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# Differences in Emotional Expressions in Western Romantic Literature and Classical Chinese Literature Based on Computational Modeling

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Abstract In this paper, the BERT model containing a large number of encoders is used to complete the preprocessing operation of literary text data and generate the corresponding word vectors. The frequency-intended document frequency (TF-IDF) algorithm and the sentiment computation model SnowNLP are introduced to count the word frequency and calculate the sentiment polarity. Build a metaphorical sentiment polarity computation modeling framework. Embedding culturally relevant attributes in word vectors, modeling contextual semantics by combining long and short-term memory networks, and using the attention mechanism to train to get the attention weight matrix of the word items to accurately classify the emotional polarity of the word items. Taking the selected comparison works as an example, the average word length of classical Chinese literature is 1.08-1.20, and the proportion of real words accounts for 74.15%. The percentage of negative sentiment for the 6 keywords was 20%, 15%, 21%, 15%, and 10%. Five of the six represented pieces are dominated by negative emotions. The average word length in Western Romantic literature is 2.26-2.46, with 78.27% real words. The 6 keywords positive emotions accounted for 15%, 5%, 20%, 25%, 20%, 15%. 5 of the 6 represented works were dominated by positive emotions.

Index Terms BERT preprocessing, TF-IDF, SnowNLP, long and short-term memory network, literary emotion classification

### I. Introduction

Literature, has been one of the core elements of culture [1]. Literature plays an important role in the formation of a country, region or national culture, and literature influences people's thinking and values by spreading ideas and concepts [2]. Literature is a specific form of manifestation in a certain cultural sense, different cultural background soil will produce different literature, different literature represents different cultural characteristics [3]. Comparative study of Chinese and foreign literature from the perspective of cultural differences, through the contrast way to understand the differences and similarities of literary characteristics, can effectively promote cultural and literary exchanges. [4].

The differences between Chinese and Western cultural backgrounds have led to two very different literary concepts and writing styles, the most representative of which is Western Romantic literature and Chinese classical literature [5], [6]. Western culture is characterized by a scientific core, which advocates the interactive integration of freedom and social harmony, and therefore can build a matching social structure on top of the individual [7]. Chinese culture, on the other hand, is more ethically oriented, characterized by the pursuit of active social norms and passive acceptance by the individual, including the formation of a social order on this basis [8]. Against the background of global cultural pluralism, the modern Western thinking expressed in Western Romantic literature has penetrated into classical Chinese literature from all aspects and at all levels [9], [10]. On the basis of the inherent characteristics of classical literature, Chinese literature has absorbed many beneficial factors of Western Romantic literature, as a result of which the multiple transformations of classical Chinese literature have been promoted, forming a diversified and complex creative situation and realizing the fusion of Chinese and Western literature [11], [12].

The ideology expressed in classical Chinese literature is very different from that in Western Romantic literature, originating from the deviation between Chinese and Western understanding of human nature itself [13]. China believes that human nature is inherently good, while the West believes that human beings are born with a sense of guilt, and therefore they need to go through life and death after birth to be able to cleanse themselves of their sins [14]. Therefore, in the West, there are many believers who believe that through their own good deeds, God can



help them to be universal. However, Buddhism existed in China in the early days, and with China's reform and opening up, the Chinese people are more inclined to believe in atheism, thus, two distinct differences in the expression of emotions emerge [15]-[17].

Combining digital technology to analyze the differences in the expression of emotions between Chinese and Western literature, providing new perspectives and methods for cross-cultural literature research. In this paper, the BERT pre-training model is utilized to complete the preprocessing and word vector representation of the text data in the dataset. Combined with the frequency-intended document frequency (TF-IDF) algorithm, the keywords in Western Romantic literature and Chinese classical literature are extracted. Further using the SnowNLP sentiment analysis model based on the plain Bayesian algorithm, the word sentiment polarity probability is calculated. For the metaphorical sentiment of words, a metaphorical sentiment polarity calculation model integrating culturally relevant attribute knowledge, attention mechanism and long and short-term memory neural networks is constructed to comprehensively calculate the attention weights of words and realize the final classification of the sentiment polarity of words in literary works.

## II. Technical support related to the study of differences in emotional expression based on computational modeling

#### II. A. Text data processing and feature extraction

Firstly, the text data in the constructed dataset is subjected to preprocessing operations such as data cleaning, clause and word segmentation, stemming extraction and lexical annotation, followed by word vector representation of the text. Common word vector representations include One-Hot coding, TF-IDF coding, word embedded representation, etc. In this paper, we use the BERT pre-training model to transform word vectors and preliminary feature learning on the text data. The BERT model is characterized by high efficiency and convenience, which contains 10 Transformer encoders with 10 heads in each encoder. Fig. 1 is the structure of the BERT pre-training model. Where,  $E_1 \sim E_N$  is the input word or words,  $E_1 \sim E_N$  is the output, and the Transformer in the middle contains only the Encoder part and no Decoder part.

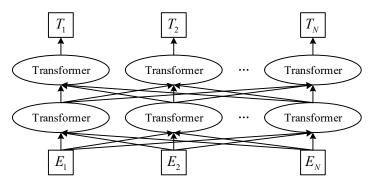


Figure 1: Structure of the BERT model

#### II. B. Research methodology

#### II. B. 1) Text Sentiment Calculation Method

SnowNLP is a Python class library specialized in sentiment analysis for Chinese texts, and comes with a general dictionary and a sentiment calculation model. In this paper, SnowNLP based on the plain Bayesian algorithm is used to calculate the score of the difference in sentiment expression between Chinese and Western literature using each literary work's utterance as the calculation unit. Assuming that each word in the text utterance is independent of each other, i.e., the contribution of each word to the classification of sentiment polarity is independent of each other, the calculation method is as follows:

- 1) Represent all text utterances as combinations of multiple words,  $X = \{a_1, a_2, \dots, a_n\}$ , based on the segmentation results and divide them into training and testing sets according to a certain proportion.
- 2) Label each text utterance in the training set with sentiment polarity  $C = \{Positive, Negative\}$ , and calculate the prior probability  $P(C_{Positive}), P(C_{Negative})$ .
- 3) Iterate over all the words in the training set and compute the probability that each word belongs to a different sentiment polarity  $P(a \mid C_{\text{Positive}}), P(a \mid C_{\text{Negative}})$ .
  - 4) Calculate the probability of the sentiment polarity to which the text utterance  $\chi$  belongs in the test set:



$$P(C \mid X) = \frac{P(X \mid C)P(C)}{P(X)} \tag{1}$$

$$=\frac{P(a_1 \mid C)P(a2 \mid C)\cdots P(a_n \mid C)P(C)}{P(X)}$$
 (2)

5) Based on  $MAX\{P(C_{Positive} \mid X), P(C_{Negative} \mid X)\}$ , the sentiment polarity of the textual statement X is determined to be "positive/negative".

#### II. B. 2) Keyword extraction algorithm

TF-IDF is one of the most commonly used keyword extraction algorithms, which is based on the principle that if a word occurs frequently in a certain document but rarely in other documents, it is considered to represent the main idea or feature of the document, and is suitable for distinguishing between different documents.

Word frequency (TF) is the frequency of occurrence of a particular word in a document. The higher the word frequency, the more important the word is in the document. The calculation formula is:

$$TF_{i,j} = \frac{n_{i,j}}{n_j} \tag{3}$$

where  $TF_{i,j}$  is the frequency of word i in document j,  $n_{i,j}$  is the number of times the word i occurs in document j, and  $n_i$  is the total number of words in document j.

Inverse Document Frequency (IDF) is used to measure the prevalence of a word in all documents, and is obtained by dividing the total number of documents by the number of documents containing the word and then taking the logarithm of the number of documents, which is calculated as:

$$IDF_i = \log \frac{N}{N_i + 1} \tag{4}$$

where,  $IDF_i$  is the inverse document frequency of word i in the document set, N is the total number of all documents,  $N_i$  is the number of documents containing word i, and  $N_i+1$  prevents the denominator from being 0.00.

The formula for TF-IDF calculation is as follows:

$$TF \_IDF_{i,i} = TF_{i,i} \times IDF_i \tag{5}$$

#### II. C. A Computational Model of Metaphorical Affective Polarity Considering Cultural Factors

According to the characteristics of metaphorical emotional polarity, this paper proposes a metaphorical emotional polarity computational model based on culturally relevant attribute knowledge, attention mechanism and long and short-term memory neural network. In the input layer of the model, this paper transforms the knowledge of culture-related attributes into a vector of culture-related attributes and constructs the input of the model based on this vector: the LSTM network layer is responsible for modeling the semantics of the metaphorical context: the attention network layer simulates the interaction between the metaphorical ontology and the context, so as to compute the attentional weight (importance) of the words in the context in the metaphorical expression of emotional polarity. Figure 2 shows the model structure. Where  $\{w_1(w_{target}), w_2, ......, w_n\}$  represents the word vector,  $\{k_1(k_{target}), k_2, ....., k_n\}$  is the attribute knowledge vector,  $\{h_1(h_{target}), h_2, ....., h_N\}$  is the hidden layer vector,  $\alpha$  is the attention weight, and  $\alpha$  is the categorization feature vector.



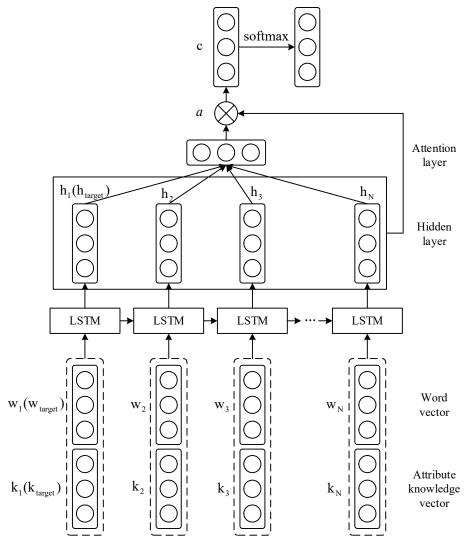


Figure 2: Model structure

#### II. C. 1) Vector embedding of culture-related attributes

Formally represent the "cultural attribute knowledge base" as a collection:  $\{K \mid K_i(T, \{A \mid a_1, a_2, ..., a_m\}), i \in [1, n]\}$ , when T is a noun,  $K_i$  represents the "Haveattribute" semantic relationship; When T is an adjective,  $K_i$  represents the "Attribute-of" semantic relationship. In order to facilitate the calculation, the input sample is preprocessed, the sample is segmented, and the first word of the sample points to the ontology of the metaphor. For example, "City = At night, the city becomes a forest of stones." Among them, "city" is the ontology of metaphor. Let  $c_1(c_{target}), c_2, ..., c_N$  represent the sequence of words in the input sample, the length of which is N.  $k_1(k_{target}), k_2, ..., k_N$  are the vector sequences of culturally relevant attributes corresponding to the word sequences of the sample. For each word  $c_i$  in the input sample, if  $c_i$  is an index term T in the "cultural attribute knowledge base"  $\{K\}$ , then the average word vector of all attribute words  $a_j$  in the attribute knowledge set  $\{A\}$  of T is used as a vector of culturally relevant attributes  $k_i$  of  $c_i$ . The computation of  $k_i$  is formalized as follows:

$$k_i = \frac{1}{m} \sum_{j=1}^{m} A_j^{c_i} \tag{6}$$

where m is the number of attributes that  $c_i$  has in the "Cultural Attributes Knowledge Base", and  $A_j^{c_i}$  is the word vector of the j th attribute of  $c_i$ , which is obtained by looking up the pre-trained word2vec word vector model



obtained. Let  $\{w_1(w_{target}), w_2, ...., w_N\}$  denotes the input sequence  $\{c_1(c_{target}), c_2, ...., c_N\}$  corresponding to the original word2vec word vector sequence, then the culture-related attribute vector embedding can be expressed as:

$$x_i = w_i \oplus k_i \tag{7}$$

where  $\oplus$  is a semantic join operation operator that does semantic splicing operations on the original word vector  $w_i$  and the attribute knowledge vector  $k_i$ . If  $w_i$  is a vector of dimension  $V^w$  and  $k_i$  is a vector of dimension  $v^k$ , then the dimension of  $v^k$  is a vector of dimension  $v^k$ , then the dimension of  $v^k$  is a vector of dimension  $v^k$ , as input to the LSTM.

#### II. C. 2) Long and short-term memory neural networks

In this paper, we use LSTM for semantic modeling of context.LSTM inputs a sequence of word vectors and outputs a vector representation of the context as a classification feature.LSTM is an improved version of recurrent neural networks, which solves the problem of its gradient vanishing and is able to achieve long time-steps of memory, and thus has an advantage in dealing with context-dependent problems. The computation of the state of each hidden layer of the LSTM uses not only the current moment's input, but also depends on the previous moment's state. Each LSTM cell contains an input gate, an output gate, and a forgetting gate, and the LSTM controls the input, output, and memory of the data through a gating mechanism. Figure 3 shows the structure of an LSTM cell.

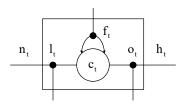


Figure 3: Structural schematic diagram of an LSTM unit

In Fig.  $\overline{\mathbf{3}}$ ,  $x_i$  is the input information at time step t,  $i_i$  is the input gate state,  $o_i$  is the output gate state,  $f_i$  is the oblivion gate state, and  $h_i$  is the hidden layer state. Each LSTM cell state is computed as follows:

$$i_{t} = \sigma(W_{t}x_{t} + U_{t}h_{t-1} + b_{t})$$
(8)

$$\tilde{C}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{9}$$

$$f_{t} = \sigma(W_{f}x_{t} + U_{f}h_{t-1} + b_{f})$$
(10)

$$C_{t} = i_{t} * \tilde{C}_{t} + f_{t} * C_{t-1}$$
(11)

$$o_{t} = \sigma(W_{o}x_{t} + U_{o}h_{t-1} + b_{o})$$
 (12)

$$h_t = o_t * \tanh(C_t) \tag{13}$$

where  $W_i, W_c, W_f, W_o, U_i, U_c, U_f, U_o$  represent the weights,  $b_i, b_f, b_c, b_o$  represents the deviation,  $\tilde{C}_t$  is the alternative state value of the LSTM cell,  $C_t$  is the state value, and  $\sigma$  and tanh are the nonlinear activation functions.

#### II. C. 3) 2.3.3 Attention mechanisms

The attention mechanism is an algorithm used in neural network modeling to simulate human cognitive attention, with the goal of selecting from a large number of inputs the information that is critical to the history of the current target task. For a neural network without an attention mechanism, such as a standard LSTM network, the input is a sequence of vectors, and the model distributes the attention equally to each vector, considering them all to be of the same importance to the current task, and uses the same formula to process the information at each time step. The attention mechanism, on the other hand, allows the model to be trained to learn the importance weights of different vectors in a sequence of vectors, and thus assign different weights to the inputs at each time step. For the task at hand, the attention mechanism is designed to learn which parts of the input context are more important for expressing the emotional polarity of the metaphor. We argue that the importance of a word in the context in expressing the emotional polarity of a metaphor is determined by the interaction between that word and the ontology.



The attention mechanism in this paper is realized by training a neural network model, and the purpose of training is to obtain the attention weight matrix  $\alpha$ . An input context of length N corresponds to a one-dimensional weight matrix of length N. The values of the matrix elements represent the importance of the corresponding words in the context, and the information corresponding to a position with a higher weight is more critical. The attention network layer takes the output of the LSTM hidden layer  $(h_1(h_{target}), h_2, ....., h_n)$  as inputs, inspired by related work, this paper describes the interaction process between the ontology of the metaphor and other words, and thus calculates the attentional weights, using the following formula:

$$\alpha_i = \frac{\exp(F(h_i, h_{target}))}{\sum_{j=1}^{N} \exp(F(h_j, h_{target}))}$$
(14)

$$F(h_i, h_{target}) = \tanh((h_i \cdot W_a)^T \cdot h_{target} + b_a)$$
(15)

where  $W_a$  and  $b_a$  represent the weights and biases in the attention neural network, respectively. T is the transpose operation of the matrix.

Tanh and exp are two nonlinear functions. Next, the model can compute the semantic representation with attention weights:

$$c = \sum_{i=1}^{N} \alpha_i * h_i \tag{16}$$

#### II. D. System core

Literature is the subjective image of the objective world, which has a double relationship between subjectivity and objectivity, but the Western literary theory favors the object relationship, i.e., focuses on "reproduction"; while the Eastern (Chinese) literary theory favors the subject, i.e., pays attention to "performance". I am afraid that the root cause of this is the positive social characteristics of both sides. In the West, business, including foreign trade, the development of earlier, has long been reflected in the ancient Greek epic. China, on the other hand, has always emphasized agriculture, focusing on activities such as farming, mulberry cultivation, and logging. Commerce actively requires one to constantly seek new markets, so they think outward, whereas agriculture is actively self-sufficient and one thinks inward. Perhaps the more immediate reason for this is the different ways in which East and West practiced creativity. China, as a "great poetic nation", has long emphasized lyricism in its literature, while the West has long favored narrative genres.

The development from image to typical concept is a high degree of unity between the characteristic individual and the highly generalized general, which is still the individual and the general in the objective reality. The Chinese also emphasize the unity of the individual and the general, but it is the unity of emotion and reason. The difference in expression and reproduction in turn creates a difference in appreciation. In the West, appreciation is emphasized on cognitive activities, when appreciating a work, the reader will feel interesting, that is because the reader guesses that the work will reproduce some people and things in real life while reading it. On the contrary, the Chinese believe that reading a work is mainly about experiencing and comprehending the writer's emotions.

Along these two different streams of expression and reproduction, more differences between Eastern and Western literary theories can be found in detail.

# III. Analysis of differences in emotional expression between Chinese and Western literature based on computational modeling

# III. A. Comparison of Lexical Characteristics of Chinese and Western Literary Works III. A. 1) Comparison of vocabulary length

Byron is one of the most important representatives of Western Romantic literature, and Du Fu is one of the representatives of Chinese classical literature, and the two poets also have more typical literary works. This paper chooses the literary works of Du Fu and Byron as the research object of the differences in emotional expression between Chinese and Western literary works. The choice of vocabulary is an important manifestation of emotional expression in literary works. In this section, through statistical methods and formulas, vocabulary length and vocabulary density in the works of the two authors are counted to lay a good data foundation for revealing the differences in emotional expression between Chinese and Western literary works.

Figure 4 shows the results of the comparison of the average word length of the literary works of the two authors. The average word length is the ratio of the total number of words to the total number of words in the text, which can be used to reflect the emotional richness and expression habits of the text. If the average word length is small, the



text has more short words, and it is more inclined to express complex and implicit emotions through the combination of short words; if the average word length is large, the text has more long words, and the text contains more semantic information, and the expression of emotions is more delicate and precise. The average word length of Du Fu's literary works ranges from 1.08 to 1.20, and most of them are distributed between 1.10 and 1.18. The average word length of Byron's literary works, on the other hand, ranges from 2.26-2.46, with a concentrated distribution between 2.30-2.42. The overall comparison shows that Du Fu's literary works tend to use about 1 short word to express emotion, while Byron's literary works tend to use 2-3 long words to express emotion. This lexical feature is also in line with the actual differences between Chinese and Western literary works.

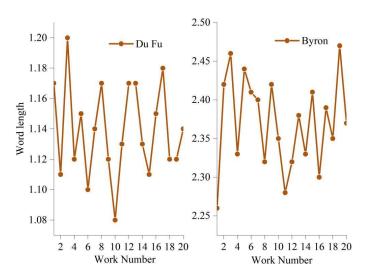


Figure 4: Comparison of the average word lengths of literary works by 2 writers

#### III. A. 2) Vocabulary density analysis

Real words are words that express real meaning and can act as the base constituents of a sentence, and are the main bearers of the content of the text. The so-called lexical density refers to the ratio between the total number of real words and all words in the text. Calculating lexical density can be used to measure the lexical richness of the text and the amount of information contained in the text.

Unlike single-occurrence words, the results of lexical density analysis are less affected by corpus capacity or text length, and thus more scientific for the writers' works selected in this paper. Generally speaking, the amount of information loaded by real words is higher than that of imaginary words, so the larger the proportion of real words and the higher the vocabulary density in a work, the richer the vocabulary of the work and the greater the amount of information loaded. In this paper, real words are categorized into 6 types of nouns, verbs, adjectives, pronouns, number words and quantifiers, and imaginary words are categorized into 5 types of adverbs, conjunctions, prepositions, auxiliaries and onomatopoeia.

Table 1 shows the percentage of word categories contained in the collated Chinese and Western literary works. As shown in Table 1, the lexical density (percentage of real words) of Du Fu and Byron literary works is 74.15% and 78.27% respectively. The lexical density of Dufu's literary works is lower than Byron's, indicating that the lexical richness of Byron's literary works is higher than Dufu's, which is related to the fact that Byron mainly writes long poems, and the length of his poetry is longer than that of Dufu's poems. And as shown by the statistics of the proportion of each word category of real words, the proportion of nouns in Byron's literary works is significantly higher than that of Du Fu (about 2.7 percentage points), while the proportion of verbs and adjectives in Du Fu's literary works is slightly higher than that of Byron (about 1.07 and 1.45 percentage points). Nouns contain nouns of place, nouns of time, names of people and other proper names, etc., suggesting that Byron's literary works may have a richer variety of characters, temporal places and imagery than Du Fu's, who tended to use verbs and adjectives more often in his literary works. In the section on imaginary words, in total, although Dufu's imaginary words and other words are used more frequently than Byron's, the difference in specifics of each item is not really significant.



Table 1: The proportion of word classes

Part of speech	Grammatical category	Du Fu	Byron
	Noun	26.72%	29.42%
	Verb	25.24%	24.17%
Dool word	Adjective	6.10%	4.65%
Real word	Pronoun	12.31%	14.87%
	Quantifiers (including numerals, quantifiers and numerals)	3.78%	5.16%
	Total content words	74.15%	78.27%
	Adverb	5.19%	6.40%
	Conjunction	3.73%	1.56%
Constinuous and	Preposition	3.98%	5.71%
Function word	Particle	10.17%	6.33%
	Onomatopoeia	1.93%	1.00%
	Total of function words	25.00%	21.00%
Other	ldiom	0.25%	0.23%
Other	Other words	0.60%	0.50%

#### III. B. Analysis of lexical affective polarity

The classic literary works of the two authors are used as examples to analyze the differences in emotional expression between The Song of the Thatched Cottage Broken by the Autumn Wind (Du Fu) and The Travels of Childe Harold Byron. The extracted words are embedded with cultural attribute vectors using the model of this paper, and the metaphorical sentiment polarity of the keywords of the resulting literary works is calculated and categorized. Table 2 shows the results of the analysis of the metaphorical emotional polarity of the keywords of the literary works of the two authors. Du Fu's The Thatched Cottage Broken by the Autumn Wind and the Song mainly uses six keywords, namely, thatched cottage, autumn wind, thatched grass, broken, song, and shelter, to express the emotional connotations of this literary work, which are dominated by the negative emotions, thatched cottage (20% of the negative emotions), autumn wind (15% of the negative emotions + 2% of the positive emotions), thatched grass (15% of the negative emotions), broken (21% of the negative emotions), and song (15% of the negative emotions), Shelter (10% negative emotion + 2% positive emotion). Byron's "Travels of Childe Harold" similarly uses six keywords to express the emotions of the work, which tend to be positive, including travel (15% positive emotion), travelogue (5% positive emotion), hero (20% positive emotion), freedom (25% positive emotion), exploration (20% positive emotion), and reflection (15% positive emotion). The Song of the Thatched Cottage for the Autumn Wind uses three nouns and three verbs to express its somber and staccato negative emotion, while Childe Harold's Travels uses four nouns and two verbs to express its passionate, individualistic, positive and enterprising spirit. Overall, it is in line with the emotional expression habits of the two writers' literary works and the characteristics of Chinese and Western literary works. This shows that the metaphorical emotional polarity calculation in this paper is accurate and can be continued to analyze the other literary works of the two writers and other representative writers' literary works for continuous lexical metaphorical emotional polarity analysis.

Table 2: Analysis results of metaphorical emotional polarity

Writer	Kaywarda	Metaphorical emotional polarity		
	Key words	Positive emotion (%)	Negative emotion (%)	
Du Fu	Thatched Cottage	0	20	
	Autumn Wind	2	15	
	Quilt	0	15	
	Break	0	21	
	Roll	0	15	
	Sprinkle	2	10	
Byron	Travel	15	0	
	Pilgrimage	5	0	
	Hero	20	0	
	Freedom	25	0	
	Explore	20	0	
	Reflect	15	0	



#### III. C. Emotional polarity statistics of literary works

After calculating and categorizing the metaphorical emotional polarity of the vocabulary contained in different literary works, the differences in emotional expression in the relevant literary works of Byron, a representative writer of Western Romantic literature, and Du Fu, a representative writer of Chinese classical literature, are determined by combining the semantic correlation calculations of the vocabulary and the context. Table 3 shows the statistical results of metaphorical emotional polarity of different literary works. Among the 6 classic representative poems of Du Fu, only the positive emotion of "Hearing the Official Army Collecting Henan and Hebei" reaches 87%, and the remaining 5 works are dominated by negative emotions, reaching 89%, 65%, 13%, 90% and 95%. In contrast, among Byron's six classic works, only Manfred reaches 55% of negative emotions, and the remaining five works are dominated by positive emotions, which are: 78%, 60%, 59%, 60% and 55%, respectively. As can be seen from the statistics of metaphorical emotional polarity of representative poets' surrogate literary works, Western Romantic literature is accustomed to glorifying people and things, and prefers to use long words and phrases to express the passion for changing society and the pursuit of personal values. On the other hand, classical Chinese literature tends to use short nouns and verbs to express worries about the country, society and people's lives, and emotionally to be implicit and deep, full of grief and indignation for the sufferings of the world.

Metaphorical emotional polarity Writer Words Positive emotion(%) Negative emotion(%) 89 View in Spring 11 Climbing High 35 65 Song of My Thatched Cottage Unroofed by Autumn Winds 10 90 Du Fu On Hearing the Official Army Has Recovered the Central Plains 87 13 Climbing Yueyang Tower 10 90 Composed on a Traveler's Night 5 95 Childe Harold's Pilgrimage 78 22 Don Juan 60 40 The Age of Bronze 59 41 Byron Manfred 45 55 60 40 Cain The Lonely One 55 45

Table 3: Statistics of metaphorical emotional polarity in different literary works

#### IV. Conclusion

This paper analyzes the differences in the tendency and expression of emotion between Western Romantic Literature and Chinese Classical Literature by constructing a computational model of emotional polarity. Western Romantic literature is accustomed to expressing positive and aggressive emotions through long words and phrases (average word length 2.26-2.46) and real words (78.27% of the total) (the sum of positive emotions of 6 keywords reaches 100%, and 5 out of 6 representative works express positive emotions). On the other hand, classical Chinese literature is used to express positive and aggressive emotions through short words and phrases (average word length 1.08-1.20) and real words (74.15%) (the sum of negative emotions for 6 keywords is 96%, and 5 out of 6 representative works express negative emotions). The differences in emotion expression stem from the differences in Chinese and Western culture and economic politics, etc. In the future, multidimensional difference factors can be introduced to explore the root causes of the differences in emotion expression.

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#### References

- [1] Pashkurov, A. N., & Razzhivin, A. I. (2016). Literary culture its types and lessons. European journal of science and theology, 12(2), 155-164.
- [2] Eslit, E. R. (2023). Enduring Synergy of Values Integration, Critical Thinking, and Moral Reasoning in Language and Literature Education.

  Online Submission.
- [3] Abida, F. I. N. (2016). Critical thinking skills to literary works: A method of teaching language through literature. JEES (Journal of English Educators Society), 1(1), v1i1-148.



- [4] Wang, C. M. (2012). Geopolitics of literature: Foreign literature studies in early twentieth-century China. Cultural Studies, 26(5), 740-764.
- [5] Ming, C. (2024). A comparative evaluation of the narrative thoughts in Chinese and Western classical literature. Trans/Form/Ação, 47(5), e02400135
- [6] de Almeida, H. (2007). Literature, Science and Exploration in the Romantic Era: Bodies of Knowledge. Clio, 36(2), 275.
- [7] Kapishin, A. E. (2024). Transgression of the romantic movement in Western society: The unity of Romanticism and Modernism. RUDN Journal of Sociology, 24(4), 906-927.
- [8] Qunying, X. (2007). Cultural difference between the East and the West. Canadian Social Science, 3(5), 114-117.
- [9] Wang, Z. D., Wang, Y. M., Li, K., Shi, J., & Wang, F. Y. (2021). The comparison of the wisdom view in Chinese and Western cultures. Current Psychology, 1-12.
- [10] Li, Z. (2024). Study on the Influence of Western Literature on Modern Chinese Literature under the Effect of Translation Culture. Academic Journal of Humanities & Social Sciences, 7(4), 160-164.
- [11] Jiang, Z. (2015). Identification of Issues Concerning Contemporary Western Literary Criticism: With Concurrent Reflections on the Reconstruction of Chinese Literary Criticism. Social Sciences in China, 36(1), 5-29.
- [12] Keping, W. (2017). Interactions between western and Chinese aesthetics. In The Pursuit of Comparative Aesthetics (pp. 123-136). Routledge.
- [13] Zhu, Z. (2020). Western theory and historical studies of Chinese literary criticism. CLCWeb: Comparative Literature and Culture, 22(5), 11.
- [14] Cao, S., & Wang, M. (2014). Variation study in Western and Chinese comparative literature. Mo Yan in Context: Nobel Laureate and Global Storyteller, 183-93.
- [15] Sun, H., & Han, Y. (2025). A Philosophical Examination of Cultural Absorption and Linguistic Expression in Religious Literary Works. Cultura: International Journal of Philosophy of Culture and Axiology, 22(4).
- [16] Li, J. (2022). Emotion expression in modern literary appreciation: An emotion-based analysis. Frontiers in Psychology, 13, 923482.
- [17] Acerbi, A., Lampos, V., Garnett, P., & Bentley, R. A. (2013). The expression of emotions in 20th century books. PloS one, 8(3), e59030.