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Online Ideological Opinion of Students Based on Deep Learning in the New Media Environment

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Abstract. *With the arrival of the new media era, college students publish a large number of subjective texts on online platforms, and it takes a lot of manpower and time to analyze these texts manually, so it is important to use computer technology to analyze the textual sentiment analysis of college public opinion information on the Internet. Intending to the issue that existing models ignore the emotional semantics of students' comment texts, which leads to low classification performance, this article investigates a deep learning-based model for analyzing students' online ideological opinions in the new media environment. Firstly, to address the issue of insufficient emotional information embedded in the CBOW model, the emoji word vectors are operated with the original word vectors to construct the TCBOW model with rich emotional semantic information. Second, the TCBOW model is utilized to represent the text embedding of word vectors and word vectors with added lexical properties to enhance the semantic representation ability. The encoded student comment text is then fed into the Convolutional Neural Network (CNN), and the word vectors and the blended word vectors are feature extracted using two channels respectively, and the key features are enhanced using the attention mechanism. Finally, the fused feature vectors of words and mixed words are used for sentiment classification using softmax classifier. The experimental outcome indicates that the suggested model has high classification accuracy and F1 value, and exhibits good performance in sentiment classification.*

Keywords: Deep learning; Thought opinion; Sentiment analysis; CBOW Model; Convolutional neural network

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1. **Introduction.** As the Internet technology growing, the complexity and diversity of network information data gradually increased. Under the joint action of various network information media media, the network public opinion environment of college students' thinking is changing significantly, and the Internet has become an important position that colleges and universities have to pay attention to and strive for [1]. The high popularity of the Internet provides a brand new development opportunity for the educational work of colleges and universities. Meanwhile, due to the characteristics of the Internet, such as suddenness, complexity, wide audience, fast dissemination speed, and freedom of expression, as well as the keen insight and high empathy of college students, who are the main body of the generation and dissemination of network information, and their high concern about the social events and focus issues in the new media environment, the Internet has become the main way for college students to express their attitudes and emotions,

which leads to many serious challenges for colleges and universities. The Internet has become the main way for college students to express their attitudes and emotions, which has led to many serious challenges for colleges and universities, such as the negative crisis of online public opinion [2, 3, 4]. How to analyze public opinion data in the complex network environment of college students is a hot research topic nowadays.

1.1. **Related work.** The analysis of students' online opinion data can be regarded as a kind of text sentiment class analysis. Zhang et al. [5] used SVM as the classification base model, extracted the sentiment features and semantic features, and made a 5-level classification of the text sentiment of the comments. Zhao [6] constructed an opinion evolution system model of the complex Agent network based on the characteristics of the college students' online opinion and the evolution law. Huang et al. [7] used LDA topic model to model microblog text, and applied GBDT regression model algorithm to classify the text. Liu et al. [8] extracted text features based on Word2vec & LDA and used SVM to classify the sentiment of evaluation text of student network. Hew et al. [9] used sentence syntax tree to introduce various student sentiment features into the bag of basic words and classified the text sentiment by using machine learning techniques. Fang et al. [10] suggested a simple Bayesian based sentiment analysis method for student network based on its polarity. Ezaldeen [11] used a model that fuses sentiment lexicon and machine learning so as to uncover internal hidden sentiment states. Aissaoui et al. [12] used unsupervised machine learning to predict the sentiment tendencies of student evaluation texts with good results on datasets such as microblogs. Park and Dooris [13] used a model to classify the sentiment of students by extracting the contextual features of sentiment words and emotion words, constructed a decision tree model using an information gain algorithm, and used automatically extracted rules for feature selection and classification. However, neither stand-alone machine learning methods nor comprehensive sentiment lexicon methods can successfully express the complete meaning of the context in the text, and deep learning algorithms are able to automatically learn the hidden deep features in the comment text data to improve the classification outcome. Orkphol and Yang [14] suggested Word2vec, which utilizes an unsupervised representation of the textual word distribution vectors. Liu [15] used CBOW model to pre-train word vectors and used RNN for comment text classification. Onan [16] used BP (Long Short-Term Memory) to learn the sentiment representation of student comment text. Yu et al. [17] proposed the use of bi-directional GRU to learn the sentiment representation of text. Huang et al. [18] used a bi-directional LSTM to learn the sentiment representation of text, and used a two-layer attention mechanism to enhance the performance of the model. Since CNN can extract features at different levels of abstraction in multiple convolutional layers compared to RNN, LSTM, and GRU, Tian et al. [19] used a convolutional neural network to model the input sentences and used a normalized classifier to classify the sentences. Koufakou [20] used a Transformer to learn textual representations of the comments, and then used a CNN to capture the aspect information and perform the modeling to capture aspectual information and perform student network sentiment polarity classification.

1.2. **Contribution.** The analysis of the current state of research shows that the existing studies are based on a single method of machine learning or deep learning, or a hybrid method combining pre-trained language models for sentiment classification, and do not take into account the affective semantic information of student comment texts. To address this issue, this article investigates a deep learning-based model for analyzing students' online ideological opinions in the new media environment. Firstly, a CBOW model incorporating emoticons is suggested, which makes full use of the feature of clearer emotional information of emoticons in the text of students' comments, and constructs a

TCBOW model with richer emotional semantic information by correlating emoticon word vectors with the original word vectors. Second, TCBOW is used to encode word vectors and word vectors with added lexical properties in the text representation stage to enhance the semantic representation ability. Then the TCBOW-encoded student comment text is input to the CNN, and the convolution kernel and residual structure are used for feature extraction of word vectors and mixed word vectors, respectively, and the attention layer is added to enhance the key features.

2. Theoretical analysis.

2.1. Convolutional neural network. CNN can capture local features in text through convolutional operations to identify the sentiment polarity of words or phrases, which is computationally faster compared to networks such as RNN and LSTM, and can extract text features at multiple scales [21, 22]. A simple text CNN consists of an input level, a convolutional level, a pooling level, and a classification level, and its basic structure is implied in Figure 1.

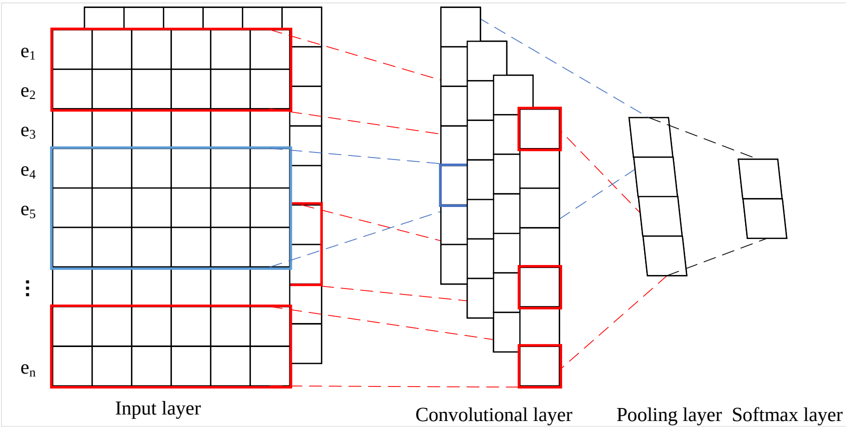

Figure 1. The basic structure of the CNN

(1) Input level. Word vectors of words are stitched into a matrix, where each row represents a word in a sentence. Generally, the Pretraining Language Model (PLM) is used to convert the text into fixed length vectors, and initially set a fixed sentence length n. If the length is not enough for n, padding is used to fill it.

(2) Convolutional level. Multiple convolutional kernels are used to convolve the input matrix $x_{1:n} \in \mathbb{R}^{n \times l}$ to learn the local features between sentences and neighboring words. The computational process is shown below.

$$c_i = f(V \cdot x_{i:i+g-1} + b) \tag{1}$$

where V is the weight of convolution kernel, b is the bias, f is the activation function, and g is the window size. The feature vector of text acquisition is $c = [c_1, c_2, ..., c_{n-g+1}]$.

(3) Pooling level. The pooling level has a sliding window like the convolutional layer, and every slide to a certain region takes the maximum value as the output $\hat{C} = [\max(c_1), \max(c_2), ..., \max$

(4) Classification level. The output feature vector of the pooling layer is used as the input of the classification layer, and its output is based on the size of the probability to get the positive and negative sentiment of the comment text.

$$y = \mathrm{softmax}(V_t \cdot \hat{C} + B_t) \tag{2}$$

where $V \in \mathbb{R}^d$ denotes the fully connected weight, B_t denotes the bias value, and y is the output.

2.2. **CBOW model.** CBOW is a Neural Network Language Model (NNLM) [23], and the model structure is implied in Figure 2. Compared with BERT, Word2Vec and other models, it is less computationally intensive and efficient, and the basic idea is to take the intermediate words in a certain text as the target words and simplify it based on the entire architecture of the NNLM model [24].

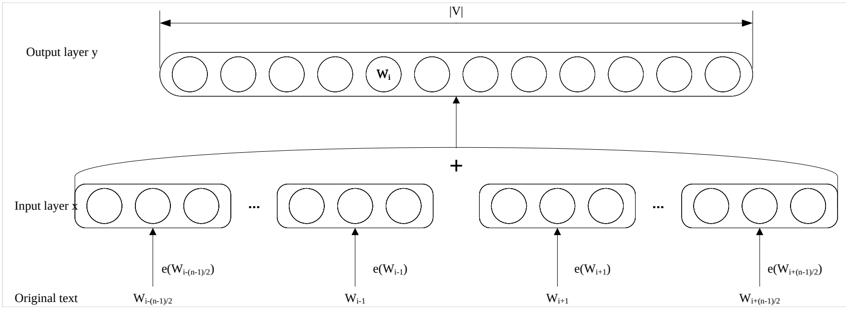

Figure 2. The model structure of CBOW

(1) By removing the obscured level, the model is reduced to the same linear structure as the logistic regression. Compared with the original three-layer neural network structure, the amount of computation is reduced and the training speed is increased.

(2) Simplification of the sample input method for the NNLM model. It consists of splicing the contextual word vectors into the average of these word vectors.

$$x = \frac{1}{n-1} \sum_{j \in c} e(v_j) \tag{3}$$

where v is the word.

After removing the obscured level, the CBOW model forecasts words directly relied on the context in terms of the following equation.

$$P(v|c) = \frac{\exp(e'(v)^T x)}{\sum_{v \in V} \exp(e'(v)^T x)} \tag{4}$$

3. **A CBOW word vector model incorporating sentiment symbols from students' online comments.** The TCBOW model proposed in this article, which integrates students' comments text, first sorts the emoticons in a large number of comments text according to the frequency of use and saves them into an emoji dictionary, then finds out the word vectors corresponding to all emoticons in the emotion symbol dictionary and groups them into an emoji delegacy matrix. Every word vector drilled by CBOW model is correlated with the affective symbol representation matrix, and the TCBOW model with affective symbol is finally obtained.

(1) **Word vector training.** The essence of students' online ideological opinion in the new media environment is the sentiment analysis of evaluation texts in social media networks. The words composing the text contain important information about students' emotions. In this paper, we take words as the smallest component to study the sentiment information of a sentence, i.e., a sentence is denoted as a tie of word series, and the words require to be denoted as related multidimensional vectors before splicing. In the CBOW model, the words in the context of the center word v are used for predicting v in the provided window length, i.e., for the context, beside the center word v, which is a positive sample, the other dataset's words are all negative instances. Assuming that the set of negative samples for $context(v)$ be $NEG(v)$, then the label $L_v(v')$ for any word v' be as bellow.

$$L_v(v') = \begin{cases} 1, & v' = v \\ 0, & v' \neq v \end{cases} \tag{5}$$

For a set of positive samples $(context(v), v)$, maximize $g(v)$.

$$g(v) = \prod_{u \in \{v\} \cup NEG(v)} p(u|context(v)) \tag{6}$$

$$p(u|context(v)) = \begin{cases} \delta(X^T\theta_u), & L_v(u) = 1 \\ 1 - \delta(X^T\theta_u), & L_v(u) = 0 \end{cases} \tag{7}$$

where X is the sum of the individual word vectors, $\theta_u \in \mathbb{R}^n$ is the practiced parameter vector of u in TCBOW, and $\delta(X^T\theta_u)$ is the distribution of forecasting the middle word v. The practicing objective of TCBOW is to maximize Equation (8).

After simplification,

$$g(v) = \delta(X^T\theta_v) \prod_{u \in NEG(v)} [1 - \delta(X^T\theta_u)] \tag{8}$$

That is, the distribution that a chosen word is a positive instance is increased while the distribution that it is a conflicting instance is decreased. Then, for a provided corpus V, the whole improvement objective operation $F = \prod_{v \in V} g(v)$ is achieved.

The random gradient descent algorithm is adopted to refresh the model's parameters after the derivation of the objective function F, and finally the word vectors are obtained.

(2) **Computation of word vectors incorporating emoticons.** The word vectors of dimension d related to the top m emoji in the TCBOW model are spliced horizontally to form the emotion symbol space matrix $E = [\alpha_1, \alpha_2, ..., \alpha_m] \in \mathbb{R}^{d \times m}$. The word vector model is traversed, and the corresponding vectors of each word are operated with the emotion symbol space matrix according to Equation (9), and the saved result is used as the word vector model TCBOW for fused emojis, in which the dimensions of the word vectors represent the similarity with these m emojis. Thus, the TCBOW model gives the CBOW model richer emotional information.

$$TCBOW_{ij} = \cos(\alpha_i, \beta_j) = \frac{\alpha_i^T \cdot \beta_j}{|\alpha_i||\beta_j|}, \quad i \in [1, m], j \in [1, n] \tag{9}$$

where α_i is word vector of the emoji, β_j is the initial word vector, m is the amount of emoji, and n is the entire amount of words in the traditional CBOW model, which is transformed into the TCBOW model with a word vector dimension of m.

4. **Research on students' online ideological opinions based on deep learning in the new media environment.**

4.1. **Text coding of student comments based on the TCBOW model.** For the goal of deeply exploring the connection between student comment texts in the novel media environment and realize the accurate analysis of student online ideological opinion data, this article builds a deep learning-based student online ideological opinion analysis model in the new media environment. The overall framework of the suggested model is implied in Figure 3. Firstly, the TCBOW model is used to embed the word vectors and word vectors in the text representation stage, and then two-channel feature extraction is carried out by two types of convolutional methods of CNN, and the attention mechanism is incorporated to amplify the key features. Finally, the fused feature vectors are utilized for sentiment classification using softmax classifier.

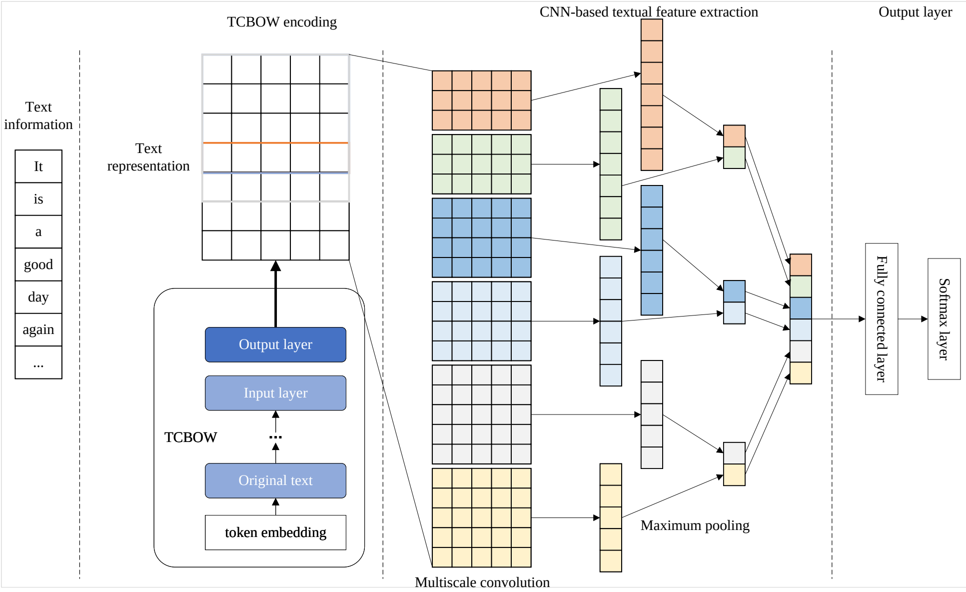

Figure 3. The overall structure of the suggested model

To improve the representation of students' comment texts, this paper uses a multi-channel input that combines a two-channel hybrid representation based on the TCBOW model of word vector embedding and word and lexical vector embedding. The input comment text is represented as $X = [x_1, x_2, x_3, \ldots, x_n]^T$. The word vector representation is consistent with that in the multi-scale convolutional model of word granularity, represented as $C = [c_1, c_2, c_3, \ldots, c_n]^T$.

In this article, the TCBOW model is used to train the word vectors, and the negative sampling threshold of word frequency is set to a, which means that N negatives are randomly selected to update the corresponding weights each time the weights are updated to reduce the computational cost. The trained word vectors are implied below.

$$V = [v_1, v_2, v_3, \ldots, v_n]^T \tag{10}$$

The comment text in the student network is spliced by several words, and it is easy to lose part of the information only by the number of words, and lexicality can supplement the formal characterization of the text, and the extraction of the emotional level can be strengthened by the lexical correlation in the text sequence. The lexical properties are randomly encoded to generate the embedding sequence $\{\text{pos}_1, \text{pos}_2, ..., \text{pos}_n\}$, where $\text{pos}_i \in \mathbb{R}^d$ and d are the dimension values.

Finally, the word embeddings and lexical embeddings are summed to obtain vp_i, as indicated in Equation (11), and the embedding sequence used for the hybrid word vector channel in the generative model is implied in Equation (12).

$$v_{p_i} = v_i \oplus \text{pos}_i \tag{11}$$

$$V_p = \left[\ v_{p1}, v_{p2}, ..., v_{p_n}\ \right]^T \tag{12}$$

4.2. **CNN-based textual feature extraction for student comments.** The above encoded text is input to the CNN and feature extraction is performed using two channels for word vectors and hybrid word vectors respectively.

The feature extraction of the word vector channel uses convolution kernels of 2, 3, 4 and 5 scales to extract local features from the text representation data, and the convolution operation is implied in Equation (13).

$$W_c = \mathrm{Conv}(C) \tag{13}$$

The global maximum pooling [25] operation is applied to retain the largest component in the convolutional computation window at each scale to re-extract the features, while reducing the dimensionality to reduce the computational effort.

$$w_c = \mathrm{GlobalMaxPooling}(W_c) \tag{14}$$

The feature extraction of the hybrid word vector channel uses a word-based deep convolutional structure, which can capture long-distance textual dependencies by increasing the depth of the network. When randomly initializing the convolution kernel, the initial values of the weights of each layer are small, which makes the network converge gradually after several iterations. To solve this problem, the residual connection [26] is introduced, which adds a shortcut to every two layers between the convolutional and pooling layers to form a residual structure block, which can effectively alleviate the gradient vanishing. The feature extraction process of residual structure is indicated as follows.

$$W_v = \mathrm{Conv}(V) + V \tag{15}$$

The features extracted by deep convolution are fed into the maximum pooling layer to scan the maximum value in the region and suppress the mean drift caused by estimation error, which is calculated as bellow.

$$w_v = \mathrm{MaxPooling}(W_v) \tag{16}$$

In sentiment analysis, Chinese text has many words that highlight sentiment, and certain sentiment words will affect the sentiment direction of the whole sentence. Adding the attention mechanism [27] selects the key sentiment words from many word and character vectors, and increases the proportion of weight assigned to the key points in the feature map in order to improve the performance of sentiment analysis. Calculating the attention distribution is the dot product operation of the input vectors and the target vectors, and the specific calculation is implied in Equation (17) and Equation (18).

$$a_c = \frac{\exp(w_{ci})}{\sum_{i=1}^{n} \exp(w_{ci})} \tag{17}$$

$$a_v = \frac{\exp(w_{vi})}{\sum_{i=1}^{n} \exp(w_{vi})} \tag{18}$$

where $w_{ci} \in w_c$, $w_{vi} \in w_v$. The weight function is mapped to a fixed interval by the softmax function, which weights and sums the attention weights in the vectors as implied in Equation (19) and Equation (20).

$$W_{ac} = \sum_{i=1}^{n} a_{ci} \cdot W_c \tag{19}$$

$$W_{av} = \sum_{i=1}^{n} a_{vi} \cdot W_v \tag{20}$$

After two channels of different granularity of text information feature extraction, respectively, the feature vector W_{ac} based on word representation and the feature vector W_{av} based on mixed word representation are obtained, and the two vectors are spliced to get the fused feature vector W.

4.3. **Classification of students' emotional polarity.** The fused feature vectors W are fed into the fully connected network and the probability p values of the text data in all the categories are obtained using the softmax classifier, where the category with the highest probability value is the final sentiment analysis category, and the computation process is implied in Equation (21) and Equation (22).

$$p = \text{softmax}(V_f[W_{ac} \oplus W_{av}] + b_f) \tag{21}$$

$$y = \frac{\exp(p_i)}{\sum_{j=1}^{m} \exp(p_j)} \tag{22}$$

where V_f is the weight transformation matrix of the fully connected level, b_f is the bias vector of the fully connected level, $\oplus$ denotes the connectivity operation, and m is the type of classification label.

Cross Entropy is used to calculate the difference between two probability distributions in space. When it is used as a loss function, the slow parameter iteration process that may occur during the training process due to parameter problems can be well avoided by the cross-entropy loss operation. In this paper, the cross-entropy loss function is used in the model [28], which is implied as bellow.

$$Loss = -\sum_{i=1}^{N} y_i \log \hat{y}_i \tag{23}$$

where $\hat{y}_i$ denotes the probability that the instance is forecasted to be i, y_i denotes the probability that the instance is forecasted to be correctly classified as i, and N represents all labels.

5. **Performance testing and analysis.**

5.1. **Comparison of classification performance of different models.** To prove the effectiveness of the suggested model, this article utilizes Python to obtain positive and negative microblogging data from the open source API interface of microblogging platform on college microblogging public numbers on the topics of the beginning of the school year and the entrance examination for graduate school, the total amount of the data is 45,643. The data are de-emphasized to make sure that all the texts are original microblogs, and the remaining 34,496 pieces of data are saved as csv file format. 80% of the positive and negative microblogs are selected as the training data, the remaining 20% is the test data. The parameters of the experiment include: window size of 5, minimum word frequency of 10, learning rate of 0.001, and maximum of 1000 iterations. The experimental environment configuration is implied in Table 1.

Table 1. Experimental environment

Environment	Configurations
Hardware environment	Intel i7 CPU, 8G RAM, 512 G hard drive
Operating system	Windows 10 64 bit
Development platform	PyCharm community edition 2020
Libraries used	Python 3.7, tensorflow, jieba, scipy and etc.

For the goal of testing the effectiveness of the suggested model Ours, this paper is compared with the SOC-SVM model in literature [8], PSE-DT model in literature [13], CM-GRU model in literature [17], AE-LSTM model in literature [18] and CR-CNN model in literature [20]. The evaluation indicators were accuracy (A), precision (P), recall (R) and F1, and the experimental outcome were implied in Table 2.

Table 2. Comparison of classification performance of six models

Model	Positive emotion				Negative emotion			
	A/%	P/%	R/%	F1/%	A/%	P/%	R/%	F1/%
SOC-SVM	69.3	71.9	67.2	69.5	67.6	70.8	66.4	68.5
PSE-DT	72.4	74.8	71.1	72.9	71.9	72.3	70.8	71.5
CM-GRU	77.6	79.4	75.1	77.2	75.4	78.6	74.4	76.4
AE-LSTM	80.2	83.6	79.7	81.6	81.4	82.2	80.1	81.1
CR-CNN	84.5	87.1	83.9	85.5	85.3	86.1	83.2	84.6
Ours	89.5	91.3	89.6	90.4	88.9	92.7	87.9	90.2

As can be seen from the above table, compared with SOC-SVM and PSE-DT models based on traditional machine learning, the classification performance of CM-GRU, AE-LSTM, CR-CNN and Ours models based on neural networks has been improved. Ours classification accuracy rate of non-negative emotion is 89.5%, F1 value is 90.4%, negative emotion classification accuracy rate is 88.9%, F1 value is 90.2%. The accuracy rate and F1 value are higher than the other five models in non-negative emotion and negative emotion, which indicates that Ours model has better ability in acquiring semantic and emotional features of microblog text. Compared with the input layer without TCBOW word vector model, the positive emotion classification accuracy of CM-GRU, AE-LSTM and CR-CNN models increased by 11.9%, 9.3% and 5%. It indicates that the word vector model with emoji fusion has certain advantages in initializing text representation and can more fully represent the emotion information of text, which further proves that the semantic synthesis vector with emoji integration plays an important role in the emotion analysis task.

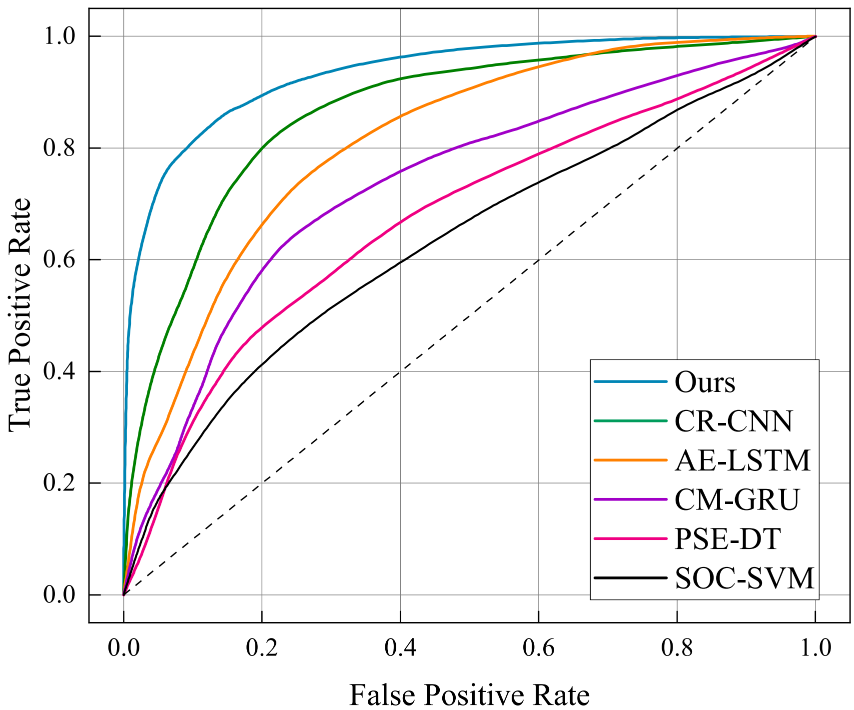

Figure 4. Comparison of ROC curves of six models

Figure 4 implies the comparison of ROC curves of different models, and the performance is evaluated by the area index (AUC) of the curve. PR represents the degree of response to the model's misrepresentation, while TPR represents the degree of coverage of the response provided by the model. The lower the FPR and the higher the TPR (the steeper the ROC curve), the better the classification of the model will be. The results indicate that the performance of SOC-SVM and PSE-DT models is the worst, with AUC values of 0.65 and 0.73, respectively, while the AUC values of CM-GRU, AE-LSTM and CR-CNN are 0.78, 0.82 and 0.86, respectively, which are superior to SOC-SVM and PSE-DT. The AUC value of Ours model is 0.9, which achieves the best performance. This is because SOC-SVM and PSE-DT classify the comment text in the student network based on SVM and decision tree respectively, and extract coarse-grained text features. CM-GRU uses a single text representation and does not learn more semantic information. Both AE-LSTM and CR-CNN models enhance key information in sentences by introducing attention mechanism, which has certain advantages compared with SOC SVM, PSE-DT and CM-GRU. However, they do not consider various semantics of word vector and word vector of text, so their performance is weaker than Ours model. Ours model adds static word vector and part-of-speech vector, and uses attention mechanism to enhance emotion feature value after convolution extraction, which improves the performance of emotion classification.

5.2. **Ablation studies.** To clarify the impact of each part of the Ours model on the model performance, this paper designs ablation experiments, where w/o TCB means not using the TCBOW model for embedding representations of word vectors and word vectors; w/o rs means not using residual joins to combine the input vectors and the output vectors in multilayered convolutional structures; and w/o att means not using the attentional mechanism to amplify the key sentiment features, and the experimental outcome are implied in Figure 5.

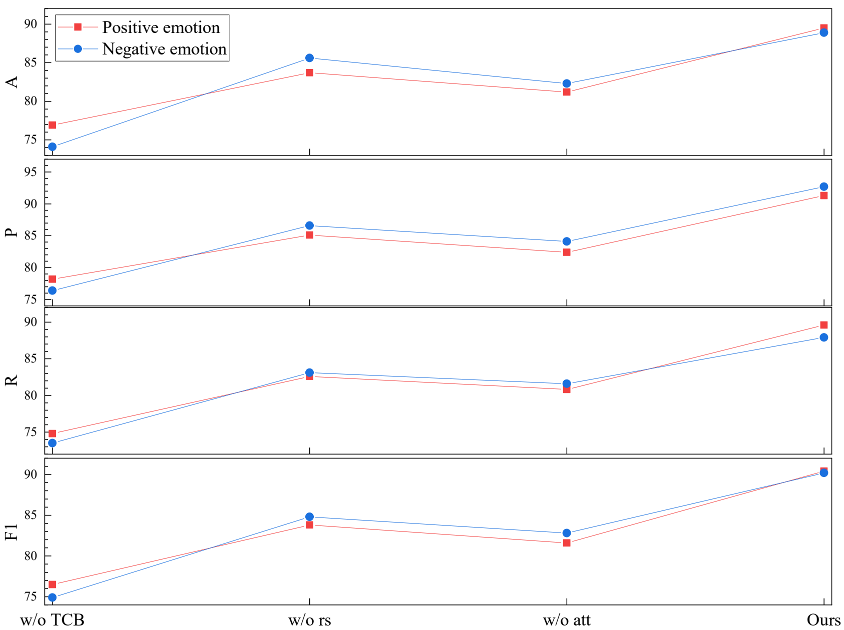

Figure 5. Ablation experiments with different components in the Ours model

In terms of the experimental outcome, it can be seen that the accuracy, precision, recall, and F1 value of the Ours model decreased after removing any of the modules. Among them, in the classification of positive sentiment, the accuracy and F1 value of w/o TCB decreased especially significantly, by 12.6% and 13.9%, respectively, which further illustrates the importance of the TCBOW model for the representation of semantic associations of word vectors and word vectors within the text of students' comments. The accuracy and F1 value of w/o rs decreased by 5.8% and 6.6%, which suggests that in the multilayer convolutional structure the use of residual connection to combine the output vectors and input vectors before entering into the next layer of network structure has an important role. w/o att's accuracy and F1 value decreased by 8.3% and 8.8%, respectively, which indicates that the use of attention mechanism to amplify the sentiment feature value after convolutional extraction of the features is more conducive to the extraction of the key information in the sentence, which can lead to more accurate sentence features. Taking the above analysis together, in general, all components are beneficial to the model suggested in this article.

6. **Conclusion.** The development of new media has brought about the proliferation of false rumor information, and the student group, with strong self-consciousness, is easily incited by public opinion information and influenced by rumors, thus generating a large number of negative public opinion feelings. To maintain the mental health of students and realize the intelligent judgment of the tendency of public opinion, this article investigates a deep learning-based model for analyzing students' online ideological public opinion in the new media environment. Firstly, a CBOW model incorporating emoticons is proposed, which makes full use of the feature of clearer emotional information of emoticons in students' texts, and constructs a TCBOW model with richer semantic information by correlating the emoticon word vectors with the original word vectors. Second, the TCBOW model is used to represent the text embedding of word vectors and word vectors with added lexical properties to enhance the semantic representation ability. Then the TCBOW-encoded student comment text is input to CNN, and the convolution kernel and residual structure are used to extract features from word vectors and mixed word vectors respectively, and the attention mechanism is added to adjust the weights of key text information and amplify the key features. The experimental outcome implies that the suggested model outperforms the comparison model in sentiment classification.

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