Retraction

Retracted: Comparison and Research on the Applicability of Combining Information of Chinese and Foreign Literary Genres Based on Data Analysis

Mathematical Problems in Engineering

Received 13 September 2023; Accepted 13 September 2023; Published 14 September 2023

Copyright © 2023 Mathematical Problems in Engineering. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

1. Discrepancies in scope
2. Discrepancies in the description of the research reported
3. Discrepancies between the availability of data and the research described
4. Inappropriate citations
5. Incoherent, meaningless and/or irrelevant content included in the article
6. Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article’s content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

Research Article

Comparison and Research on the Applicability of Combining Information of Chinese and Foreign Literary Genres Based on Data Analysis

Mingyue Xing,1 Qiang Lu,2 Qi Cui,3 and Jiamin Xie1

1School of Humanities, Chang’an University, Xi’an 710018, Shaanxi, China
2College of Management and Economics, Tianjin University, Nankai 300110, Tianjin, China
3Sangong Bureau of China Communications Construction Group, Baodi 301800, Tianjin, China

Correspondence should be addressed to Mingyue Xing; 2019903521@chd.edu.cn

Received 14 January 2022; Revised 11 February 2022; Accepted 25 February 2022; Published 30 March 2022

Academic Editor: Gengxin Sun

Copyright © 2022 Mingyue Xing et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Western literature has a later history of factual connection with Chinese literature, and the resources for empirical research are far less abundant than in other Eastern countries. It is also because Western culture is a different cultural system from Eastern and Chinese cultures, which also lends itself to parallel studies that seek common ground in differences and see differences in the same. In this paper, we will mainly compare Chinese and Western literature from the perspective of the lack of factual relationship between Chinese and foreign literature and explore the integration and development of the national traditional literature by combining computer algorithms.

1. Introduction

In terms of race, the Chinese are more practical than metaphysical, with moral creeds being the most developed and systematic metaphysics being silent; in terms of literature, works on human and social issues are the most developed, while works based on imaginary structures are rare. Chinese nationality is the most “practical” and “humane.” This is its strength and weakness. Its weaknesses are also reflected here. Its strength lies in the importance it places on human relations, enabling a disorganized society to remain stable for more than two years, but its weakness lies in its overemphasis on humanism and existentialism and its inability to pursue a higher status [1]. The first, the most superficial, is “sensualism,” the second begins with tacit love and joy, and the third is pantheism, in which nature is seen as a manifestation of God and his mysterious and superhuman sense of power, and the worship of nature becomes a religion. This is the attitude of most Western poets toward nature, and few Chinese poets have reached this level. In terms of philosophy and religion, Zhu Guangqian argues that “Western poetry is deeper and broader than Chinese poetry because it has a deeper and broader philosophy and religion that nurtures its roots and backbone [2].”

As an example, language textbooks have limited pedagogical capacity, and most of the foreign literature is chosen based on the principles of genre complementarity and adequate argumentation. The authors use Hamlet (excerpt), text in the human education version of the high school language, as an example, where the references to Christian imagery and biblical structure can be clearly seen and the text moves towards mysticism from the appearance of the old king’s ghost. However, in contrast, the selection of domestic literature in the textbook, such as the large proportion of ancient poems in the textbook, reflects the recognition of the “practicality” and solidity of tradition in contemporary Chinese literature, in addition to the realistic content and moral connotations of the ancient poems themselves.

In fact, the more active a literary work is, the less it will fade away from the heraldic symbols of national life and spirit, and the less it will sever its natural connection with the
national literary tradition [3], as opposed to sticking to tradition. Both Chinese literature and the history of the national literature of the world provide such indications. It is hard to imagine that a particular country or nation could build its own sublime literary temples on the ruins of its culture. It is hard to imagine that any one nation or people could build its own sublime literary temples on cultural ruins [4, 5]. The argument that the so-called "yellow culture" should be transformed into "blue culture" has become a theoretical fashion and guide for the practice of literary should be transformed into "blue culture" has become a theoretical fashion and guide for the practice of literary creation. This trend of thought is also a symbol of the era of reform and opening up, which increases the complexity of distinguishing right from wrong [6].

However, the dichotomy between "yellow culture" and "blue culture" has led to the lack of a close relationship between the language materials of Chinese and foreign literature, which are scattered in the language materials of primary and secondary schools. In the author’s opinion, foreign literature in language textbooks should strengthen the horizontal connection with Chinese literature, absorb the favorable factors that keep foreign literature alive, and strengthen the means of traditional culture education [7], so as to make use of the clear framework, long history, and coherent development of Chinese literature and establish corresponding connections, so that the study of foreign literature from the perspective of Chinese traditional culture not only enables us to analyze foreign literature in a more profound way but also allows us to analyze foreign literature from the perspective of Chinese traditional culture. Works in a more profound way, but also to transmit traditional culture and improve the proportion of traditional culture in the teaching of secondary school [8], the authors also hope to use the framework of experimental research on traditional culture and traditional literature to provide a reference for better dissemination of traditional culture in teaching and for further integration of language teaching and traditional culture transmission, textbook texts and group reading [9].

Since the 21st century, artificial intelligence techniques have evolved as computer performance has improved and massive amounts of data have become available. In 2012, AlexNet, designed by Hinton and his student Alex Krzyzewski, won the image classification competition [10], and since then, deep learning has become increasingly well known. Deep learning is a branch of machine learning that has achieved great success in breaking through traditional machine learning bottlenecks such as image recognition, audio processing, and natural language processing and has opened a new era of artificial intelligence. Natural language processing (NLP) usually includes linguistics, mathematics, computer science, and other related knowledge, is a fusion of multiple disciplines, and is an important research direction in the field of artificial intelligence [11].

In this paper, based on the existing research results of 2. Related Work

Literature is a representative poetry genre in Chinese traditional poetry, and the study of literature generation-related work can be seen as a study of poetry generation-related work. The study of literary production can be seen as the study of poetry generation, so this section focuses on the current state of research on literary production. Therefore, this section discusses the current state of research on literary production, mainly in terms of the current state of research on poetry production. [12] proposed a poetry generation method, but it only uses the random combination of phrases to generate poetry. The main rule- and template-based generation methods are template-based methods [13, 14] and instance-based reasoning methods [15], which are more likely to generate poems by filling in the blanks and combinations through template settings, and the generated poems are very incoherent and cannot even be called poems in the traditional sense. In the stage based on statistical machine learning, [16] introduced genetic algorithms in Song word generation and regarded Song word generation as an optimization problem; [17] regarded the poetry generation problem as a summary generation problem specifying the writing intention by retrieving words in a poetry corpus for sorting and then combining them to form verses; [7] regarded poetry generation as a machine translation problem for poetry generation and proposed a poetry generation model based on statistical machine translation-based Chinese poetry generation model.

With the development of deep learning technology, poetry generation methods based on deep learning technology began to appear, and the research on poetry generation has entered a new stage. Recurrent neural network-based Chinese traditional poem generation (RNN-based Poem Generator, RNNPG) [11] generates the whole poem line by line by user-supplied keywords, then expands the keywords, given the relevant metrical restrictions, and then selects the best-ranked one as the first line of the poem. Reference [6] combines the attention-based mechanism of neural network machine translation method. Attention based Neural Machine Translation Network (ANMT) [12] is applied to the generation of song lyrics, which treats song lyrics generation as a translation problem, and takes the generated verses as the input and the verses to be generated as the target output for poetry generation. iPoet is a poetry generation system based on the encoder-decoder framework [13], which generates poems by Hafez and it is a program that generates any number of poems based on a user-provided theme [14], which implements the generation of English poems based on the encoder-decoder framework.

The Planning based Poetry Generation (PPG) model [15] imitates the human action of writing a poem to outline and divide the poetry writing process into two stages, poetry planning and poetry generation, by planning subthemes for poetry generation, which solves the problem of theme drift to some extent, but its theme planning is based on modern vernacular. It is easy to cause the problem of poor semantics. The Natural Language Processing and Social Humanities Computing Laboratory of Tsinghua University proposed a
poetry generation method based on Salient-Clue Mechanism [16], which extracts words with salient features from generated verses and restricts the type of generated poems to generate poems, which has good contextual coherence and better overall effect.

3. Design of the Literature Generation Model Based on Keyword Transformation Extension

3.1. Literary Generation Problem Description. The study of literature generation in this paper is based on deep learning techniques, and its overall process is shown in Figure 1.

3.2. Design of the Literature Generation Model Based on Keyword Transformation Extension. From the above studies of literature generation-related work, we can find that the generation of poetry in literature and other genres generally faces two problems: (1) thematic drift. That is, in the process of literary generation, as the length of the generated verses increases, the subsequent generated verses appear to deviate from the theme of the writing; (2) semantic incoherence, i.e., the generated verses have semantic incoherence, such as vernacular language and incoherence in the verses. This study addresses the above problems. Based on the existing literary generation methods, we propose a literary poem generation model based on keyword transformation extension. Based on the existing literature generation methods, we propose a Keyword Transformation and Expansion Quatrain Generation Model (KTEQG), which first extracts the unique topic keywords through the user’s input of writing intention and then transforms the keywords into a literary language to generate the poem. The transformed keywords are subjected to literary transformation, and then the transformed keywords are subjected to thematic expansion, and each line of verses by assigning relevant topical words, and an encoder-decoder model based on the attention mechanism, which takes each keyword and history generation as input for a literary generation.

The model is divided into three stages: keyword conversion, keyword expansion, and literature generation. In the keyword conversion stage, keyword extraction is first performed on the user’s writing intention (user input topic words, sentences, or text passages) to determine the unique topic keywords, and then the unique keywords are converted into literary keywords words. The keyword expansion stage expands the literary keywords to four subtopic keywords based on the literary corpus, which are assigned to each line of literature. In the literature generation phase, the subthemes generated in the keyword expansion phase and the historically generated verses are used as input to output the next line of poetry and repeated until the whole poetry generation is completed.

3.2.1. Keyword Conversion. In this study, since there is no keyword annotation data in the collected literary corpus, and the supervised and semisupervised methods need to annotate the poetic corpus with keywords, if the literary corpus is manually annotated, the workload is huge, too tedious, and too costly. Therefore, the unsupervised method is chosen for user writing intention keyword extraction in this study. The commonly used unsupervised methods include the TF-IDF algorithm [8], LDA topic model [4], and TextRank algorithm [9], etc. The TF-IDF algorithm judges the importance of words purely by word frequency, which usually works better in long texts but is not suitable for short texts like literature.

The TextRank algorithm is derived from Google’s PageRank algorithm, which is a graph-based ranking algorithm. The PageRank algorithm slices the text into several component units and then builds a graph model and ranks the words in the text through a voting mechanism. The algorithm only needs the information of a single text itself to achieve keyword extraction. This algorithm only requires information from a single text to achieve keyword extraction, and it is used by Google Let’s Rank to rank web pages by calculating the number and quality of web links. The algorithm is used by Google to rank web pages by calculating the number and quality of web links to measure the importance of web pages. The TextRank algorithm, on the other hand, performs keyword extraction by first dividing the text into multiple text units. The similarity between several text units is the edge between nodes. The graph model is formed by using the PageRank algorithm to iterate the graph model until it converges.

The TextRank algorithm model is usually denoted by $G = (V, E)$, where $V$ denotes the set of nodes in the graph, $E$ denotes the set of edges in the graph, and $E$ is a subset of $V \times V$. The score of node $V_i$ is shown in the following:

$$WS(V_i) = (1 - d) + d \sum_{V_j \in \text{In}(V_i)} \frac{w_{ij}}{\sum_{V_k \in \text{Out}(V_j)} w_{kj}}.$$  

When using the TextRank algorithm, the initial value is usually set to 1 for all nodes, and the convergence threshold is usually set to 0.0001, i.e., convergence is achieved when the error rate is less than 0.0001, and the iteration is stopped. When applied to keyword extraction specifically, the TextRank algorithm focuses on keyword extraction through cooccurrence relationships between lexical items. The steps are as follows [9]:

1. Segmenting the text: the input text (i.e., the poetry writing intention) is segmented into sentences, and then the sentences are divided into words and lexical annotations.
2. Filtering lexical items: firstly, deactivated words are filtered; then, lexical filtering is performed to retain specific lexical items such as nouns and adjectives.
3. Constructing graph model: lexical items are used as nodes, and cooccurrence relations between lexical items are used as edges. If two lexical items cooccur in a window of length $N$, an edge is determined to exist between these two nodes, and thus an undirected unweighted graph is constructed, where $N$ usually takes a value from 2 to 10.
4. Substitute into the formula; iterate until convergence. When TextRank algorithm is used for
keyword extraction, there is no weight size between words, and the initial value is assumed to be 1. Therefore, formula (2) is modified and adjusted as follows:

$$WS(V_i) = (1 - d) + d \times \sum_{V_j \in \text{In}(V_i)} \frac{1}{\text{Out}(V_j)} WS(V_j).$$

(2)

(5) Output keywords: all nodes are sorted, and the word with the highest score is the unique keyword for poetry theme extraction.

After the unique keyword extraction of writing intention is completed by the above way, since the extracted keywords are prone to vernacular words in modern Chinese, and in literature generation, it is based on ancient literary words in literary corpus verses, so the mismatch between modern vernacular words keywords and it is not conducive to literature generation, which may result in poor semantics of generated poems. To solve this problem, the literary generation model proposed in this paper will perform literary conversion after extracting the unique topic keywords and then perform topic expansion based on the converted literary words to generate literary subtopic keywords words before literary generation. This study will directly use the relevant interface of the Baidu translation open platform to perform keyword conversion.

Baidu Translation Open Platform is a platform for Baidu Translation to provide open services for developers, relying on Baidu’s powerful natural language processing technology and high level translation technology and providing powerful, simple and easy-to-use translation APIs and SDKs and other interface services for developers. Its universal translation API supports 28 languages such as Mandarin, Chinese, English, Japanese, and Korean translation for free. Simply call the universal translation API, input the corresponding translated content, and set the source and target languages to get the desired translation results [2]. Therefore, the extracted unique keywords can be translated by using the universal translation API to realize the translation service of converting modern vernacular words to literary words. The Baidu Universal Translation API is used as follows [8]:

1. Login to the Baidu translation open platform (http://api.fanyi.baidu.com) with a Baidu account.
2. Register as a developer, obtain the APPID of universal translation, and perform developer authentication to open the universal translation API service and open the link.
3. Call the translation API through the HTTP interface, pass in the content to be translated, specify the source language and target language, and get the corresponding translation results. Among them, Input: access the service by sending a field to the Universal Translation API HTTP address via the POST or GET method.

3.2.2. Literary Generation. The literary generation phase, where the subject keywords are transformed and expanded, is achieved by assigning subsubject keywords, which can be seen as a sequence-to-sequence generation process, which will be based on the previously extracted and transformed expanded subsubject keywords. The literary generation will be based on the previously extracted and transformed extended subtopic keywords and the historically generated content, and this paper will use an attention mechanism based encoder-decoder model for literary poem generation. This paper will use an attention-based encoder-decoder model for literary poem generation.

The encoder-decoder is a sequence-to-sequence model, which transforms the input sequence into a fixed vector in the encoding phase and a fixed vector in the decoding phase. Into a fixed vector, the decoding stage decodes the fixed vector output from the coding side into an output sequence, and its input sequence and output sequence are the same length. This model is widely used in image processing, translation, and other fields. It is a framework class model rather than a specific model. The input and output can be various data forms, such as text, audio, image data, etc., and can also be various deep learning models, such as CNN, RNN, LSTM, GRU, etc. Its model framework can be GRU, etc., and its model framework can be abstractly represented as in Figure 2.

In the field of natural language processing, the encoder-decoder framework can be understood as a processing
model that turns a sentence into another form but without changing its meaning into a processing model. For a sentence pair \( <X, Y> \), given a sentence input sequence \( X \), we can obtain the generated target \( Y \) by the model, where \( X \) and \( Y \) are composed of different word sequences each:

\[
X = (x_1, x_2, \ldots, x_m),
\]

\[
Y = (y_1, y_2, \ldots, y_n).
\] (3)

The encoder encodes \( X \) and transforms the input sequence into a fixed-length vector of intermediate semantic expressions \( C \) using the model \( f \), where

\[
C = f(x_1, x_2, \ldots, x_m).
\] (4)

The decoder uses the intermediate vector \( C \) with the generated \( y_1, y_2, \ldots, y_{i-1} \) information to generate the words to be generated at time \( i \), where

\[
y_i = g(C, y_1, y_2, \ldots, y_{i-1}).
\] (5)

In practical applications, in the field of translation, such as English to Chinese, the input is an English sentence and the output is a Chinese sentence, while for speech recognition, the input is an English sentence and the output is a Chinese sentence; for translation from Chinese to English, the input is a Chinese sentence and the output is an English sentence, and for speech recognition, the input is a Chinese sentence and the output is an English sentence. For long sequence data, the semantic information expression is composed of different word sequences. Each segment is encoded into a vector and the vector finally composed of different word sequences is an input to the encoder, so it has the same effect on generating words in the target sentence, and the vector \( C \), which makes the detailed information easily lost.

In order to solve the above problem, the attention model is introduced, and the attention model is changed from the original fixed middle semantic vector \( C \) to \( C_i \), which can be dynamically changed according to the current output words, and the encoder-decoder framework with the added attention model is shown in Figure 3.

At this point, the word \( y_i = g(C, y_1, y_2, \ldots, y_{i-1}) \) is generated for time \( i \), where

\[
C_i = \sum_{j=1}^{T_x} a_{ij} h_j.
\] (6)

The length of the input sequence is \( T_x \), \( a_{ij} \) indicates the attention weight distribution of the input \( j \)th word at the output \( i \)th word, and \( h_j \) indicates the semantic encoding of the input \( j \)th word. The probability distribution of the input word \( y_i \) can be compared with the node state \( x_1, x_2, x_3 \) of the RNN implicit layer at the output \( i-1 \) moment and the node state \( s_{i-1} \) of the RNN implicit layer for each input word; i.e., the function \( h_j \) is used to obtain the alignment between the target word and the input word. The alignment of the target word \( F(h_j, s_{i-1}) \) and the input word is finally normalized by the softmax activation function to obtain the value of the attention allocation probability distribution.

The above is the common method for calculating the probability of attention allocation for most attention models, where the definition of the F-function may differ for different attention models, as shown in Figure 4.

The traditional encoder-decoder model based on the attention mechanism has only one input, and in literary generation studies, in addition to the subject keywords, there is also historically generated content as input. Here we refer to the design of the PPG model and modify it based on the encoder-decoder model based on the attention mechanism in order to realize both keywords and already generated poems as poetry input.

4. A Comparative Guide of Traditional Chinese and Western Literature

In 1925, Shen Yanbing’s (real name Shen Dehong, pen name Mao Dun, 1896–1981) first mythological research paper, “A Study of Chinese Mythology,” was published in Fiction Monthly, Vol. 16, No. 1. He tried to apply the mythological theories of the European school of anthropology to explain the problem of Chinese mythology. Before discussing Chinese mythology, he quoted the main ideas of Andrew Lang (1844–1912) and A. Mackenzie (commonly known as Mackenzie) as the theoretical basis for his discussion of Chinese mythology, saying, “When we discuss Chinese mythology on the basis of this basic idea, we have a scope, a standard,” he says. Based on Lan’s principles, he has worked out “three levels of formalities” (i.e., three principles) for the study of Chinese mythology.

First, to distinguish which are primitive myths and which are fairy tales.

Secondly, to distinguish which are foreign myths and which are indigenous myths.
Third, to distinguish which myths were influenced by Buddhism.

He argues that if Chinese mythological materials are studied according to these three principles, then myths that express the primitive beliefs and living conditions of the Chinese people will come to the fore. These three principles, especially the last two, emphasize the diversity of literature in the comparative study of Chinese mythology and foreign mythology. Qian Zhongshu (1910–1997), who, like Zhu Guangqian and Liang Zongdai, had the same experience of studying abroad and the same solid training in Chinese and Western studies, also stepped into the field of comparative literature in his own way.

Like Zhu Guangqian and Liang Zongdai, his research interests were mainly in the field of Chinese and Western poetry, but unlike Zhu Guangqian’s logical and systematic research, Qian was more inclined to make comparisons between the West and the East in the manner of Su’s essays, somewhat similar to Liang Zongdai in this respect. However, he was an extremely documentary researcher who was not tired of citing literature, in contrast to Liang Zongdai’s straightforward and brisk style of criticism. In this period, apart from a few articles in Chinese and English, such as “A Feature of Chinese Inherent Literary Criticism” (Literary Magazine, vol. 1, no. 4, 1937), Qian’s main work in academic research was a collection of essays and journals centered on the evaluation of classical Chinese poetry, “Tangyi Lu” [18].

The book was written between 1939 and 1942 and published by Kaiming Bookstore in 1948. The entire text is written in Mandarin, and the text is rather archaic, with some quotations in English interspersed in between, making the quotations seem piled up, complicated, and trivial, and not easy to read for nonspecialist readers. There are ninety-one journals in The Book of Talks and Art, and eighteen “addenda” were added later. It is a collection of fragmentary texts with no logical connection between chapters, few terms and concepts, no theoretical propositions, and no systematic construction. The structure is loose, the content is mixed, and the text is free and loose, all of which make “Tal-Yi Lu” resemble traditional Chinese poetic discourse. After the modern era, this traditional poetic style of writing and research is almost unheard of. However, this style of writing seems to be very suitable for Qian Zhongshu’s academic personality, which does not follow the fashionable trend and does not follow the crowd, and which is free and spontaneous, so it seems to be comfortable to use. More importantly, the “art of speaking” is not a poetic discourse, as it contains a large amount of indirect material from foreign literature and culture while extensively citing material from ancient and modern China, composing a special structure.

Discourse text: It is for this reason that those who study comparative literature have reason to regard it as the fruit of comparative literature. When Qian Zhongshu talks about the topic of Chinese cuisine, he must use similar or relative multimaterial from the West as supporting evidence or circumstantial evidence, in order to emphasize his overall view of world literature, as he says in the preface: “The East and the West are the same in psychology; the South and the North are the same in learning, but not in the art of Taoism.”

5. Experiment

Due to the special structure of literature and its metricality, it is usually difficult to conduct a simple quantitative evaluation of literature generation models. In this paper, automatic evaluation, manual evaluation, and Turing test are designed to verify the validity of the model. The following is a description of the relevant evaluation methods in this paper.
5.1. BLEU Automated Evaluation. BLEU (bilingual evaluation understudy) is a common evaluation algorithm for machine translation, which is used to define the similarity between machine translation and reference translation. When the machine translation is closer to the human reference translation, the translation quality is higher. BLEU uses the N-gram matching rule to compare the similarity

\[
\text{BLEU} = \frac{\text{the number of words in the machine translation that appear in the reference translation}}{\text{total number of words in machine translation}}
\]

Example:

Original text: I ate an apple today
Machine translation: I eat an apple today
Reference translation: I ate an apple today

If there are 5 words in the machine translation, and 3 words are the same as the reference translation, the BLEU value is 3/5.

As shown in Figure 5, because the literature generation model proposed in this paper is based on the previous sentence history to generate poems and subthemes for generation, its generation process is to some extent similar to machine translation because literature generation is unlikely to produce poems that are exactly the same as the training poetry prediction, which is not the working principle of the objective function; BLEU can only roughly calibrate the generation ability of poems, reflecting the similarity of the generated poems to the training prediction, but the results are also instructive and can reflect the fluency of the generated poems to some extent. Therefore, for the evaluation of the literary generation model, the BLEU algorithm was borrowed for automatic evaluation [18, 19]. In this method, BLEU takes a value between 0 and 1, and its value can only be 1 when the translation is exactly the same as the reference translation. Hence, a larger BLEU value indicates a better translation model. When the generated verses are close to the reference next lines of the training corpus, then a larger BLEU value is considered a better poetry generation.

5.2. Manual Assessment. The quality of poetry production is mainly assessed manually, usually based on four evaluation criteria: fluency, coherence, metricality, and meaning [6, 10, 11]. The existing assessment of the quality of poetry generation is mainly conducted manually, usually based on four evaluation criteria: fluency, coherence, metricality, and meaning [6, 10, 11], which mainly consider the fluency, coherence, metricality, and meaning of the generated poems, i.e., whether the metricality is qualified, whether the verses are fluent, whether the verses are coherently related, and whether the verses have content and meaning. Combined with studies related to the literary aspects of literature, it is found that the evaluation of literature from these four criteria only is one-sided, as shown in Figure 6 the probability of the distribution of literary vocabulary; the above four criteria can be said to be the most basic requirements for generating sentences that can be called poetry, and a qualified poem, in addition to the basic requirements such as semantic coherence, flatness, and rhyme, the context/emotion of the poem is more important, and contextual interplay is the most appropriate criterion for evaluating poetry. The most appropriate criterion for evaluating a poem is the blending of moods and emotions [5].

Therefore, in this paper, based on the existing manual evaluation criteria for poetry, we add two evaluation indicators of mood/emotion and tangency. The improved manual evaluation criteria are shown in Table 1.

In the specific manual evaluation process, the evaluator was required to have a professional background in poetry, and then, according to the above table, he or she looked at “fluency,” “coherence,” “metricality,” “meaning,” “mood/emotion,” and “tangibility” respectively. “meaning,” “mood/emotion,” and “relevance.” The final score of the poetry generation model is then taken as the average value of the evaluation scores. Then, the average score of the evaluation is taken as the final score of the poetry generation model, which is used to evaluate the goodness of the generated literature.

5.3. Turing Test. The concept of the Turing test was introduced by Alan Matheson Turing in his 1950 article “Computers and Intelligence” [1]. Turing used the test as a criterion for determining whether a computer possessed normal human intelligence. Turing’s test is administered by isolating a human from a computer and then asking the participant questions to determine which one is the correct one. If the error rate exceeds 30%, the computer passes the test and has human intelligence, and this test is called the Turing test [2]. The effect of different vocabulary clustering is shown in Figure 7, so in the literary generation study of this paper, if it passes the Turing test, it can prove that the literary generation model proposed in this paper reaches the level of ordinary human creativity. This experiment has feasibility and reference value for assessing the good and bad literary generation.

Firstly, by extracting any number of human-created literature for theme generalization, the computer-generated poems and the human-created poems are composed into test cards, randomly labeled as Literature I and Literature II, and the evaluator makes judgments on the literature in the cards
in turn. As shown in Figures 2–7, the test participants were asked to make judgments from the following three options: A. Literature 1 was written by humans; B. Literature 2 was written by humans; C. Both could not be judged. When the test results were tallied, if the computer-generated literary poem was judged to have been composed by humans, it was recorded as incorrect; otherwise, it was recorded as correct.

By performing statistics on the test cards, the final judgment of the correct rate, the error rate, and the inability to judge rate were obtained to perform Turing test result analysis.
6. Conclusions

In this paper, we first describe the deep learning problem of literature generation, in general; then, we describe the rule-based and template-based generation approach, the statistical machine learning-based approach, and the deep learning-based approach; Rule- and template-based generation methods, statistical machine learning-based methods, and deep learning-based methods; then the three phases. The evaluation system of literary generation in this study is introduced, and this study will be conducted from automatic evaluation, manual evaluation, and Turing test. This study evaluates the model from three aspects: automatic evaluation, manual evaluation, and Turing test.
Data Availability
The raw data underlying the results presented in the study are included within the manuscript.

Conflicts of Interest
The authors declare that they have no conflicts of interest regarding this work.

References