification in Thai language. Their result showed that classification accuracy was the best when the hidden layer parameter was set to five. Refer to their study, we also set the hidden layer parameter as five. Using the created model, we estimated $PEST$ for each user.

If a certain period of time has passed since the last tweet, it is considered that the influence on the next tweet would be small. Therefore, we did not weight tweets which passed for a certain period from the previous tweet. To decided the time period, we referred to Fujita's study [4]. They studied the influence of users' emotional tweet in chronological order, and they collected users who tweeted more than 10 times in a day. In this study, we set the time period as 146 min, which is the average interval of one tweet.

We examined the following four experiments to weight scores.

- Experiment 0: Baseline (Dependency analysis and Naive Bayes)
  Emotional state prediction is not used. Polarity classification is carried out using the score obtained by Naive Bayes classification after dependency analysis. In this experiment, we directly use $TPST$ and $TNST$ in Eqs. (1) and (2) as polarity scores ($PS$).
- Experiment 1: We adjust $PS$ as follows.

$$PS = \begin{cases} (1 + \frac{PEST - 0.5}{0.5})TPST & (PEST \geq 0.5) \\ (1 + \frac{0.5 - PEST}{0.5})TNST & (PEST < 0.5) \end{cases} \tag{4}$$

  If $PEST$ is larger than or equal to 0.5, the weight is set based on $TPST$, and when $PEST$ approaches 1, the weight approaches doubles. Conversely, if it is smaller than 0.5, the weight is set according to $TNST$, and when $PEST$ approaches 0, the weight becomes 2 times.
- Experiment 2: We adjust $PS$ using $TPST$ only as follows.

$$PS = \begin{cases} (2PEST)TPST & (PEST \geq 0.5) \\ (PEST + 0.5)TPST & (PEST < 0.5) \end{cases} \tag{5}$$

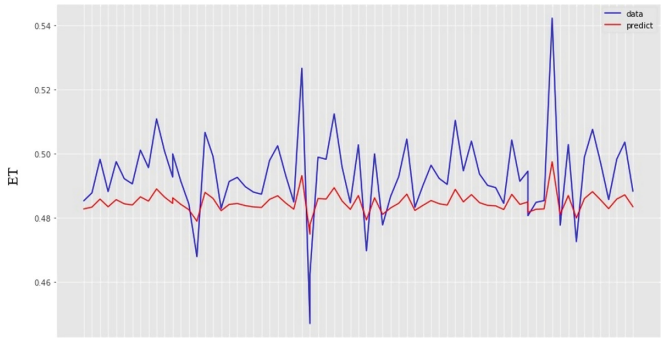
  If $PEST$ approaches 0.5 to 1, the weight approaches doubles. Conversely, if it approaches 0, the weight becomes half.
- Experiment 3: Firstly we change the range of $PEST$ from $-1$ to 1, and we adjust the weight of $PS$ using $TPST$ and $TNST$ as follows.

$$PS = \begin{cases} (1 + PEST)TPST & (PEST \geq 0) \\ (1 - PEST)TNST & (PEST < 0) \end{cases} \tag{6}$$

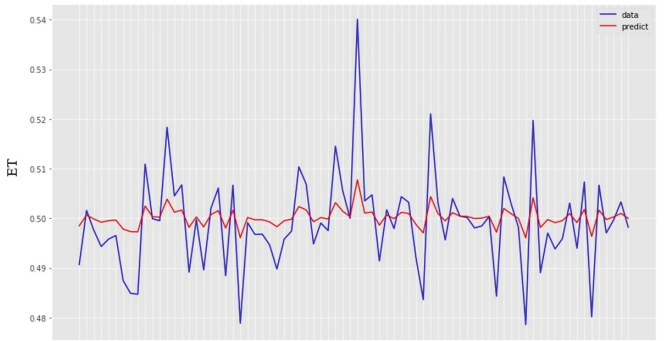
  If $PEST$ is larger than or equal to 0, the weight is set according to $TPST$, and when $PEST$ approaches 1, the weight becomes doubles. Conversely, when $PEST$ is smaller than 0, the weight is set according to $TNST$, and when $PEST$ approaches $-1$, the weight becomes 2 times.

### 4.4 Results and Discussions

The classification accuracies are shown in Table 1, and $PEST$ is shown in Fig. 2. The accuracy of Experiment 3 was better than the baseline and Uysal's study [13]. Uysal trained classifiers using the Sentiment140 and investigated the appropriate word feature. Our training dataset is also based on Sentiment 140. The classifier is expected to have similar accuracy. From the result, our approach is of higher accuracy than Uysal's study, which implies that it is effective to consider emotional states for polarity analysis.




(a) mcraddictal




(b) SallytheShizzle




(c) VioletsCRUK

**Fig. 2.** Predicted emotion states for three users

**Table 1.** Classification accuracy (%)

| | Positive | Negative | Total |
|---|---|---|---|
| Uysal [13] | - | - | 71.5 |
| Experiment 0: Baseline | 75.9 | 75.1 | 75.5 |
| Experiment 1 | 81.0 | 56.4 | 62.8 |
| Experiment 2 | 75.9 | 75.2 | 75.5 |
| Experiment 3 | 74.1 | 78.8 | **77.6** |
| Vateekul [14] * | - | - | 75.3 |

* This study classified polarity tweets using LSTM with a different dataset they collected themselves.

In Experiment 1, the accuracy for negative category declined. In Experiment 2, the total accuracy was the same as the baseline. Experiment 3 got the best result, which shows that by adjusting the emotion scores it becomes an optimization problem, and there is a possibility that classification accuracy can be improved.

Through the experiments, we found some improvements could be made. The first is that we should get all the tweets of a poster. In this study, we created the model using tweets explicitly positive and negative only. When $TPST$ and $TNST$ are almost the same, it can be regarded as a neutral tweet. How to detect neutral tweets should be considered. With the same reason, we should use all the tweets to estimate emotional states.

## 5 Conclusion

In this paper, we proposed an improved approach to take into account emotional states of human users in polarity analysis. Firstly, we performed the dependency analysis and analyzed the relationships between words. Next, a Naive Bayes classifier was trained, and the score for each category was calculated in consideration of the result of dependency analysis. A user's emotional state was estimated from the calculated scores and a time series model was created by LSTM. Finally, the category scores were weighted based on the predicted emotional states and classification was performed. As a result, our method showed better classification accuracy than the baseline and other related study.

For our future work, we will create the time series model using all tweet, not limited to explicitly positive or negative, including neutral tweets. Moreover, we will further investigate the hyper-parameters setting of LSTM and adjust the weights for polarity scores.

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