Estimation of Inter-Sentiment Correlations Employing Deep Neural Network Models

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ABSTRACT

This paper focuses on sentiment mining and sentiment correlation analysis of web events. Although neural network models have contributed a lot to mining text information, little attention is paid to analysis of the inter-sentiment correlations. This paper fills the gap between sentiment calculation and inter-sentiment correlations. In this paper, the social sentiment is divided into six categories: *love, joy, anger, sadness, fear, and surprise*. Two deep neural network models are presented for sentiment calculation. Three datasets – the titles, the bodies, the comments of news articles – are collected, covering both objective and subjective texts in varying lengths (long and short). From each dataset, three kinds of features are extracted: explicit expression, implicit expression, and alphabet characters. The performance of the two models are analyzed, with respect to each of the three kinds of the features. In terms of the features, it is shown that the alphabet character features perform better than the other two features on short texts. In terms of sentiment in subjective text, *sadness* is easy to be recognized as other sentiments. All the sentiments are easy to be recognized as *anger*. In terms of sentiment in objective text, the text which actually arouses *anger* is relatively unpredictable and likely to be classified to *love*.

CCS CONCEPTS

• **Computing methodologies** → Artificial intelligence; Natural language processing; Information extraction • **Computer systems organization** → Architectures; Other architectures; Neural networks

KEYWORDS

Sentiment Analysis, Sentiment Correlation, Deep Neural Network, LSTM

1. INTRODUCTION

Social sentiments are valuable. Effective sentiment calculation does not only help product developers to understand the preference of their customers, but also helps governors to evaluate the public opinion to a social event. In recent years, many machine learning algorithms have contributed to sentiment analysis in text. However, even though the performance of these algorithms has been improved a lot, little attention is paid to the complexity of social sentiments: in social psychologist's views, social sentiments are compound and diverse. For instance, someone could say, "You stupid farmer, why did you save the snake when you knew he could kill you?", where a strong sentiment of empathy can be easily confused with anger. Given the same social event, the sentiments of different people are diverse. People with different personalities and prior knowledge may pay attention to different aspects. If a reader concerns more than one aspect of the sentiment, then his/her words may carry more than one sentiment. In the field of psychology, there is still some controversy about the classification of sentiments. However, in engineering scientist's views, the learning algorithms often treat the social sentiments as a simple classification (e.g., positive/negative). The social psychologists and the engineering scientists focus on their own perspectives of sentiment calculation, leaving a gap between the performance of sentiment classification and the analysis of sentiment correlations. To fill this gap, this paper focuses on six kinds of human sentiment, i.e., *love, joy, anger, sadness, fear, surprise*[34], builds two deep learning models, and extracts three different kinds of features, to support mining both the text sentiment and the inter-sentiment correlation. The above six categories of sentiments are widely accepted as one of the mainstream classification today [34]. If other sentiment categories are chosen, the analyzing process can be analogized.

Essentially, the performance of a sentiment calculation model is affected by both the quality of data and the effectiveness of model. Just as described above, the public's sentiments to a social event are compound. On one hand, even to the same text, the cognition of its sentiment is heterogeneous among people. It means there are no absolutely accurate data for everyone. Consequently, a better understanding of sentiment data can help interpreting the performance of sentiment calculation models. On the other hand, the sentiment calculation result could provide clues for data understanding, improving the comprehension of inter- sentiment correlations.

To understand the sentiment data, three datasets – the titles, the bodies, and the comments of news articles – are collected, covering both objective and subjective texts in varying lengths (long and short). From each dataset, three kinds of features are extracted: explicit expression, implicit expression, and alphabet characters. In order to calculate sentiment for both the short and long texts uniformly, this paper presents two deep neural network models. The performance of the two models are analyzed, with respect to each of the three features. It is shown that the alphabet character features perform better than the other two features on short texts, while the other two features perform better on long texts. Taking all the combinations of the three datasets and the three features as the input of the two deep learning models, the sentiment calculation provides results to analyze the inter-sentiment correlations. It is shown that *anger* is more likely to be confused with other sentiments, especially in sentences where multiple sentiments are expressed simultaneously and one of them is emphasized. Such kinds of sentiment cognitive biases are also revealed in other sentiment categories.

The rest of the paper is organized as follows. We start by reviewing related work. In Section 3, we describe the sentiment calculation models and the inter-sentiment correlation analysis method. In Sections 4, the details of the experiment are introduced. Finally, we draw conclusions in Section 5.

2. RELATED WORK

Social media is playing increasingly important roles in scientific research as well as our daily life. The data from social media contribute to the improvement of text-related analyses, such as sentiment analysis [3, 7, 23], sarcasm detection [1, 2], event dissemination [3], short text clustering [4], user clustering [5, 6], knowledge recommendation [7], and user behavior analysis [8, 9]. Continuous word representations, including word2vec [10], glove [11], and weighted word embedding [12], also provide new ideas on knowledge mining.

Sentiment analysis, as an important branch of knowledge mining, can be categorized into three levels, namely word level, sentence level, and article level. In word level, sentiment words are extracted mainly through three ways: 1) manual approach [13], 2) dictionary-based approach [14, 15], and 3) corpus-based approach [16]. In sentence level, intra-sentential and inter-sentential sentiment consistency were explored [17]. Qiu et al. [18] employed dependency grammar to describe relations for double propagation between features and opinions. Ganapathibhotla and Liu [19] adopted dependency grammar for sentiment analysis of comparative sentences. The Conditional Random Fields (CRF) method [20] was used as the sequence learning technique for extraction. Machine learning methods are widely used in both sentence and article level. Naive Bayesian [21, 22], maximum entropy classification [22], Support Vector Machines (SVMs) [22], and pattern recognition methods [23] are employed frequently. In recent years, neural network models, such as Long Short Term Memory (LSTM) [24, 25], convolutional neural network (CNN) [26, 27], recursive auto-encoders [28, 29], adversarial learning [30] and attention mechanism [31, 32], also contribute to sentiment analysis and classification tasks.

All of the above works have improved the performance of sentiment analysis. However, just as Wilson et al. [33] pointed out, a single text may contain multiple opinions. Parrott [34] demonstrated that human sentiments are prototyped and complex. Most of the recent works just focus on recognizing the sentiment expressed in text. Little attention is paid to associate sentiment calculation in engineering with inter-sentiment correlation in psychology.

3. MODEL

Sentiment data and model are the two factors which influence the performance of sentiment calculation, and they impact on each other. The compound sentiment in data impacts on the result of the sentiment calculation model, and the model's result furthermore impacts on analysis of the inter-sentiment correlation in return. The interaction process is shown in Fig. 1. This section introduces the sentiment calculation models and the inter-sentiment correlation analyzation method separately.

3.1 Sentiment Calculation Models

The sentiment calculation models aim to discriminate the sentiment orientation of input texts. In this paper, two deep neural network models, CNN-LSTM2 and CNN-LSTM2-STACK, are proposed to calculate sentiment. In both models, the length of an input text can be either short or long. The output of the models is one of the six kinds of sentiments, i.e., *love*, *joy*, *anger*, *sadness*, *fear*, and *surprise*. The calculation process can be divided into three parts, as shown in Fig. 2. CNN-LSTM2 is constructed with Part I and Part II. CNN-LSTM2-STACK is constructed by adding an additional Part III to CNN-LSTM2. The details of the three parts are represented as follows.

3.1.1 Part I: Feature Processing. Part I focuses on feature processing which transforms the original features into dense vector information. There are four operations in this part: vector lookup, window sliding, convolutional calculation, and ReLU activation.

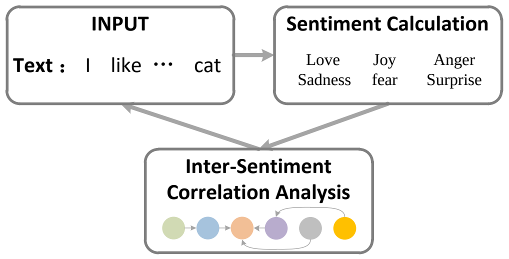
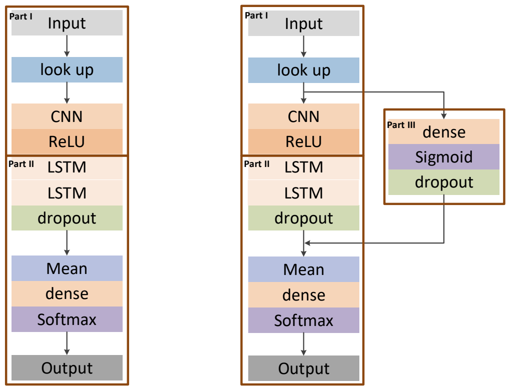


Figure 1: Interaction diagram of sentiment calculation and inter-sentiment correlation analysis



(a) CNN-LSTM2 (b) CNN-LSTM2-STACK

Figure 2: Sentiment calculation models

Let input be denoted as w_i^j, which means the i-th feature of the j-th sample text. The j-th sample text is indicated as $[w_1^j, w_2^j, \dots, w_N^j]$, where the text is padded by 'none' to length of N. Here, 'none' is the reserved symbol in the vocabulary. For instance, if the first sample text is 'I like small cat' and $N = 5$, then $w_1^1 = \text{'I'}$, $w_2^1 = \text{'like'}$, $w_3^1 = \text{'small'}$, $w_4^1 = \text{'cat'}$, $w_5^1 = \text{'none'}$.

The first operation, vector lookup, searches the embedding representation v_i^j of the corresponding input feature w_i^j, which is formulated as:

$$v_i^j = \text{LOOKUP}(w_i^j) \tag{1}$$

The second operation, window sliding, packets a targeted input feature and its context together after 'none' padding. Specifically, the window size in this paper is set to be 5, and $w_0^j = w_{-1}^j = \text{'none'}$. Then, in the third operation, a convolutional layer is applied.

$$h_{i,1}^j = \text{CNN}([v_{i-2}^j, v_{i-1}^j, v_i^j, v_{i+1}^j, v_{i+2}^j]) \tag{2}$$

where $h_{i,1}^j$ is the first hidden layer. And $[.]$ means embedding concatenation. In the last operation, a ReLU activation layer is added.

$$h_{i,2}^j = \text{ReLU}(h_{i,1}^j) \approx \log(1 + h_{i,1}^j) \tag{3}$$

where $h_{i,2}^j$ is the second hidden layer of the i-th feature of the j-th sample. $h_{i,2}^j$ acts as the input of Part II.

3.1.2 Part II: Sentiment Calculation. Part II focuses on the sentiment calculation after feature processing of Part I. There are five operations in this part, i.e., Long Short Term Memory (LSTM) calculation, dropout operation, average calculation, fully connect calculation, and sorftmax.

Firstly, the $h_{i,2}^j$ output of Part I is fed into a two-layer LSTM component. The outputs of the two LSTM layers are represented as $h_{i,3}^j$ and $h_{i,4}^j$ respectively. After that, the dropout operation is applied to prevent over-fitting. Then, we can get:

$$h_{i,3}^j = \text{LSTM}(h_{i,2}^j) \tag{4}$$

$$h_{i,4}^j = \text{LSTM}(h_{i,3}^j) \tag{5}$$

$$h_{i,5}^j = \text{DROPOUT}(h_{i,4}^j) \tag{6}$$

where i is the index of the text sequence, which is an integer ranging from 1 to N.

In practice, even though the texts have been padded to the same length of N, their actual lengths still vary. To settle this problem, we define $ms_i^j \in \{0, 1\}$ as mask. The sequence data is combined to fixed-length vector.

$$h_{\_6}^j = \frac{1}{N}\sum_i (h_{i,5}^j \cdot ms_i^j) \tag{7}$$

If the i-th feature of the j-th sample text is valid (i.e., not "none"), then $ms_i^j = 1$. Otherwise, $ms_i^j = 0$. Note that $h_{\_6}^j$ denotes the sixth hidden layer. The last two steps are a fully connected layer and a softmax layer.

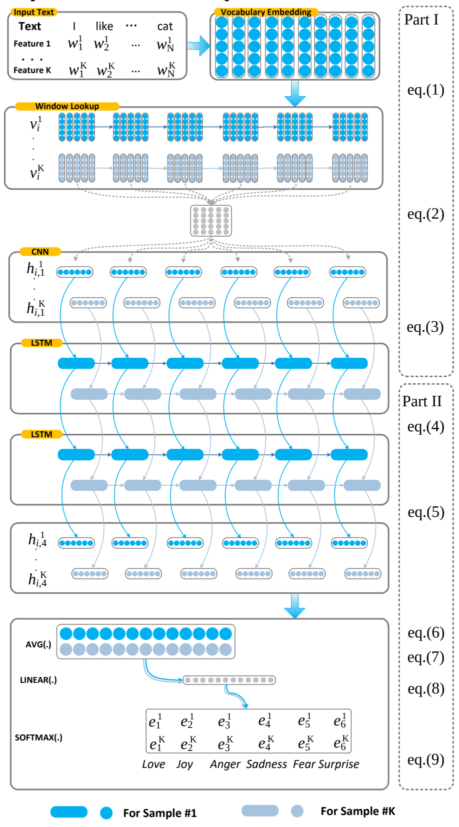


Figure 3: Model of CNN-LSTM2

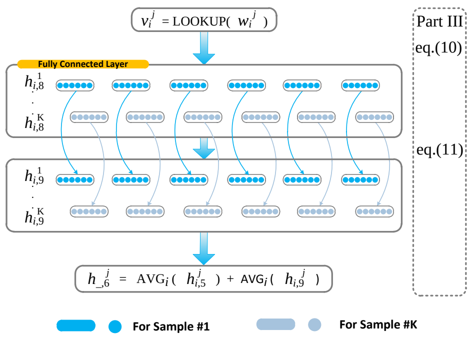


Figure 4: Model of CNN-LSTM2-STACK

$$h^j_{\_7} = \mathrm{LINEAR}(h^j_{\_6}) = \mathrm{W}^{\mathrm{T}} h^j_{\_6} + b \tag{8}$$

$$\mathrm{P}(e^j_l) = \mathrm{SOFTMAX}(h^j_{\_7}) = \frac{e^{h^j_{\_7,l}}}{\sum_{m=1}^{M} e^{h^j_{\_7,m}}} \tag{9}$$

where W and b are the weight matrix and bias. l is the sentiment index which ranges from 1 to 6, corresponding to the six categories of sentiments.

3.1.3 Part III: Original Feature Attention. Part I and Part II construct the model CNN-LSTM2. However, with the neural network going deep, the backward fine-tuning process in CNN-LSTM2 becomes weak, and the vanishing gradient problem occurs. To solve this problem, a second model CNN-LSTM2-STACK is constructed by associating CNN-LSTM2 with Part III. This part links the input feature embedding v^j_i to the layer $h^j_{\_6}$ through linear and sigmoid operations.

$$h^j_{i,8} = \mathrm{LINEAR}(v^j_i) \tag{10}$$

$$h^j_{i,9} = \mathrm{SIGMOID}(h^j_{i,8}) \tag{11}$$

Then, layer $h^j_{\_6}$ is adjusted by $h^j_{i,9}$, i.e., the inputs of the sixth hidden layer changes to both $h^j_{i,5}$ and $h^j_{i,9}$.

$$h^j_{\_6} = \frac{1}{N}\sum_i \left(h^j_{i,5} \cdot ms^j_i\right) + \frac{1}{N}\sum_i \left(h^j_{i,9} \cdot ms^j_i\right) \tag{12}$$

The other operations in Part II remain the same. Part III aims to emphasize the impact of the input feature embedding on the sentiment calculation result. In other words, by stacking Part III, the network pays more attention to the original feature information.

The two models CNN-LSTM2 and CNN-LSTM2-STACK use deep neural network methods to calculate text sentiment. In our model design, both long and short texts can act as input. Three parts – feature processing, sentiment calculation, and original feature attention – are introduced. The details are shown in Fig. 3 and Fig. 4. The sentiment calculation result of the two models supports the inter-sentiment analysis below.

3.2 Inter-Sentiment Correlation Analysis

In terms of the content, sentiment data can be divided into two categories: objective texts and subjective texts. Objective texts tell the story of what happens in an event. Subjective texts are the comments from readers, which are aroused by the objective texts. In this paper, the titles and the bodies of news articles are collected as objective texts, which are edited and published by journalist. The comments of news articles are collected as subjective texts, which are generated by the public. Analysis of objective texts aims at finding the correlation of objective information to subjective sentiment. Analysis of subjective texts intends to mine the correlation of subjective information to sentiment cognition.

Suppose E is the input sentiment label of a sample text, which is marked manually. $\widetilde{\mathrm{E}}$ is the ground truth of the sentiment, and $\widehat{\mathrm{E}}$ is the output label predicted by a learning model. If $\widetilde{\mathrm{E}} = \widehat{\mathrm{E}} = \mathrm{E}$, it means our model prediction, the manually marked label, and the ground truth of the sentiment are in consistence. However, it is almost impossible to completely keep this consistence in all the sample texts in practice. On one hand, the learning model often has a generalization error rate, which generates the differences between $\widehat{\mathrm{E}}$ and E. On the other hand, the difference between E and $\widetilde{\mathrm{E}}$ stems from the human sentiment cognitive bias. The sentiment cognitive bias restricts the quality of data, and impacts on the prediction in further steps. To estimate the above two factors that influence the consistence, a voting mechanism based on multiple models and datasets is put forward, as shown in Fig. 5.

Let $\mathrm{C}(e_a|e_b, D_i, F_j, M_k) \in [0,1]$ represent the probability that e_b is recognized as e_a, given data D_i, feature F_j and model M_k. Let $\mathrm{Cr}(e_a|e_b, D_i, F_j, M_k) \in \{0,1\}$ denote the indicator of e_b being recognized as e_a, where Cr is calculated by the following equations:

$$\begin{cases} \mathrm{Cr}(e_a|e_b, D_i, F_j, M_k) = \{\mathrm{C}(e_a|e_b, D_i, F_j, M_k) > \theta\} \cdot \{1\} \\ \{\mathrm{True}\} \cdot \{1\} = 1 \\ \{\mathrm{False}\} \cdot \{1\} = 0 \\ \theta \in [0,1] \end{cases} \tag{13}$$

where D_i, F_j, M_k indicate corresponding dataset, input feature, and model respectively. θ is a threshold. Cr is the sentiment correlation matrix with elements belonging to $\{0, 1\}$. The voting process can be formulated as:

$$\mathrm{T}(e_a|e_b) = \wedge_{i,j,k}\, \mathrm{C}(e_a|e_b, D_i, F_j, M_k) \tag{14}$$

The voting result of objective texts (i.e., $\mathrm{T}(e_a|e_b)$ for news titles and bodies) implies the correlations from objective information to subjective sentiment. The voting result of subjective texts (i.e., $\mathrm{T}(e_a|e_b)$ for news comments) give clues on the correlations from subjective information to sentiment cognition. The result is shown in the experiment section.

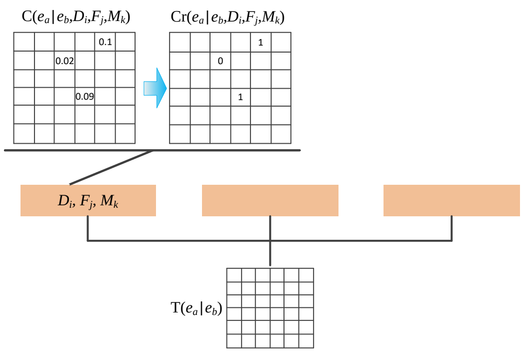

C(e_a|e_b,D_i,F_j,M_k)
0.1
0.02
0.09
Cr(e_a|e_b,D_i,F_j,M_k)
1
0
1
D_i, F_j, M_k
T(e_a|e_b)

Figure 5: Process of sentiment correlation analysis

4. EXPERIMENT

4.1 Datasets

The datasets used in this paper is crawled from one of the most popular social network, news channel (http://news.sina.com.cn/society/moodrank/). Each news article is split into three parts: the comment (Data #1), the body (Data #2), and the title (Data #3), where Data #1 is treated as subjective, and Data #2 and Data #3 are regarded as objective. The sentiment labels of the three datasets are generated through the vote of the public, strong rules, and manual selection. The distribution of the sentiments in the three datasets is introduced in Table 1. The comment dataset contains more than 150,000 sample texts. News body and news title data both contain more than 24,000 sample texts.

4.2 Data Feature and Model Parameters

A text is composed of words, words are composed of characters, and character is one of the most basic features of text. This paper presents three different ways to extract features from a sample text. They are explicit expression, implicit expression, and character features. In explicit expression, the features are all the words in the text. In implicit expression, the features are the synonym tags of the words, where the synonym tags, extracted through HIT synonymous dictionary (HIT IR-Lab Tongyici Cilin (Extended)), share the same symbol if the corresponding words are synonyms. In character features, each letter (or character) in the text is an independent feature. Table 2 shows the statistical information of features in the three datasets. The number of features, the maximum, minimum and average number of features per document are listed in the table.

Table 1：Data Distribution of Sentiments

Sentiment	Data #1 News comment		Data #2 News body		Data #3 News title	
	Train	Test	Train	Test	Train	Test
Love	29,658	7,398	6,788	1,698	6,717	1,680
Fear	2,098	520	5,240	1,309	5,211	1,302
Joy	15,426	3,848	5,178	1,295	5,159	1,290
Sadness	9,238	2,304	1,457	364	1,451	364
Surprise	13,283	3,311	323	82	272	68
Anger	51,610	12,882	578	144	571	142
Total	121,313	30,263	19,564	4,892	19,391	4,846

Table 2：Statistical Information of Features in the Datasets (Fea: feature; Exp: explicit expression; Imp: implicit expression; Char: Character features; #Fea: the number of features; #f/doc: maximum, minimum, and average number of features per document)

	Data #1 News comment		Data #2 News body		Data #3 News title	
Fea	#Fea	#f/doc	#Fea	#f/doc	#Fea	#f/doc
Exp	81,519	1,553/1/21	155,327	8,297/4/718	20,643	1,936/6/13
Imp	55,058	1,553/1/21	86,057	8,297/4/718	14,585	1,936/6/13
Char	5,707	2,529/2/31	5,939	12,493/8/1,164	3,327	1,937/12/21

In both the sentiment calculation models, the dimension of embedding is set to be 100, of which the initial value is assigned randomly. The output dimension of the convolutional layer is set to 100 and the output dimension of LSTM layers are set to 128. The dimension of the stack layer (i.e., Part III) is also set to 128. The final output dimension of the model is 6, corresponding to the six categories of sentiments.

4.3 Sentiment Calculation Result

Considering the two models (CNN-LSTM2 and CNN-LSTM2-STACK), the three kinds of features (explicit expression, implicit expression and character), and the three datasets (comments, bodies and titles) together, there are 18 ($2 \times 3 \times 3$) combinations of choices in total to set up the sentiment calculation. The performance of the sentiment calculation on all the combinations are observed. During the training process, cross entropy is employed as the loss function. The loss and accuracy trends are recorded. Precision, recall, and F1-score on test sets are also recorded for all the sentiment labels in each training epoch. The tags listed in Table 3 are used to presents the six sentiment categories. We use 'tag'-precision, 'tag'-recall, and 'tag'-f1 to represent sentiment precision, sentiment recall, and sentiment F1-score respectively. Besides, the accuracy on test data is also recorded as shown in Fig. 6, Fig. 8 and Fig. 10.
In this section, we firstly show the results grouped by dataset. A comprehensive discussion combining all the results is given in Section 4.4.

Table 3：Tags of Sentiments

Sentiment	Tag	Sentiment	Tag
Love	gd	*Sadness*	ng
Fear	zj	*Surprise*	xq
Joy	gx	*Anger*	fn

4.3.1 Data #1: News Comments. In Data #1, among all the combinations, model CNN_LSTM2 with the explicit expression features rank the top on accuracy (85.0%). If given the same model (either CNN_LSTM2 or CNN_LSTM2_STACK), the explicit expression features always perform the best in all the three kinds of features, followed by the character features. It is also shown that given the same features, model CNN_LSTM2 performs better on accuracy than model CNN_LSTM2_STACK does. The details are shown in Fig. 6 and Table 4.

The precision, recall, and F1-score of sentiment *joy* (gx) performs well. *Sadness* (ng) performs badly on both models. This phenomenon also reflects that sentiment *sadness* is more difficult to be recognized than other sentiments are, for example, the sentiment in the text 'so happy to cry'.

The accuracy and loss trends on training set of Data #1 are shown in Fig. 7. In every combination of the features and the models, the accuracy becomes steady after several iterations and achieves larger than 90%. Explicit expression features and implicit expression features both reach to higher than 97% of accuracy on both models. The accuracy of character features on CNN_LSTM2 and CNN_LSTM2_STACK reach to 91.63% and 92.52% respectively, and the corresponding loss of the two models are 22.96% and 21.69%.

All the three kinds of features (i.e., explicit expression, implicit expression, and character) are effectively fitted by both models. The fitting result of explicit expression and implicit expression is

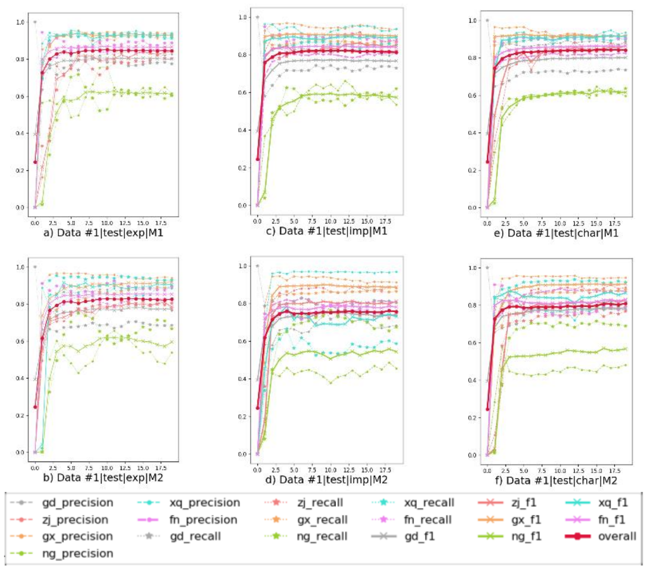


Figure 6: Precision, recall, and F1-score trend on test set of Data #1

Table 4: Accuracy Rank on Test Set of Data #1

Rank	Feature	Model	Accuracy
1	Explicit	CNN_LSTM2	85.0%
2	Character	CNN_LSTM2	84.4%
3	Explicit	CNN_LSTM2_STACK	82.9%
4	Implicit	CNN_LSTM2	82.2%
5	Character	CNN_LSTM2_STACK	81.5%
6	Implicit	CNN_LSTM2_STACK	76.1%

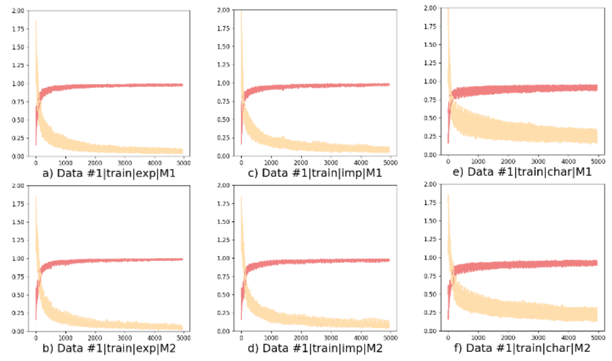


Figure 7: Accuracy and loss trends on training set of Data #1

slightly better than that of the character features on the training set. However, the fitting result on the test set shows an overfitting problem for explicit expression and implicit expression on the two models. Character features perform relatively consistent in both the training and test sets.

4.3.2 Data #2: News Bodies. In Data #2 (news bodies which is kind of long text), model CNN_LSTM2_STACK with explicit expression features achieves the best score on accuracy (82.5%) among all the six combinations of models and features. In terms of the features, it is shown that explicit expression features always perform the best, no matter which model is applied. Implicit expression features give a little lower accuracy than explicit expression features. However, character features fail to achieve a good score on accuracy in both models. The result is shown in Fig. 8 and Table 5.

Precision, recall, and F1-score of sentiment *love* (gd) perform well, while those of *anger* (fn), *surprise* (xq), and *sadness* (ng) perform bad. It shows differences on performance among sentiments. We will discuss the reasons for this phenomenon in Section 4.4. In terms of the features, explicit expression features perform best, while character features perform worst, which

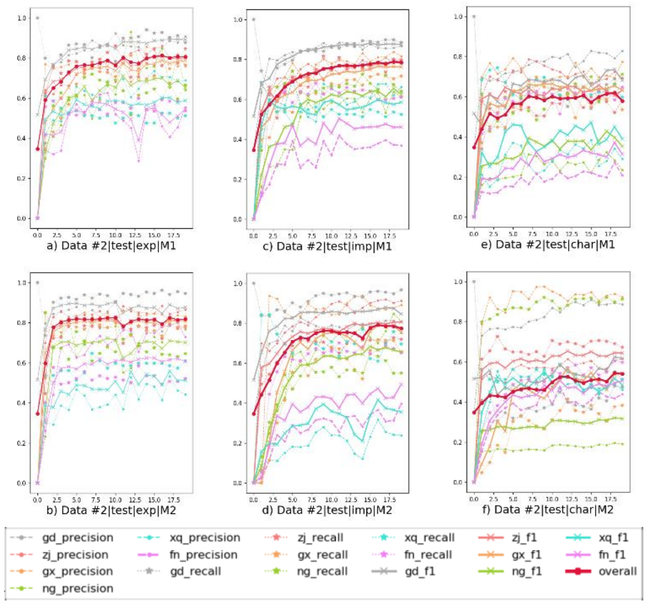


Figure 8: Precision, recall, and F1-score trend on test set of Data #2

Table 5: Accuracy Rank on Test Set of Data #2

Rank	Feature	Model	Accuracy
1	Explicit	CNN_LSTM2_STACK	82.5%
2	Explicit	CNN_LSTM2	81.2%
3	Implicit	CNN_LSTM2	79.6%
4	Implicit	CNN_LSTM2_STACK	79.1%
5	Character	CNN_LSTM2	62.0%
6	Character	CNN_LSTM2_STACK	55.3%

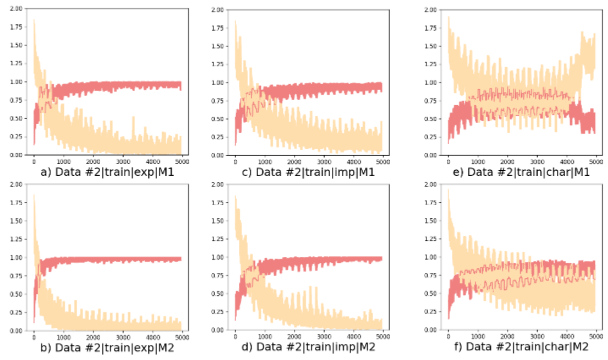


Figure 9: Precision and loss trends on training set of Data #2

indicates that character features are not suitable for long texts in our models.

The accuracy and loss trends on training set of Data #2 are shown in Fig. 9. The accuracy and loss of both implicit expression and explicit expression features come to steady after several iterations. The accuracy of these two kinds of features on model CNN_LSTM2_STACK achieves higher than 98%, and the loss reaches to 0.03 and 0.05 respectively. On model CNN_LSTM2, the accuracy of these two features are 79% and 85% respectively, and loss are 0.68 and 0.49 respectively. From the above results, it can be concluded that model CNN_LSTM2_STACK fits better than model CNN_LSTM2. The accuracy of character features on the two models cannot converge, which means character features are not suitable for long text process, which is in line with the former description.

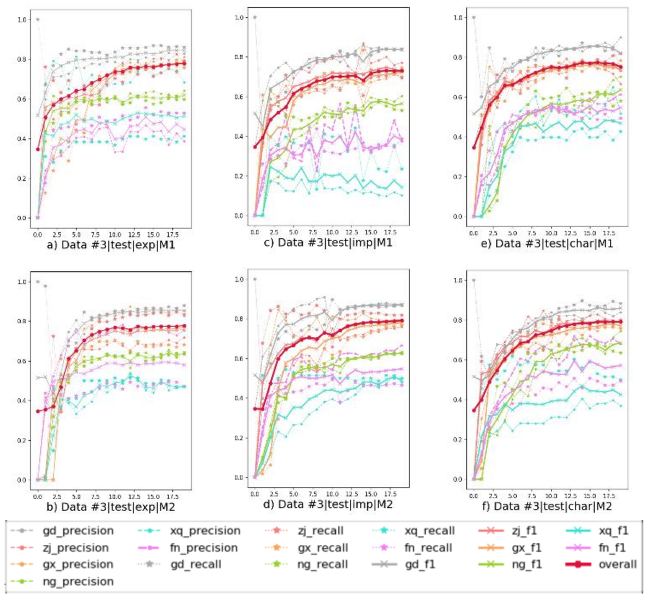


Figure 10: Precision, recall, and F1-score trend on test set of Data #3

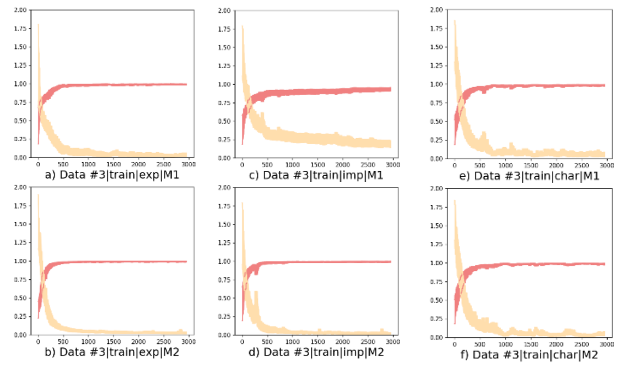


Figure 11: Precision and loss trends on training set of Data #3

4.3.3 Data #3: News Titles. In Data #3, all the six combinations of the models and the features give relatively similar scores of accuracies, ranging from 77.8% to 82.0%. Model CNN_LSTM2_STACK combined with the character features performs the best, with an accuracy of 82.0%. Model CNN_LSTM2_STACK performs better than model CNN_LSTM2 does, no matter which kind of features is chosen. In terms of the precision, recall and F1-scores in the six sentiments, *love* (gd) performs the best, while *anger* (fn) and *surprise* (xq) perform the worst. More details are shown in Fig. 10 and Table 6.

The result of Data #3 is consistent with the result of Data #2. The objective texts with the ground truth of *anger* (fn) or *surprise* (xq) can confuse the models, making the models incorrectly classify the texts which belong to *anger* (fn) or *surprise* (xq) into other sentiment categories.

Table 6. Accuracy Rank on Test Set of Data #3

Rank	Feature	Model	Accuracy
1	Character	CNN_LSTM2_STACK	82.0%
2	Implicit	CNN_LSTM2_STACK	81.2%
3	Explicit	CNN_LSTM2_STACK	80.5%
4	Explicit	CNN_LSTM2	80.0%
5	Character	CNN_LSTM2	79.6%
6	Implicit	CNN_LSTM2	77.8%

Table 7: The Stable Sentiment Calculation Results (on test sets) of Three Features of Three Datasets on Two Models. (D: data; M1: model CNN_LSTM2; M2: CNN_LSTM2_STACK; A: Accuracy)

D #1	gd_f1	zj_f1	gx_f1	ng_f1	xq_f1	fn_f1	A
exp|M1	0.804	0.796	0.926	0.622	0.928	0.869	**0.850**
exp|M2	0.778	0.803	0.913	0.619	0.886	0.855	0.829
imp|M1	0.772	0.855	0.903	0.588	0.895	0.844	0.822
imp|M2	0.738	0.796	0.886	0.558	0.741	0.785	0.761
char|M1	0.803	0.842	0.917	0.620	0.917	0.864	0.844
char|M2	0.794	0.820	0.915	0.586	0.842	0.837	0.815
D #2	**gd_f1**	**zj_f1**	**gx_f1**	**ng_f1**	**xq_f1**	**fn_f1**	**A**
exp|M1	0.888	0.808	0.789	0.699	0.601	0.517	0.812
exp|M2	0.890	0.816	0.812	0.709	0.558	0.616	**0.825**
imp|M1	0.876	0.800	0.772	0.660	0.553	0.531	0.796
imp|M2	0.868	0.803	0.787	0.666	0.417	0.473	0.791
char|M1	0.736	0.606	0.654	0.398	0.450	0.372	0.620
char|M2	0.668	0.634	0.566	0.312	0.494	0.497	0.553
D #3	**gd_f1**	**zj_f1**	**gx_f1**	**ng_f1**	**xq_f1**	**fn_f1**	**A**
exp|M1	0.851	0.817	0.802	0.645	0.500	0.527	0.800
exp|M2	0.874	0.801	0.800	0.648	0.444	0.613	0.805
imp|M1	0.859	0.790	0.773	0.626	0.266	0.416	0.778
imp|M2	0.881	0.818	0.800	0.648	0.525	0.596	0.813
char|M1	0.866	0.794	0.791	0.642	0.441	0.544	0.796
char|M2	0.884	0.815	0.805	0.722	0.456	0.625	**0.820**

The accuracy and loss trend are shown in Fig. 11. The accuracy of all the three kinds of features on the two models come to steady after iterations. Among them, model CNN_LSTM2 combined with implicit expression performs the worst, achieves an accuracy of 94% and a loss of 0.16. The accuracy of the other five groups are higher than 97% and the losses are less than 0.1.

All the three kinds of features perform well on Data #3. Character features perform better than explicit expression and implicit expression. It can be concluded that character features are more suitable for short texts in our models, compared with the results on Data #1 and Data #2.

The three datasets have their own distinguishable characteristics. Among them, news titles are the shortest and the most coherent. News comments are relatively short, and the length, content and style of comments are free and abundant. News bodies are the longest, with fixed format and rich content. The three kinds of features in this paper show different capabilities on calculating the sentiment orientation in different datasets. The detailed results are shown in Table 7. From the table, it can be seen that character features perform better on news titles and news comments than on news bodies, which means character features perform better on short texts than on long texts in our models. The results of explicit expression and implicit expression are relatively stable. Model CNN-LSTM2 shows better performance than CNN-LSTM2-STACK does on news comments and bodies, while CNN-LSTM2-STACK performs better on news titles.

4.4 Analysis

This section focuses on the analysis of inter-sentiment correlation. The confusion matrix is employed to represent $C(e_a|e_b, D_i, F_j, M_k)$ in eq. 13. Instead of setting the fixed value of the threshold θ, a dynamic θ is set in the analysis as selecting the top confusing sentiment pairs.

The confusion matrix of Data #1 is illustrated in Fig. 12. It can be seen that the models are likely to be confused between the sentiments *sadness* (ng), *love* (gd), and *anger* (fn). Specifically, *sadness* (ng) is likely to be recognized as *anger* (fn) or *love* (gd). *Love* (gd) is likely to be judged as *anger* (fn). By contrast, *anger* (fn) is unlikely to be judged as *fear* (zj) or *surprise* (xq). In short, comments can be easily mistaken as *anger*, even though they are not.

The confusion matrix of Data #2 and Data #3 are shown in Fig. 13 and Fig. 14. The two datasets are both objective data, which are used to observe the inter-sentiment correlation. It can be seen from the figures that the confusion degree of news bodies is higher than that of news titles, which means that it is harder to recognize the sentiments aroused by news bodies than news titles. Based on the voting result, the objective contents that cause *sadness* (ng) and *anger* (fn) are easy to be misjudged as *love* (gd) and *joy* (gx).

If our models are seen as a person who has sentiment cognitive bias, then the above results can explain and estimate how people misunderstand other's words. In subjective texts, it is likely to misinterpret the sentiment in one's words as *anger* (fn), rather than *fear* (zj) or *surprise* (xq). If the sentiment in one's words is actually *sadness* (ng), it is more likely to be judged as other sentiments incorrectly. In objective texts, if a sample text causes *anger* (fn), the models are likely to predict that it will cause *love* (gd), but not likely to cause *surprise* (xq).

It can be seen that there is a controversial phenomenon on the interpretation of *anger* (fn) and *love* (gd). In subjective news comments, a text is likely to be considered as *anger*. By contrast, in objective news bodies and titles, it is easy to predict that a text may cause *love* (gd). One of the reasons for this phenomenon may be the fact that the news articles have to be written without prejudice. Therefore, it is not easy to predict *anger* from the news articles through its text features. However, the readers are free to express their feelings. The netizen's sentiments are easy to be transferred to *anger* (fn), no matter what sentiment they want to express. Thus, as a comment conversation keeps going on, it is likely to end up with *anger*.

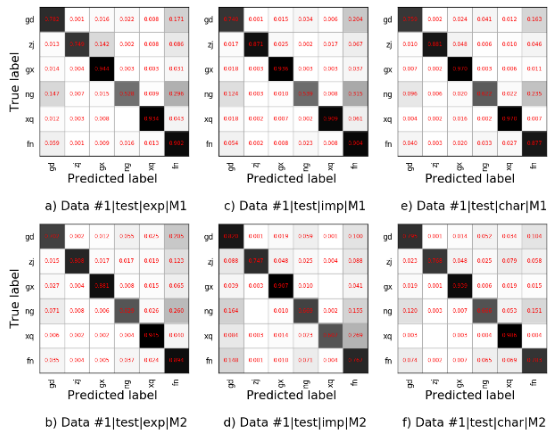


Figure 12: Confusion matrix on test set of Data #1

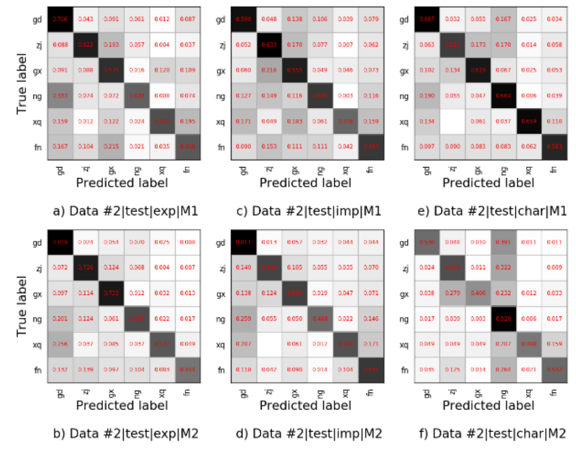


Figure 13: Confusion matrix on test set of Data #2

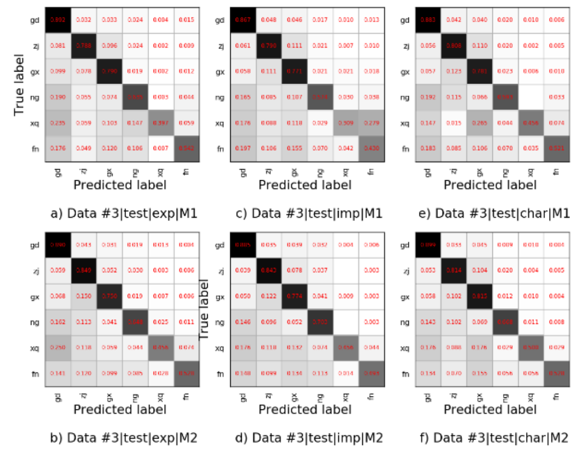


Figure 14: Confusion matrix on test set of Data #3

5. CONCLUSIONS

Mining the inter-sentiment correlations in web events is significant to track its development. The sentiments, though caused by objective information, are subjective, compound, and diverse, which makes the sentiment recognition being hard. This paper employs six basic kinds of sentiments – *love, joy, anger, sadness, fear, and surprise* – to analyze the sentiment in texts. Three kinds of features and two deep neural network models are proposed and applied to three datasets.

The two deep neural network models are presented for sentiment calculation. Three datasets – the titles, the bodies, the comments of news articles – are collected, covering both objective and subjective texts in varying lengths (long and short). From each dataset, three kinds of features – explicit expression, implicit expression, and alphabet characters – are extracted. In terms of the features, it is shown that the alphabet character features perform better than the other two features on short texts. In terms of the subjective comment data, the sentiment *sadness* is hard to be recognized, which is likely to be misinterpreted to other sentiments. The reason might be the overlap of the words or characters between the sentiment *sadness* and the others. All the sentiments are likely to be recognized as *anger*. In terms of the objective information, the text which actually arouses *anger* is relatively unpredictable and likely to be classified to *love*.

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