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Article

Combining Textual Emotion Analysis and Gender Role Theory to Study the Portrayal of Women in Seven Male Maodun Literature Prize Winning Works

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Abstract: In this paper, we construct a text sentiment analysis model based on BERT-Attention-BiLSTM, which is combined with the gender role theory to analyze the female character images in the award-winning works of male Mao Dun Literature Prize.The BERT-Attention-BiLSTM model combines the BERT model as a word vector training model, which can solve the word in word vectorization with the The BERT-Attention-BiLSTM model combines the advantages of the BERT model as a word vector training model in word vectorization, which can solve the problem of multiple meanings in word quantization, with the introduction of the Attention mechanism which distinguishes the degree of influence of different words in the text on the task of sentiment classification. By comparing with several text sentiment analysis models, the Bert-BiLSTM-Attention model has an accuracy of 81.20%, and the value of F1 is 58.42%, which is the best among all models. Then, the basic information and interpersonal network of seven Mao Dun Literature Prize works were quantitatively studied, and four works were selected for quantitative analysis of emotional trends, and the emotional trend lines portrayed fit with the plot development of the works. This study provides a literary perspective reference for understanding the interaction between female development and social progress.

Keywords: BERT-Attention-BiLSTM; text sentiment analysis; Mao Dun literary works; gender role theory

1. Introduction

As we all know, in Chinese society, which is deeply influenced by patriarchy, the social status of women has always been relatively low, and most of the time, they only appear as a supporting role in historical narratives [1]. After the New Era, many literary works are characterized by more epic narratives, which is evident in the award-winning works of Mao Dun Literature Prize, and women, as an indispensable role in history, have also been greatly emphasized [2-3]. Therefore, in the movie adaptation of the award-winning works of Mao Dun Literature Prize, there is an important description and presentation of women's life in history.

Sentiment analysis, also known as opinion mining, integrates, summarizes, processes and then deduces the audience's acceptance and evaluation of the work by integrating, summarizing and processing the text containing emotional expressions. Currently, the methods of sentiment analysis are mainly divided into two categories, one is based on sentiment lexicon, and the other is based on machine learning [4]. Sentiment dictionary methods mainly use the text with emotionally inclined words to classify the text, and after identifying and extracting the sentiment words contained in the target text, individual sentiment words are matched according to the existing data in the dictionary, and the overall sentiment value of the target text is calculated through algorithms such as summation or weighted average [5-6]. For example, Zhang, Y et al. proposed a classification method based on sentiment dictionary, which extracts keyword topics through TF-IDF algorithm, then extracts evaluation objects by combining lexical and keyword similarity, and extracts sentiment resources based on lexical and positional rules, and finally constructs sentiment dictionaries and inverse dictionaries for different evaluation objects [7]. Ji, Q and Raney, A constructed and validated the Self-Transcendence Emotion Dictionary (STED) based on the statistical paradigm of word frequency in text analytics, aiming at identifying and analyzing positive emotions such as awe, admiration, gratitude, hope, and so on in large-scale texts [8]. Xu, G et al. constructed an extended sentiment dictionary covering basic sentiment words, domain sentiment words and polysemantic sentiment words, determined the text domain to which the polysemantic sentiment words belonged through a simple Bayesian classifier, and then obtained their sentiment values in the corresponding domain, and combined the extended sentiment dictionary with the sentiment score rules to realize text sentiment analysis [9]. Bandhakavi, A proposed a Generative Unimodal Mixture Model (UMM) based method for generating Domain Specific Sentiment Lexicon (DSEL), which utilizes labeled texts such as blogs, news headlines, event reports, etc. along with weakly labeled texts such as tweets to learn for sentiment feature extraction from texts [10].

Machine learning approaches, on the other hand, rely heavily on the use of machine learning models that train a text sentiment classifier using the annotated text as a training set, and based on this classifier, perform sentiment analysis on a new target text [11]. For example, Batbaatar, E et al. proposed a novel neural architecture called Semantic-Emotional Neural Network (SENN), which contains two sub-networks, Bidirectional Long Short-Term Memory Network (BiLSTM) for capturing contextual semantic information and Convolutional Neural Network (CNN) for extracting the emotional features in the text [12]. Raza, H et al. constructed a classification system containing six machine learning algorithms, namely, Plain Bayes, Support Vector Machines, Logistic Regression, Decision Trees, K Nearest Neighbors and Random Forests, and introduced feature selection techniques such as word shape reduction, n-gram, participle and deactivation removal to optimize the model's performance, which provided an effective technological path for the researchers to identify high-quality scientific papers based on sentiment analysis [13]. Zhang, X and Zheng, X address the problem that there are relatively few studies on Chinese sentiment analysis and the classification performance is affected by the feature representation and feature selection mechanism. They take verbs, adjectives and adverbs as text features, use TF-IDF to calculate the word weights, and apply Support Vector Machines (SVMs) and Kernel-Limit Learning Machines (ELMs) to perform the textual sentiment tendency analysis [14]. Tang, D et al. outlined the successful application of deep learning in the field of sentiment analysis, stating that deep learning, as a powerful computational model that automatically learns semantic representations of text without the need for feature engineering, significantly improves the performance of sentiment analysis compared to traditional machine learning methods that rely on feature engineering [15]. Focusing on core tasks such as sentiment polarity, Dang, N et al. compared the performance of different models such as TF-IDF and word embedding on multiple datasets, and found that deep learning models show promising prospects in solving the challenges of natural language processing and improving the efficiency and accuracy of sentiment analysis [16].

Sentiment analysis techniques have also been used by scholars to understand readers' evaluations of emotional connotations in literary works. For example, Rebora, S explores the possible applications of sentiment analysis in narratology and reader response studies, revealing the gap between literary theories and computational models and proposing solutions to bridge it [17]. Yu, J and Qi, C applied sentiment analysis techniques to 500 English novels for analysis and successfully identified emotional themes such as joy, fear, and sadness, as well as content themes such as love, betrayal, and vengeance, demonstrating the potential of deep learning to reveal the multilayered structure of emotions and themes in literary analysis [18]. Jacobs, A proposed a tool called SentiArt for sentiment analysis, and used the "Harry Potter" series as the object to analyze the emotional potential of text fragments and the emotions and personality traits of the main characters [19]. Focusing on the emotional analysis of Russian literary texts in the context of socio-political changes and war revolutions in Russia at the beginning of the twentieth century, Sherstinova, T et al. used a variety of automated methods for the emotional analysis of short stories and correlated the results with the average expert emotional assessment of the texts evoked by modern readers [20]. Chu, K et al. proposed a text analytics lifecycle framework designed to detect and visualize themes in a corpus of literary texts, using theme modeling algorithms such as LDA, LSI, NMF, and HDP to identify six major themes: sexuality, family, revolution, incarceration, intellectuals, and death [21]. Using Ernest Hemingway's novel The Old Man and the Sea as a case study, Yuri, B and Pascale, F compare the performance of different sentiment analysis tools ranging from lexicon-based to Transformer-based in capturing the sentiment potency of a literary text with the construction of sentiment arcs, and compare their results with manual annotation [22]. Elov, B et al. used machine learning techniques to analyze the sentiment of classic and modern literature, and found that classic literature involves archaic expressions, complex syntax and metaphors, which puts a higher demand on natural language processing models, while modern literature tends to be more direct and colloquial, and the computational requirements are also different [23]. Feng, J proposed a BERT model optimized by Dynamic Honey Badger Algorithm (DHB-BERT) for enhancing sentiment analysis of literary texts. Research based on diverse datasets of Chinese literature found that it excels in handling rhetorical language, irony and subtle emotional expressions, providing an effective path for literary sentiment analysis based on the Transformer architecture [24]. Current research mostly starts from a single dimension, either focusing on the qualitative analysis of textual emotion analysis techniques in literary criticism or limiting itself to the conceptual exploration under the theoretical framework, lacking interdisciplinary attempts to organically combine quantitative textual analysis with qualitative theoretical interpretation, and especially less systematic examination of the specific creative group of male award-winning writers of Mao Dun Literature Prize.

In this paper, the Attention mechanism is introduced on the basis of BiLSTM model, which can dynamically adjust the weight proportion of the words in the text, so that the classification model can pay more attention to the key words in the text, and improve the importance of the key words in the sentiment. Then, the BERT model is introduced as the pre-training model for model word vectors, and the text sentiment analysis model of BERT-Attention-BiLSTM is constructed, which solves the problem of word polysemousness in the representation of word vectors compared with the traditional word vector model. By setting up model comparison experiments, it is verified that the model has better results in classification tasks. It lays a good foundation for the subsequent task of analyzing the sentiment of female images in male Maodun Literature Award-winning works.

2. Algorithms and theoretical foundations

2.1. Gender Role Theory

Gender roles are a set of personality traits and patterns of social behavior based on biological sex that conform to the expectations of others. Gender roles are not innately acquired, but are formed later in different cultures. In traditional Chinese culture, men are expected to focus on their careers and play an “instrumental” role in society, while women are expected to return to their families and play an “emotional” role in the family.

In this cultural context, caregiving is closely linked to women, with a clear gender bias, and the outside world constantly emphasizes this socially accepted trait and responsibility. In order to conform to society's expectations of women's roles, women have begun to internalize their caregiving identities, recognizing that they have a caregiving ethic and responsibility. In summary, gender role theory suggests that women's role as caregivers is an acquired one, the result of constant social emphasis and discipline.

2.2. Text pre-processing

(1) Word Segmentation

The process of word separation is to cut a sentence or a paragraph into words with certain meanings according to a set of rules. In Chinese text, each character and the words composed of characters have different meanings, so Chinese word segmentation is more difficult than English word segmentation. In addition to this, the quality of word separation also has a certain impact on the results of text sentiment analysis. Common word separation tools include jieba word separation, snowNLP, etc. Commonly used word separation methods include dictionary-based matching methods, statistical-based word separation methods and deep learning-based word separation methods. Dictionary-based segmentation method is mainly to segment words by matching the words in the dictionary, and this matching algorithm includes forward maximal matching algorithm, backward maximal matching algorithm, and bi-directional maximal matching algorithm. Statistical based participle method is to utilize statistical language model to perform participle. Deep learning based method is to use deep learning technology principles through a large number of data sets to train the neural network model so that it has the ability to separate words, and to achieve the effect of accurate word separation. At present, the commonly used word separation tool in the text sentiment analysis task is the jieba word separation tool, but with the development of deep learning technology and some pre-training models, the commonly used word separation algorithms and word separation tools have been gradually replaced, and no longer need to carry out separate word separation operations in the text pre-processing process, just input the original text directly into the pre-training model, and the pre-training model will carry out the word separation process according to its own list and accurately output the corresponding words. The pre-trained model will process the words according to its own word list and output the corresponding word vectors accurately.

(2) Deactivate words

Stop words generally refer to words or phrases that have no specific meaning in a sentence or a paragraph. These words usually include conjunctions, particles, interjections, etc., such as "le", "la", "ah", "oh", "de", "ba", etc. These words do not have a specific meaning in the sentence, but they are used relatively frequently.

2.3. Text representation and vectorization methods

(1) One-Hot

One-Hot coding method, also known as One-Hot coding method, is an early and relatively simple and common word vectorization method. The idea of this kind of text vectorization method is that after a sentence is divided into words using a word-splitting tool, each word in the sentence is extracted to form a dictionary of size N. The words in the sentence are labeled as 1 and the rest of the words are labeled as 1. The position in the dictionary where the word appears in the sentence is labeled as 1 and the rest of the positions are denoted by 0. If k is used to denote the position of the kth word in a sentence, and the next kth position in the lexicon is labeled 1, then the word vector for the kth word is denoted as Vk= {0000.... .100... .000}.

(2) Word2Vec word vector representation model

Word2vec tool has been widely used in NLP field since it was proposed. It can vectorize all the words in the text, and the word vectors transformed by word2vec can also express the connection between the words well. word2vec tool mainly includes two models, they are: CBOW model and Skip-Gram model.

1) CBOW model

The main idea of CBOW model is to predict the current word according to the context.CBOW model mainly contains three layers: input layer, hidden layer, and output layer.The working process of CBOW model is as follows:

In the input layer, one-hot coding is utilized to get the one-hot coding vector by using one-hot coding for the contextual words in the sentence.

In the hidden layer, the coding vector obtained in 1) is multiplied with the weight matrix W to obtain a vectorized representation. The obtained vectors are summed and then averaged to get the output vector of the hidden layer:

$$h = \frac{1}{n} W^T \left(w_1 + w_2 + w_3 \cdots w_n \right) \tag{1}$$

where n is the number of context words.

In the output layer, the output h of the hidden layer is multiplied by the weight W' to get the vector:

$$v = W'^T h \tag{2}$$

$$y = soft\max(v) \tag{3}$$

The loss function is:

$$L = -\log P\left(w_t \left| w_1 w_2 w_3 \cdots w_n \right. \right) \tag{4}$$

2) Skip-gram model

The idea of Skip-gram model is opposite to CBOW model and belongs to the inverse form of CBOW model. The idea is to predict the context within the window size based on the center word.Skip-gram model also has three layers: input layer, hidden layer, and output layer.The loss function of the Skip-gram model is shown below:

$$L = -\log P\left(w_1, w_2, \cdots, w_n \left| w_t \right. \right) \tag{5}$$

(3) Glove word vector model

Although word2vec word vector model has made great progress in learning the connection between each word compared to the one-hot method, the two methods of word2vec can only utilize the local information to make predictions, and do not make good use of the whole word list information. So in order to overcome the shortcomings of word2vec, Pennington et al. proposed the Glove word vector technique, based on word2vec, the statistical information contained in the text is integrated into the model to train the word vectors.The Glove word vector model pays more attention to the co-occurrence of the words in the preceding and following contexts, and constructs the co-occurrence matrix by the number of co-occurrences. The process of constructing the co-occurrence matrix is as follows:

The corpus is de-duplicated to form a word list of length L , and a zero matrix of size $L \times L$ is constructed, with the coordinates of any point in the matrix being (i, j) .

We artificially specify a sliding window of radius n , the size of which is the center word coordinates plus or minus n .

Start scanning from the first word in the corpus, and slide the window with a span of step size 1.

Count the number of occurrences of the current word W_i that appear within the window of the center word W_j and fill in the number of occurrences in the position (i, j) .

Constantly moving the window and repeating the above steps can complete the construction of the co-occurrence matrix.

The specific example is as follows:

There is the following corpus: [I love deep learning. I love NLP. I enjoy swimming]

Specify the window radius size as 1. The co-occurrence matrix obtained by scanning is shown in Table 1.

Table 1. Co-occurrence Matrix

count	**I**	**love**	**enjoy**	**deep**	**learning**	**NLP**	**swiming**	**.**
I	0	2	1	0	0	0	0	0
love	2	0	0	1	0	1	0	0
enjoy	1	0	0	0	0	0	1	0
deep	0	1	0	0	1	0	0	0
learning	0	0	0	1	0	0	0	1
NLP	0	1	0	0	0	0	0	1
swiming	0	0	1	0	0	0	0	1
.	0	0	0	0	1	1	1	0

From the above matrix, it can be seen that the i th row and j th column are the number of times the word w_i co-occurs within the window size with the word w_j as the center word, and x_i denotes the sum of the number of occurrences of any word within the window range of the center word. So $x_i = \sum_k x_{ik}$, from which the co-occurrence probability is:

$$P_{ij} = P\left(w_j \middle| w_i\right) = \frac{x_{ij}}{x_i} \tag{6}$$

When given any word w_k , determining its relevance to w_i and w_j can be done by the following formula:

$$F\left(w_i, w_j, w_k\right) = \frac{P_{ik}}{P_{jk}} \tag{7}$$

Through the idea of GloVe model and the above equation, it can be seen that if the value of F is large it means that w_k is highly correlated with w_i , otherwise w_k is highly correlated with w_j . If the value of F is near 1, it means that w_k is either related to both w_i and w_j or not related to both w_i and w_j .

The loss function of GloVe word vector model is:

$$J = \sum_{i,j=1}^{V} f\left(x_{ij}\right)\left(v_i^T v_j + b_i + b_j - \log(x_{ij})\right)^2 \tag{8}$$

In the above equation V denotes the size of the word list, v_i , v_j denote the word vectors corresponding to w_i , w_j , b_i , b_j denote the offsets, $f(x_{ij})$ denotes the weight function, and $f(x_{ij})$ is specifically defined as:

$$f(x)=\begin{cases}\left(\dfrac{x}{x_{\max}}\right)^{a}, & x<x_{\max}\\ 1, & otherwise\end{cases} \tag{9}$$

The values of a and $x_{\max}$ in the above equation are set according to the specific task and corpus, and the value of a in the original paper is 0.75 and the value of $x_{\max}$ is 100.

2.4. Transformer model

Transformer model is different from the traditional neural network model, which is based on the attention mechanism.Transformer model mainly consists of two parts, which are the encoder part and the decoder part, the data will be inputted to the encoder part to calculate the value, and then the output value of the encoder will be sent to the decoder part to get the corresponding results.

In the Transformer model, although there is no network structure like CNN and RNN that can obtain the position information of the words in the text, the position encoding mechanism is introduced in the Transformer, which utilizes the sine and cosine functions to encode the position of the words in the sequence, so as to obtain the position information, and the specific formula for finding the position vectors is shown as follows:

$$PE_{(pos,2i)}=\sin\left(pos/10000^{2i/d_{model}}\right) \tag{10}$$

$$PE_{(pos,2i+1)}=\cos\left(pos/10000^{2i/d_{model}}\right) \tag{11}$$

The Transformer model introduces the self-attention mechanism and the multi-attention mechanism in order to be able to capture the information of long-distance dependencies in text sequences. The similarity calculation function of the vector of the attention mechanism in the Transformer model utilizes the calculation of dot product, whose structure is schematically shown in Figure 1, and the calculation formula is shown in (12) below:

$$Attention\left(Q,K,V\right)=soft\max\left(\frac{QK^{T}}{\sqrt{d_{k}}}\right) \tag{12}$$

The purpose of dividing by $\sqrt{d_k}$ in the above equation is to utilize the principle of deflation to reduce the computational result, and also to weaken the dependence of the computational result on the dimension d .

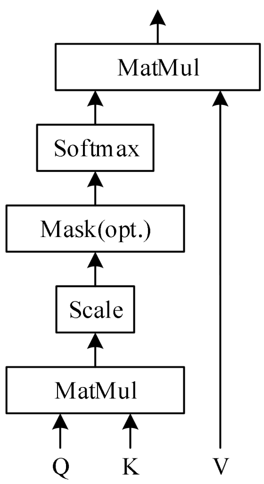


Figure 1. Structure of the dot product attention mechanism

In the encoder part of the Transformer model, the Q , K , and V of the attention mechanism come from the output of the previous layer of the encoder, so that each layer can pay attention to the position information of the previous layer, which can correlate each layer of the encoder. Unlike the encoder there are two attention layers in the decoder part. The input to the first attention layer is the input of the previous decoder layer and the input to the second attention layer comes from two parts where Q comes from the output of the previous decoder layer and K and V come from the output of the encoder. In addition to this the Transformer has two other structures which are Feed forward and Add&Norm, Feed forward feed forward neural network contains two linear transformation functions, Add&Norm is residual join and normalization operation. This structure makes the Transformer model perform well in textual sentiment analysis tasks and is widely used.

2.5. BERT model

The BERT model also adopts the Transformer structure, but the BERT model has a bi-directional structure, which is essentially an optimized combination of Embedding, Transformer, and Loss.Because of its unique structure and superior performance in word vector representation, BERT has become the mainstream word vector quantization model in text data. application model, becoming the mainstream word vector training model in natural language processing. In the extraction of word-related relations in short texts, the Transformer model is different from previous traditional models and can realize the extraction of bidirectional relations. Compared with traditional word vector models, the BERT model is not limited to its own training window, which makes the model more adaptable to new input sample data of various categories and can express the correlation between statements in the sample data.The BERT language model introduces position vectors and paragraph vectors when processing text, which provides a better solution to problems such as Sentence-Pair. The BERT language model introduces position vectors and paragraph vectors for text processing, which provides a better way to solve problems such as Sentence and Pair.

The input in the BERT model is the representation corresponding to each token, based on which the WordPiece algorithm is used to construct a dictionary of words for the input short text. In addition to this, the model needs to insert a specified categorization token [CLS] at the beginning of each sequence of short texts in the input and a specified categorization token [SEP] at the end of the sequence, so as to facilitate the specific categorization task specified by the model. The output of the tail Transformer layer corresponding to the token in the sequence can fulfill the information function of characterizing the entire short text of the sequence.

As a pre-trained model, BERT is bound to accomplish and better adapt to various types of natural language processing tasks, so the sequence text input to BERT must contain one or more than two sentences. At this point, the problem of discourse ambiguity arises, and how to discriminate the discourse of the previous sequence from the discourse represented by the next sequence becomes a key point in text categorization.

Based on this problem, BERT has its own unique solution mechanism: 1) Inserting specific classification identifiers [SEP] in a whole sequence of tokens in order to distinguish different discourse or paragraphs between the sequence of tokens. 2) Adding a learnable segmentation embedding to each token representation to determine to which discourse the statement belongs to. 3) Using a learning process, BERT is able to classify a sentence or more than two sentences in a sequence of tokens. 4) Using a learning process, BERT is able to classify the sentence in a sequence of tokens.

2.6. Pre-training for BERT

(1) Masked Language Model (MLM)

The BERT model performs the pre-training task by first erasing the words to be predicted in the input text data, and realizes the word representation by capturing the text information before and after the word to be predicted.The reason why the BERT model can be independent of the language model one-way is because of the MLM.Simply speaking, firstly, with a 15% probability of employing the Mask Token [MASK] randomly to each of the Token in the training sequence to erase the words in the original short text, and then predict the original words in the erased position by its own algorithm. However, in the actual training process, since [MASK] will not appear in the downstream task, which causes a mismatch between the pre-training phase and the fine-tuning phase. For the emergence of such problem, the BERT model adopts the following countermeasure to solve it: a Token is selected in the pre-training sequence with a probability of 15%, and the word at this position is used for the prediction of the model, assuming that the model selects the ith Token, the selected Token will be represented by 1) [Mask] 80% of the time. 2) 10% of the time converted After the conversion, the original Token is predicted using the Ti corresponding to that position.This solution allows the BERT model to become sensitive to all the Token inputs into the model instead of being sensitive to [Mask], thus allowing the model to extract the information characterized by each Token.

(2) Next Sentence Prediction (NSP)

In the previous subsection, the MLM pre-training model has been introduced, but the MLM pre-training model is better at capturing token-level representations, but it cannot directly capture utterance-level representations, and thus is no longer suitable for specific natural language inference tasks. Another pre-training model, NSP, can play a unique advantage in that it can directly determine whether there is an upper and lower correlation between two input statements, i.e., whether they are two statements connected together, which can directly enable the model to have the ability to understand the relationship between the statements. The specific workflow is shown below:

First of all, for each input sample example, the model selects two statements 1 and 2 from its own corpus, at this time there is a half probability that statement 2 is the next sentence of statement 1, at this time we label it as IsNext, and the other half of the probability is that statement 2 is a random section of statements in the original corpus, at this time we label it as NotNext, and then after the completion of the label, we then Input the sample examples in the pre-training to the BERT model, and finally realize the classification judgment on the input text based on the corresponding information.

3. Text Sentiment Analysis Model Based on BERT-Attention-BiLSTM

This chapter constructs a text sentiment analysis model based on BERT-Attention-BiLSTM. The model consists of input layer, BERT layer, BiLSTM layer, Attention layer, softmax layer and output layer. The BERT model used in the model replaces the traditional word vector model, which can better capture the bidirectional relationship in the utterance and improve the accuracy of the model's sentiment analysis, and the Attention layer mechanism can realize the function of giving higher weight to the key words to realize the accurate classification of the samples. The specific workflow of the model is shown below:

1) Suppose the input layer inputs sample data as $X=\left[X_1,X_2,X_3,\cdots,X_N\right]$, and the input layer will input the input textual data to the BERT layer.

2) The BERT layer will convert the input sample data into word vector representation, let the sample data after word vector be $E=\left[E_1,E_2,E_3,\cdots,E_N\right]$.

3) Input the text data after word vector transformation to BiLSTM layer for text feature extraction of short text, and BiLSTM is a combination of forward LSTM and backward LSTM model, so the vector trained in this layer is the splicing vector of two LSTM models, let the vector be $h_t=\left[\overrightarrow{h_t},\overleftarrow{h_t}\right]$.

4) The obtained vector is input to the Attention layer, and the addition of the attention mechanism can realize to give higher weight to the key words and realize weighted summation.

5) Finally, the acquired text features are used to realize the classification of the text through the softmax layer, and then the emotional tendency of the short text is acquired. The overall architecture of the model is shown in Figure 2.

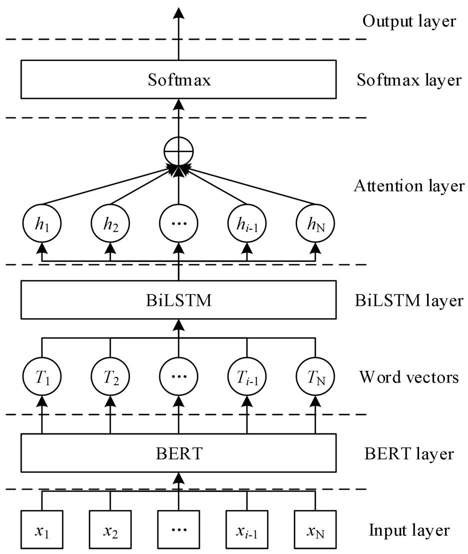


Figure 2. BERT-Attention-BiLSTM Framework

4. Model performance analysis

4.1. Experimental Parameter Setting and Evaluation Criteria

"The Ordinary World" is a long novel that expresses the social life of China's contemporary urban and rural areas from multiple angles and aspects. The author, Lu Yao, describes the historical changes in the rural areas of northwestern China in the background of the past decade, and through the complex emotional entanglements and power struggles among the characters, he depicts the difficulties and twists and turns of the ordinary people in the course of the historical process of the great era. The language of "The Ordinary World" is adopted. The language of "Ordinary World" is vernacular and universal, with a huge length of about 800,000 words. The number of training sentences available is large. The time span is long and the relationship between the characters is intricate. The number of characters is as many as about 130, with characters from all social classes, and the relationship between characters is rich and relatively clear. Therefore, "The Ordinary World" is chosen as the data set for this chapter.

After the data processing can be experimented, the B&B review dataset can be divided into a test set and a training set, of which the proportion of the test set is 3 and the proportion of the training set is 7. Table 2 shows the specific data of the experimental parameters.

Table 2. Parameter Settings

Parameter	Parameter value
Batch_size	35
Epoch	30
Loss	Categorical_crossentropy
Lr	0.0001
Dropout Ratio	0.4

Batch_size denotes the number of samples selected for each training, due to the large number of datasets, it is too difficult to complete the training at one time, so it must be carried out in batches, and the value of Batch_size has a direct impact on the running speed of the model.Dropout is an effective regularization computation method aimed at avoiding the occurrence of overfitting phenomenon. It can randomly select neural network modules according to a specific probability and discard the features in them to get the Dropout ratio, i.e., the proportion of discarded features.Lr is the learning rate, which determines whether the objective function can converge to a local minimum and whether it is appropriate to converge to the minimum. By using Python software, it is possible to draw line graphs of the accuracy and loss rate of the BERT-Attention-BiLSTM model as the number of iterations increases, in which the epoch parameter is an important indicator, which can help us to better choose the timing of the training of the model, so as to achieve the best efficiency. The Epoch value should not be too small, but it should not be particularly large, because if the Epoch is particularly large it will lead to overfitting of the model, which will affect the accuracy of the experiment. The curves of accuracy and Loss value with Epoch value are shown in Fig. 3 and Fig. 4.

According to Fig. 3, when the Epoch value reaches 0, the Accuracy value of the model starts to rise and reaches the highest value at the 30th iteration, and the gap between the Accuracy value of the test set and the training set becomes smaller and smaller. It is clear from Fig. 4 that due to the increase in the number of iterations of the model, the Loss value decreases significantly and finally stabilizes, and the gap between the Loss value of the training set and the test set becomes smaller and smaller. Based on the trend of the two graphs, it was decided to set the Epoch value to 30.

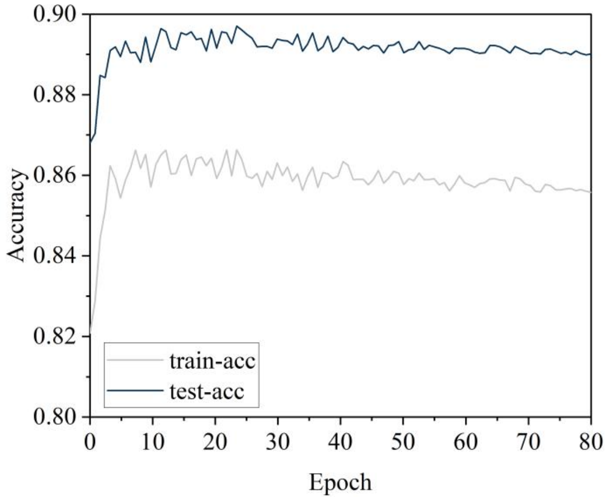


Figure 3. Line graph of model Accuracy varying with Epoch

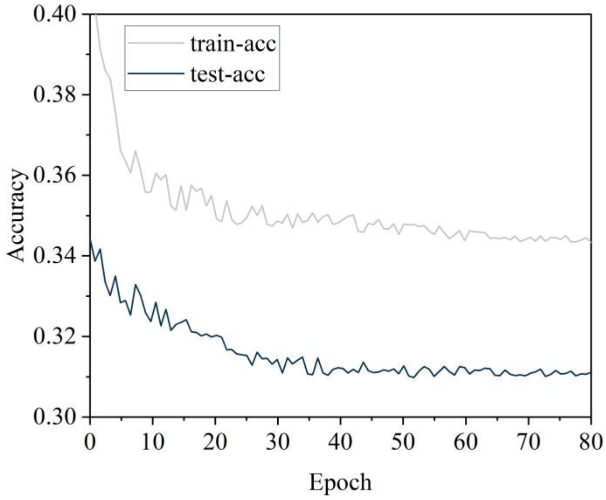


Figure 4. Line graph of model Loss varying with Epoch

(2) Model Evaluation Criteria Evaluation

The criteria usually include indicators such as accuracy, recall, $F1$ value and precision rate, and these evaluation indicators can help this paper to better assess the quality of the model. In the experimental study of this paper, the accuracy rate and $F1$ value are selected as the evaluation indexes to measure the model's ability to classify emotional tendencies. Among them, the $F1$ value is the reconciled average of the precision rate and the recall rate.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{13}$$

$$\mathrm{Pr}\,ecision = \frac{TP}{TP + FP} \tag{14}$$

$$\mathrm{Re}\,call = \frac{TP}{TP + FN} \tag{15}$$

$$F1 = \frac{2 * \mathrm{Pr}\,e * \mathrm{Re}\,c}{\mathrm{Pr}\,e + \mathrm{Re}\,c} \tag{16}$$

TP denotes the number of positive categories and the number of predictions that are also positive. FP denotes the number of non-positive categories but the number of predictions that are positive. FN denotes the number of positive categories but the number of predictions that are not positive. TN denotes the number of non-positive categories and the number of predictions that are also non-positive.

4.2. Model comparison experiment and result analysis

In order to better evaluate the effectiveness of the constructed models, it was decided that this dataset would be used for comparative experiments using Word2vec-CNN, Word2vec-RNN, Word2vec-BiLSTM, Bert-CNN, and BERT-Attention-BiLSTM models. By comparing the results of comment text sentiment analysis of several different models, Table 3 shows the accuracy rate and F1 value of each model.

The BERT-Attention-BiLSTM model outperforms the other models in terms of accuracy rate and F1 value, and it has the highest accuracy rate and F1 value. In terms of accuracy, BERT-Attention-BiLSTM model improves 52.65%, 2.59%, 3.83%, and 2.91% over Word2vec-CNN, Word2vec-RNN, Word2Vec-BilSTM, and Bert-RNN models. In F1 value BERT-Attention-BiLSTM model improves 28.28%, 2.61%, 1.91%, 7.24% than Word2vec-CNN, Word2vec-RNN, Word2Vec-BilSTM, Bert-RNN model. From the results, in terms of word vector transformation, it is found that the transformation by Bert model is higher than Word2vec model. In addition, the BERT-Attention-BiLSTM model has the best effect on the problem of sentiment binary classification of literary works, which indicates that the model can be applied to the task of sentiment analysis and can solve away some of the problems of machine models in classification research.

Table 3. Comparison Results of Experiments for each model

Model	Acc/%	F1/%
Word2vec-CNN	28.55	30.14
Word2vec-RNN	78.61	55.81
Word2vec-BiLSTM	77.37	56.51
Bert-RNN	78.29	51.18
BERT-Attention-BiLSTM	81.20	58.42

5. Emotional Analysis of the Texts of the Maodun Literature Prize Winning Works

5.1. Information about the work

In this paper, one work from each of the seven male Maodun Literature Prize winners is selected for research and analysis, and the basic information of the seven works is shown in Table 4. No special selection is made for the translations, mainly considering that the translation style does not affect the character interaction frequency data needed for social network analysis. As far as possible, the characteristics of the works in terms of genre, year of writing, gender of the author, and the popularity of the work in the home country were matched.

Table 4. Basic Information of the Works

Type of work	Work Title	Author	Character (individual)	Word count (ten thousand)
History and Epic	"White Deer Plain"	Chen Zhongshi	96	50
	"Dust Settles"	A Lai	62	48.1
	"Right Bank of the Erguna River"	Chi Zijian	68	20.5
Rural Areas and Transformation	"Ordinary World"	Lu Yao	140	79.8
	"Qin Opera"	Jia Pingwa	52	45
City and Humanity	"One Sentence Is Worth Ten Thousand Words"	Liu Zhenyun	113	39
	"Massage"	Bi Feiyu	121	18

According to the method of complex network theory analysis, the statistical measures of the character relationship networks of these literary works are statistically obtained as shown in Table 5.

In the seven Mao Dun Literary Award-winning works, not all characters are directly connected, but there are rarely more than three degrees of separation (characteristic path lengths). As the number of characters (nodes) in the works increases, the average path length increases (log-log correlation, $r=0.88$, $df=7$, $p<0.01$) and the overall connectivity decreases ($r=0.91$, $df=7$, $p<0.01$) This suggests that as the number of characters in the literary works increases, the perceptual interpersonal network becomes more and more decentralized like the real interpersonal network, and that such a decentralized group in which the number of characters may have an upper limit on its size.

Table 5. Statistics of Character Relationship Networks in Works 4

Work	Number of nodes	Edge count	Connectivity	Feature path length	Clustering coefficient
"White Deer Plain"	19	64	0.081	2.267	0.502
"Dust Settles"	22	35	0.065	2.289	0.348
"Right Bank of the Erguna River"	193	635	0.038	2.912	0.177
"Ordinary World"	88	228	0.012	2.730	0.167
"Qin Opera"	235	334	0.036	2.796	0.262
"One Sentence Is Worth Ten Thousand Words"	84	151	0.079	2.728	0.170
"Massage"	22	89	0.052	2.855	0.195

The data processing software Excel 2016 and social network analysis software Pajek 64 5.02 are used to analyze the award-winning works of Mao Dun Literature Prize. The results of the network diameter and degree distribution power law index of the character relationship of the work are shown in Table 6, and the degree distribution of the character relationship network of the novel has a power law characteristic. Of course, compared with the complex social networks with tens of thousands of nodes in the real world, this scale-free characteristic is still obvious. Therefore, it can be considered that the novel character relationship network is a scale-free network. Most of the networks in the real world are not random networks, a few nodes tend to have a large number of connections while most nodes have very few, and in general they conform to the law of two or eight. A complex network whose degree distribution conforms to a power law distribution is called a scale-free network. From the diameters of the character relationship networks of the seven literary works calculated in Table 6 (network diameter, which refers to the extent to which all characters in a network are linked to each other through a finite number of steps, i.e., the maximum distance between any two points that can be connected), the diameters of the character relationship networks of the seven literary works are all under seven. The diameter of the character relationship networks for "White Deer Plain", "The Right Bank of the Erguna River", and "Massage Therapy" is all 7. The diameter of the character relationship networks for "Ordinary World" and "Qin Opera" is both 5, which is very close to the six-degree separation theorem in sociology. While the diameter of the character relationship networks for "Settle Down" and "One Sentence Worth Ten Thousand Words" is both 6, which is highly consistent with the six-degree separation theorem. From the perspective of the characteristic path length and clustering coefficient of these networks, their characteristic path lengths are all between 2.2 and 3.0, and the clustering coefficients range from 0.17 to 0.55.

Table 6. Network Diameter and Degree distribution power-law index of Character relationships

Work	Power-law exponent of degree distribution	Network diameter	Longest path connection
"White Deer Plain"	1.534	7	Tian Xiao 'e(16)to Bai Ling(31)
"Dust Settles"	1.635	6	Tana(12)to Sanji Zhuoma(22)
"Right Bank of the Erguna River"	1.447	7	Narrator(10)to Nihao(48)
"Ordinary World"	1.356	5	Tian Xiaoxia(33)to He Xiulian(59)
"Qin Opera"	1.764	5	Bai Xue(48)to Fourth Aunt(67)
"One Sentence Is Worth Ten Thousand Words"	1.856	6	Cao Qing(35)to Pang Lina(63)
"Massage"	1.730	7	Du Hong(29)to Jin Yan(43)

Compared to the random network with the same number of nodes and edges as shown in Table 7, the characteristic path lengths of the character relationship networks of the seven works are significantly smaller while the aggregation coefficients are significantly larger. For the random network, the characteristic path length between any two points is short but the aggregation coefficient is low. For the small world network, the characteristic path length between points is small, close to the random network, while the aggregation coefficient is still relatively high. It can be seen that the character relationship networks of the seven classic literary works have obvious small-world characteristics.

In the random connection graph, the average clustering coefficient (T=0.40) is approximately equal to the connectivity (C=0.45). For literary works, the average clustering coefficient (T=0.268) significantly exceeds the connectivity of each literary work. This implies that the characters in the seven works have closer connectivity than would be expected in a randomized network.

Table 7. Comparison of topological measures of random networks of the same size

Character Relationship Network and Random Network e	Number of nodes	Edge count	Feature path length	Clustering coefficient
“White Deer Plain”	19	64	2.267	0.502
Random network	19	64	2.232	0.510
“Dust Settles”	22	35	2.289	0.348
Random network	22	35	2.286	0.365
“Right Bank of the Erguna River”	193	635	2.912	0.177
Random network	193	635	2.901	0.185
“Ordinary World”	88	228	2.730	0.167
Random network	88	228	2.722	0.173
“Qin Opera”	235	334	2.796	0.262
Random network	235	334	2.815	0.296
“One Sentence Is Worth Ten Thousand Words”	84	151	2.728	0.170
Random network	84	151	2.720	0.201
“Massage”	22	89	2.855	0.195
Random network	22	89	2.849	0.197

5.2. Sentiment analysis of text based on trend curves

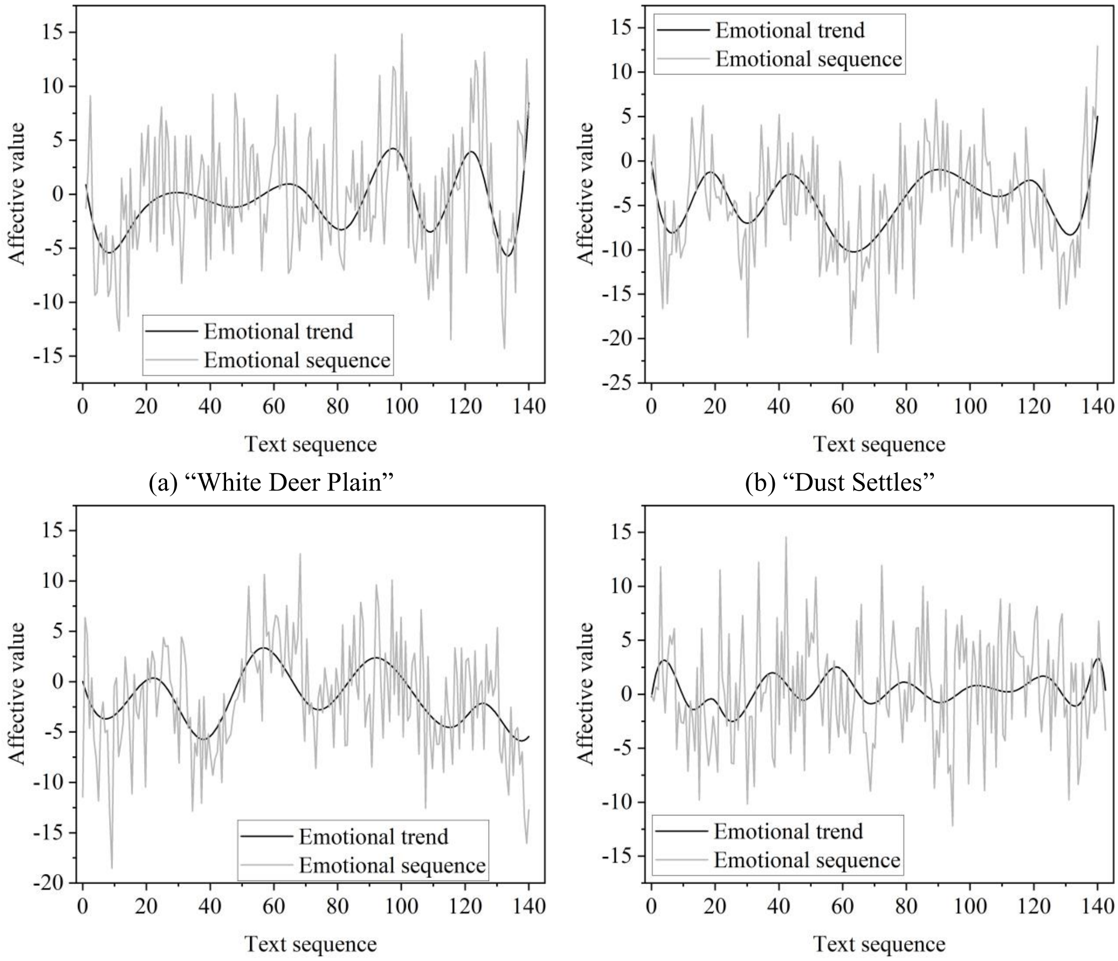
Using the sentiment analysis model based on BERT-Attention-BiLSTM and the gender role theory, the sentiment analysis calculations were conducted for the four works: "Dust Settles", "White Deer Plain", "Ordinary World", and "The Right Bank of the Ermeguna River". The encoded results formed text-sentiment time series. Subsequently, the nonlinear adaptive filtering (NAF) method was employed to obtain the sentiment trend lines of the works. Quantitative methods were used to depict the development of the sentiment trends of the four works. Figures 5(a) to 5(d) show the sentiment trends of the four works respectively.

The emotional trend line of the text of “White Deer Plains” basically fluctuates in the negative range, which is consistent with the negative emotional tone of the text of anger and sadness. The direction of fluctuation is generally positive, which is consistent with the emotional catharsis of the text. As a “foreign” woman, Tian Xiaoe possesses many elements of the social transition between the old and the new, becoming a symbol and shadow of the changing times. The red cheongsam she wears when she appears on the scene is a particularly eye-catching sight in the land of yellow and black, especially in the eyes of the defenders of the traditional order, this color represents a challenge to and destruction of the old system of etiquette, together with Tian Xiaoe's subsequent behaviors, all of which make this character, both emotionally and physically, able to have a self-consciousness and break free from the numbness of feudalistic life. This is naturally the beginning of her tragic fate. Tian Xiaoe is a marginalized person who is expelled from the ritualistic culture, but she, in turn, causes great damage to the culture. She expresses her protest against Confucian ethics and culture with her lust and body, and pays a terrible price for it, finally being killed by Deer San, who is a firm believer in the idea of rites and rituals, and after her death, she is still being crushed under the tower just like Bai Suzhen. Through the image of Tian Xiaoe, the movie sharply criticizes the traditional morality and patriarchal culture that is against human nature, and reveals the historical heaviness of the existence of individual life.

The emotional trend lines in the text of “Dust Bowl” fluctuate in the negative range. The emotional trend line fluctuates from frequent fluctuations to leveling off, which is in line with the development of the plot. The female characters portrayed in the text are always swaying between exaltation and submergence. The text portrays women with distinctive personalities, and the diversity of Han and Tibetan women can also be found in this group of women. Their personalities are full of tension, with explicit characteristics based on ethnic regionalization and age stratification. They act with an instinctive desire, which is a kind of externalized expression of their true nature. However, these images are portrayed by male writers, and in the narrative portrayal of male discourse, they are still not free from the intrinsic constraints of male chauvinism. Through the symptomatic interpretation of typical female images, it can be seen that patriarchy is further exalted, while the equality and freedom advocated by feminism are endlessly submerged. At the same time, through the analysis of the text, we can find out the life course and identity consciousness of traditional Tibetan women, as well as many other signs of regionalization, and we can also find out the weakness of women's discourse under the domination of patriarchal discourse.

The emotional trend line of the text of “The Ordinary World” shows negative-positive-negative fluctuations. Tian Xiaoxia in the book was born and grew up in a brand new era and society, and is a typical modern intellectual woman, basically free from the traditional rural culture and thought of the established social positioning of women. She has the romantic, straightforward and strong character qualities of a modern intellectual young woman, and in the family background she grew up in, she has good family education and cultural literacy, and has set up her own clear ideals and aspirations. In the storyline of Tian Xiaoxia's exchanges and dialogues with Sun Shaoping, one can strongly feel Tian Xiaoxia's ideal aspirations and grandeur. When Tian Xiaoxia enters the university, she becomes Sun Shaoping's mentor, giving him encouragement when he is going through difficult times. Her good upbringing, outstanding talent, and romantic feelings all attract Sun Shaoping and give him infinite confidence and strength, inspiring him to break into the world with his ideas and confidence. In the process of Sun Shaoping's moving from the county to the city, Tian Xiaoxia even leads him in life and constantly guides him to maturity.f When Tian Xiaoxia graduates from the university and becomes a reporter, she presents the splendor of her own life with her strong character and bravely sacrifices her young life in a news report on the flood rescue. Due to the need for literary drama, the author's setting of the storyline inevitably appears to be convoluted, but because of this, we see in the novel's creation of Tian Xiaoxia's character role the glory and splendor of women as well as the qualities and consciousness of the new-age women's boldness, dedication, and boldness and briskness.

“The right bank of the Ergun River” praises the woman's talent and intelligence, and the emotional intensity is relatively small, so the overall fluctuation of the emotional trend line of the text is flat. “The Right Bank of the Ergunar River” tells the story of the tenacious struggle and beautiful love of this weak ethnic group in the self-reporting tone of a woman who is the last chief of the Ewenki ethnic group and is nearly ninety years old. Through the narrator's inner monologue, the work shows the Ewenki people's living condition, cultural characteristics and psychological changes in the face of the impact of modern civilization. In “The Right Bank of the Erguna River”, the narrator's inner monologue is full of love and pride for Ewenki culture. From the first person's point of view, she tells about the daily life of Ewenki people in the jungle where reindeer are ridden, birches are used as tools, dead wood is used as fire, and the mountains are used as food. She depicts the religious beliefs of Ewenki people who believe in the god Maru and rely on shaman for healing and saving people, as well as their way of living in harmony with nature. These inner monologues not only show the unique charm of Ewenki culture, but also reflect the narrator's deep affection for traditional culture. The narrator's inner monologue also reveals the survival status of Ewenki people. She describes the hard journey of Ewenki people to reproduce under the attack of cold, beasts and pestilence. These inner monologues are full of reverence and cherish for life, showing the resilience and tenacity of Ewenki people. When facing the impact of modern civilization, the narrator's inner monologue also shows the psychological change of Ewenki people. She misses the past way of life and cultural traditions, but cannot resist the temptation and impact of modern civilization. Her heart is full of contradictions and struggles, not only holding on to the traditional culture, but also desiring and pursuing the modern civilization. This psychological change not only reflects the Ewenki people's survival predicament under the impact of modern civilization, but also embodies the general psychology of human beings in the face of cultural change.



(a) “White Deer Plain” (b) “Dust Settles”

(c) “Ordinary World” (d) “Right Bank of the Erguna River”

Figure 5. Text sentiment trend

6. Conclusion

In order to accurately analyze the image of women in male Maodun Literature Award-winning works, BERT-Attention-BiLST text sentiment analysis model was constructed by introducing BERT pre-training model on Attention-BiLSTM model. In terms of accuracy, the BERT-Attention-BiLSTM model improves 3.83% and 2.91% than Word2Vec-BiLSTM and Bert-RNN models. It improves 1.91%, 7.24% in F1 value. It can satisfy the purpose of sentiment analysis of literary works.

This article conducts an emotional analysis of four literary works by Aran, Chen Zhongshi, Lu Yao, and Chi Zijian: "Dust Falls to Rest", "White Deer Plain", "The Ordinary World", and "On the Right Bank of the Erguna River". The diameters of the character relationship networks in these four literary works are 6, 7, 5, and 7 respectively. The maximum distance is no more than 7, which is highly consistent with the six-degree separation theorem. This indicates that the characters in these works have more closely connected relationships than those in a randomly generated network. In the "White Deer Plain" text, the emotional trend lines of female characters mostly fluctuate within the negative range. In the "Dust Falls to Rest" text, the emotional trend line fluctuates from frequent fluctuations to a tendency towards stability, all within the negative range. In the "The Ordinary World" text, the emotional trend line begins to fluctuate negatively, then fluctuates positively in the middle stage, and finally fluctuates negatively again. In the "On the Right Bank of the Erguna River" text, the overall fluctuation amplitude of the emotional trend line is flat. The emotional trend development of these four works is in line with the plot development of the works.

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