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Research Article

Research on Literary Translation Based on the Improved Optimization Model

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Machine translation is widely used in people's daily lives and production, occupying an important position. In order to improve the accuracy of the literary intelligent translation, research on literary intelligent translation is based on the improved optimization model. Based on semantic features, the semantic ontology optimization model including an encoder and a decoder is created by machine translation. In order to improve the accuracy of the intelligent translation literature of the semantic ontology optimization model, the conversion layer, including the forward neural network layer, residual connection layer, and normalization layer, is added between the encoder and decoder of the semantic ontology optimization model. An improved optimization model is established, and syntax conversion is realized by using the conversion layer, which completes the intelligent translation of literature. It is found that the BLEU value of using this method to translate literary sentences can reach 17.23 when the number of training steps is set as 8000, and the training time is low. The translation result has a low correlation misalignment rate, which can meet the user's literary translation needs.

1. Introduction

The "Going out" of Chinese culture has become an important development strategy to enhance the soft power of national culture. Literary works are important carriers of national cultural elements. How to translate and introduce literary works with regional characteristics to overseas and achieve the dissemination and acceptance target in the context of Chinese culture and literature is the key to the "going out" of Chinese culture and literature [1]. Literary intelligent translation has received widespread attention. Although some of the current literary works are translated by practitioners, the translation workload is large, and the speed of manual translation and proofreading cannot meet the needs of a large number of literary translations, requiring a large amount of manual input [2].

With the implementation of the "One Belt, One Road" initiative and the "Going Global" strategy of Chinese culture, Chinese-English translation, especially the English translation of Chinese literature, is an important field of translation research in the future. At present, a large number of researchers have developed machines for the English translation of Chinese literature translation research. Gnevsheva K et al. are innovators in machine translation research. They studied the Australian English bilingual corpus and determined the automatic forced alignment accuracy of Russian and English [3]. However, this method takes a long time to complete when querying a literary corpus, which reduces the translation efficiency. Lestari et al. fully considered the importance of phrases in language [4] and studied amplification and description techniques in Arabic phrase translation. Neural injection of phrase translation resources is by Sen et al. [5]. The above two methods decompose long sentences into words for translation, but because the words in Chinese literature have different meanings in different long sentences, the translation accuracy of the above two methods needs to be further analyzed; Pan et al. combined machine translation with a multisource neural model [6] to improve language translation performance; Li et al. established the Attention-seq2seq model with fusion feature based on CRNN

[7], which has very high translation effect; Wunier et al. researched on improving Mongolian-Chinese machine translation based on the CNN root morphological selection model [8]; Wu et al. studied multimodel fusion Mongolian-Chinese neural machine translation based on CSGAN [9], both of which are more effective machine translation methods. The above four methods use other models to improve the original machine translation model and improve the translation performance. However, considering that Chinese characters have the characteristics of large information entropy and strong ideographic ability, they have a certain ambiguity in translating literary works.

Research on intelligent literary translation based on the improved optimization model uses the improved optimization model to achieve intelligent literary translation and achieves literary translation from an intelligent perspective, which can meet the needs of literary translation and proofreading. This research improves the optimization model applied to the intelligent translation of literature, fully considers the characteristics of Chinese use, and establishes an optimization model of semantic ontology. And add the conversion layer of changeable syntax to the encoder and decoder to meet the needs of Chinese characters with large information entropy, many types, and strong semantic ability and process literary sentences into word sequences. The experimental results verify the effectiveness of this method with high intelligent translation, and the results of this research are helpful to promote the overseas translation and dissemination of Chinese literature.

2. Research Methods

2.1. Semantic Ontology Optimization Model. Based on semantic features, machine translation is used to realize intelligent literary translation, and a literary intelligent translation semantic ontology optimization model including encoder and decoder is created.

Suppose there is a five-tuple $O = \{C, H^C, R, I, A\}$, where C and H, respectively, represent the concept set and the attribute set; R and I, respectively, represent the object set and the relationship network; A represents the semantic relationship between concepts. Applying it to the semantics of intelligent literary translation, the fuzzy mapping of machine translation can be obtained as follows:

$$\begin{aligned} &\theta\colon S \longrightarrow S^*[-0.5, 0.5],\\ &\theta(s_i) = (s_i, 0), s_i \in S, \end{aligned} \tag{1}$$

where S represents the method set of the ontology.

The distribution structure model of intelligent literary translation phrases is as follows:

$$\begin{aligned} O &= \langle C, I, H^C, R, A,\\ O' &= \langle C', I', H^C, R', A'. \end{aligned} \tag{2}$$

Using the extraction of semantic features to achieve intelligent literary translation [10], the fuzzy inference method is selected to obtain the literary intelligent translation parameters as follows:

$$\Delta\colon [0, T] \longrightarrow S^*[-0.5, 0.5]. \tag{3}$$

Formula (3) can be transformed into

$$\Delta(\beta) = \begin{cases} s_k, K = \operatorname{round}(\beta),\\ a_k = \beta - k, a_k \in [-0.5, 0.5], \end{cases} \tag{4}$$

where T represents the threshold and β represents the explanatory function.

The feature parameters of the two-tuple fusion are obtained by using associative semantic mapping as follows:

$$\begin{aligned} (\bar{s}, \bar{a}) &= \omega_2(((s_1, a_1), (\omega_1, a_1)), \ldots, ((s_n, a_n), (\omega_n, a_n))),\\ &= \Delta\left(\frac{\sum_{j=1}^{n} \Delta^{-1}(\omega_j, a_j)\Delta^{-1}(S_j, a_j)}{\sum_{j=1}^{n} \Delta^{-1}(\omega_j, a_j)}\right),\\ &= \Delta\left(\frac{\sum_{j=1}^{n} \beta_j \beta_j}{\sum_{j}^{n} \uparrow \beta'_j}\right), \end{aligned} \tag{5}$$

where ω represents the weight.

Use adaptive semantic variable optimization and context feature matching semantic ontology model to obtain the optimal semantic feature matching results of literary intelligent translation as follows:

$$J^*(m) = \max_{\beta}\{J^*(\beta) + R_m(\beta) + C\}, J^*(0) = 0. \tag{6}$$

Semantic discretization is used to process the original literary text information, and the parameters of the semantic text are adaptively estimated to obtain the feature matching degree formula output by the literary intelligent translation output as follows:

$$P(x_1^l|\alpha) = \prod_{i=1}^{L} P(y_i|\alpha, r_i, l), \tag{7}$$

where α represents the semantic feature, l represents the length of the literary sentence, x represents the text, and y represents the semantic text feature amount.

To analyze the characteristics of automatic vocabulary in intelligent translation literature, the relevant context information decomposition formula for obtaining intelligent translation vocabulary of literature is as follows:

$$E_j = \sum_{k=1}^{n} E_{j,k}, \tag{8}$$

$$P_{j,k} = \frac{E_{j,k}}{E_j}, \tag{9}$$

where E represents the degree of association.

Use the cross-comprehensive evaluation and decision-making method to obtain the output results of the correlation feature between literary vocabulary is as follows:

$$W_{E_k} = -\sum_j P_{j,k} \ln\left(P_{j,k}\right). \quad (10)$$

Thresholding processes the semantic ontology information of intelligent literary translation [11] and uses the empirical mode decomposition method to obtain the closeness of the translation result and the similarity formula as follows:

$$K_x = E\left[x^4(t)\right] - 3E^2\left[x^2(t)\right]b, \quad (11)$$

$$S_x = E\left[x^3(t)\right] + \sqrt{s}bu\left[s\left(t-\tau_0\right)\right], \quad (12)$$

where b represents the time scale of literary features and u represents the literary signal sequence.

According to the obtained closeness and similarity features, the translation results are extracted, and the translation results are corrected by differences [12], and the revised literary intelligent translation text collection is obtained as follows:

$$\text{Computition}\left(x_j\right) = \left[\left(E_j + E_k\right)\beta + E_j + \alpha b_j^2\right]l. \quad (13)$$

2.2. Improved Optimization Model. A conversion layer that can realize syntax conversion is added between the encoder and the decoder of the semantic ontology optimization model. The conversion layer mainly includes three parts: the forward neural network layer, the residual connection, and the normalization layer.

2.2.1. Forward Neural Network Layer. The ReLU activation function is selected as the nonlinear transformation of the forward neural network layer. The ReLU activation function is also called the modified linear unit [13], and its nonlinear transformation formula is as follows:

$$\mathrm{Re}LU(x) = \max(0, x). \quad (14)$$

Both h_{encoder} and c_{encoder} in the binary group need to pass through the forward neural network layer, but both have independent parameters. Using the forward neural network layer to transform the binary group $(c_{\text{encoder}}, h_{\text{encoder}})$ to (c', h'), the formula is as follows:

$$\begin{aligned} c' &= \mathrm{Re}LU\left(c_{\text{encoder}}W_{c1} + b_{c1}\right)W_{c2} + b_{c2}, \\ h' &= \mathrm{Re}LU\left(h_{\text{encoder}}W_{h1} + b_{h1}\right)W_{h2} + b_{h2}, \end{aligned} \quad (15)$$

where W_{c1} and W_{c2} represent the transformation matrices for the first and second linear transformations of c_{encoder} and b_{c1} and b_{c2} represent the offset vectors for the first and second linear transformations of c_{encoder}.

In order to keep the unit state vector dimensions of the long short-term memory (LSTM) in the decoder and encoder consistent, the input and output conversion layer dimensions are the same [14], and the normalization layer vector dimensions are not changed, c_{encoder}, h_{encoder}, c', and h' are all vectors of the same dimension.

Use h and d to denote the first linear transformation dimension and the model state vector dimension. The dimensions of W_{c1} and W_{h1} and the dimensions of W_{c2} and W_{h2} are $d \times h$ and $h \times d$, respectively, and the offsets of b_{c1} and b_{h1} and the offsets of b_{c2} and b_{h2}. The dimensions are h and d, respectively. It can be seen that the number of parameters included in this layer is $4dh + 2d + 2h$, and the number of parameters in each layer is $h = 4d$ for the model $16d^2 + 10d$ established. When the cyclic neural network contains a stacking quantity of n, a total of $16nd^2 + 10nd$ parameters exist in the forward neural network layer of the model conversion layer, and the multiplication operation of the vector and the matrix is multiplied by the number of operations $16nd^2$ times.

2.2.2. Residual Connection. $(c_{\text{encoder}}, h_{\text{encoder}})$ uses the residual connection to act on the forward neural network layer output (c', h') in the conversion layer structure, and the residual result $(c_{\text{res}}, h_{\text{res}})$ is obtained as follows:

$$\begin{aligned} c_{\text{res}} &= c' + c_{\text{ebcoder}}, \\ h_{\text{res}} &= h' + h_{\text{ebcoder}}. \end{aligned} \quad (16)$$

Taking full account of the transformation of the forward neural network layer, the residual connection processing can make the established model regain the lost semantic information and improve the accuracy of the literary intelligent translation results. The residual connection processing does not need to increase the parameters, so the computational complexity of the model does not change, and it does not affect the back propagation training results of the recurrent neural network.

2.2.3. Standardization Layer. Normalized processing is commonly used in deep learning. Normalized processing can not only be applied to the preprocessing stage in deep learning [15] but it can also be applied to the processing of various layers in the network to implement standardized processing of input data. Use g and u to represent the variance and expectation of the normalization processing in the normalization layer, and the input c_{res} layer normalization processing formula is as follows:

$$C_{\text{trans}} = \frac{g}{\sigma}\left(c_{\text{res}} - \eta\right) + u, \quad (17)$$

where σ represents the original variance of the input feature and η represents the original expectation of the input feature. The formula is as follows:

$$\begin{aligned} \mu &= \frac{1}{d}\sum_{i=1}^{d} c_{\text{res}_i}, \\ \sigma &= \sqrt{\frac{1}{d}\sum_{i=1}^{d}\left(c_{\text{res}_i} - \eta\right)^2}, \end{aligned} \quad (18)$$

where d and c_{res_i}, respectively, represent the feature dimension and the dimension feature value and h_{res} can also be processed through the above-normalized operation process.

Using the canonical layer to normalize (c_{res}, h_{res}) into (c_{trans}, h_{trans}), the result can be used as the initial state of the decoder LSTM. The normalization layer is not only included in the conversion layer; there is also a normalization layer in the LSTM units of the decoder and the encoder to implement normalization operations.

3. Result Analysis and Discussion

In order to verify the effectiveness of the literary intelligent translation based on the improved optimization model for the translation of literary works, the Chinese-English translation dataset TED2018 in the Tatoeba project was selected as the experimental object. The dataset contains a large number of literary works, including Chinese and English translation number of sentences is 25645 and the comparative translation of each group of literary sentences starts and ends with the characters \t and \n, respectively. The method in this study uses LSTM as the encoder and decoder to obtain the Chinese and English mapping dictionary and converts the text data in the dataset to digital form through mapping. Set the number of batch training samples of the improved optimization model used in this study to 100, the number of hidden layer nodes to 128, and the number of termination iterations to 100.

3.1. Qualitative Test. In order to visually verify the intelligent translation results of literary works with the method of this study, statistics of 10 random sentences used in the method of this study to translate literary works are counted.

From the experimental results in Table 1, it can be seen that the method in this study has a high performance for intelligent literary translation. It can realize intelligent translation of sentences in literary works, and the translation results have high versatility and effectiveness.

Table 1: Translation results of the method in this study.

Serial number	English translation result
1	Pain past is pleasure
2	While there is life, there is hope
3	God helps those who help themselves
4	In doing we learn
5	Constant dropping wears the stone
6	Misfortunes never come alone
7	From small beginning come great things
8	Good advice is beyond all prices
9	Good company on the road is the shortest cut
10	A bold attempt is half success

3.2. Quantitative Test. In order to intuitively reflect the intelligent translation performance of the method in this study, the literature CNN method and the literature CSGAN method are selected as comparison methods.

Using this method to intelligently translate the literary sentences in the TED2018 dataset, the training loss function results for different training steps in the translation process are shown in Figure 1.

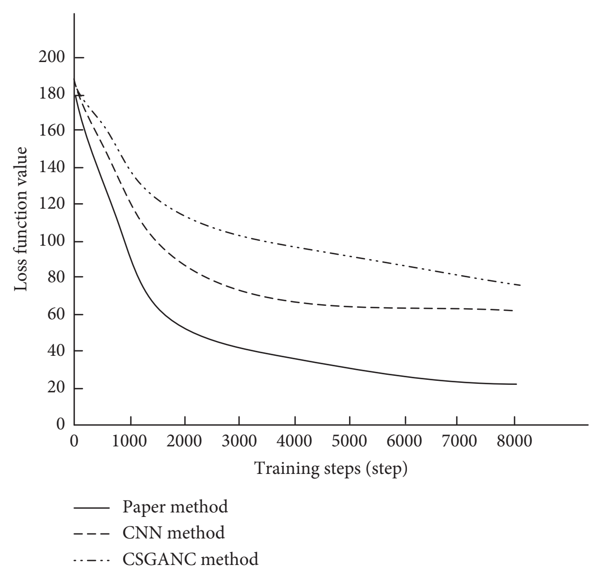

Figure 1: Loss function values of different methods.

Different data need to be selected when testing the loss function values of different methods. The obtained loss function values have high volatility, which is mainly caused by random gradient descent. Figure 1 shows the curve result after smoothing the true loss function value. As can be seen from the experimental results in Figure 1, the loss function value decreases with the increase in the number of training steps. The method in this study has the lowest loss function value at different training steps, which effectively verifies that the method in this study has higher translation performance, and the loss is small when the number of training steps increases.

The BLEU value is an important indicator for evaluating the effect of machine translation. The BLEU value of literary sentences in the intelligent translation dataset using three methods is counted. The statistical results are shown in Figure 2.

The experimental results in Figure 2 show that the BLEU value of the literary sentence translated by this method tends to be stable when the number of training steps is 4000; when the number of training steps is 8000, the highest can reach 17.23; the BLEU value of the other two methods to translate literary sentences is lower than the method in this study at different training steps, which effectively verifies that the method in this study has higher translation performance.

The statistical results are shown in Figure 3 for the statistics of the training errors of different training steps using the method in this study.

It can be seen from the experimental results in Figure 3 that using this method to intelligently translate literary sentences, the training error at different training steps is significantly lower than that of the other two methods. The method in this study can keep the training error to a minimum when the number of training steps is low, which shows that the improved optimization model used in this method has a higher convergence effect.

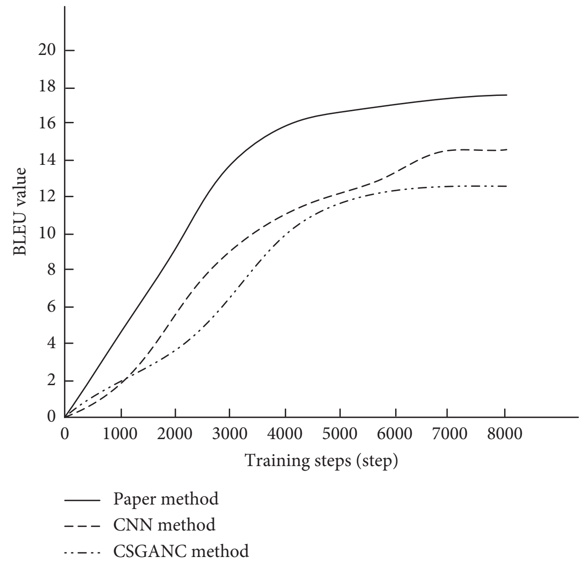

Figure 2: Comparison of BLEU values of different methods.

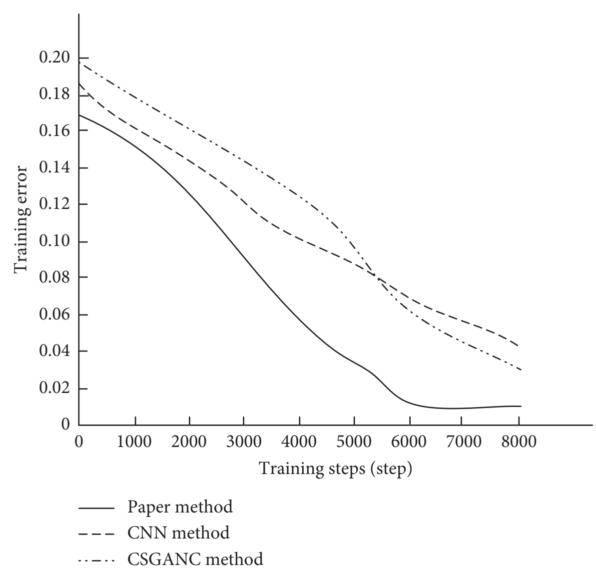

Figure 3: Comparison of training errors of different methods.

Table 2: Comparison of translation performance.

Subset number	Subset size (MB)	Method of this article		CNN method		CSGAN method	
		Training time (min)	BLEU value	Training duration (min)	BLEU value	Training time (min)	BLEU value
1	23.54	9.85	17.85	23.54	12.64	29.52	10.85
2	42.64	15.34	19.52	21.52	13.85	28.64	11.64
3	51.74	16.24	18.43	21.42	12.64	24.76	12.48
4	62.78	14.52	16.58	29.64	11.94	23.65	9.85
5	47.85	12.64	17.54	28.46	12.64	31.64	7.58
6	56.61	17.52	18.64	27.64	10.64	29.52	8.64
7	75.61	18.64	19.52	26.38	12.64	27.85	7.46
8	85.64	19.57	17.45	31.22	11.64	32.85	9.52
9	49.52	16.25	19.52	29.58	10.58	27.52	10.05
10	51.64	16.75	17.52	27.64	9.85	27.85	11.64

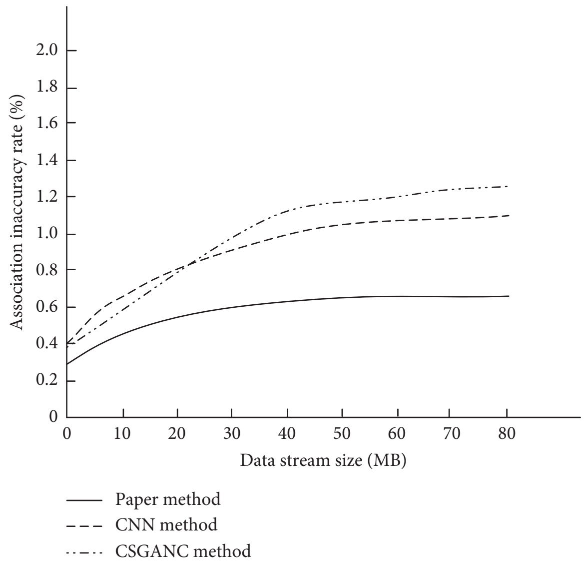

Figure 4: Comparison of correlation misalignment rate.

The statistics, using the method of this study, intelligently translate literary sentences, the training time, and the BLEU value of different training subsets. The statistical results are shown in Table 2.

It can be seen from the experimental results in Table 2 that the training time for the intelligent translation of literary sentences using this method is less than 20 minutes; while the training time for the intelligent translation of literary sentences using the other two methods is both higher than 20 minutes. This method proposes that the conversion layer idea has strong translation performance, the training time of the improved optimization model used is significantly reduced, and the BLEU value of the translation result is significantly higher than the other two methods.

The statistical results are shown in Figure 4 for the correlation misalignment rate when using different methods to translate literary sentences with different data streams.

As can be seen from the experimental results in Figure 4, using this method to intelligently translate literary sentences, the correlation misalignment rate of different literary sentence data streams is significantly lower than that of the other two methods. The comparison result of the correlation misalignment rate effectively verifies that the intelligent translation of literary sentences using the method in this study has a higher degree of relevance and higher accuracy of the translation results.

4. Discussion

Machine translation is an automatic translation technology developed with the help of computer technology and corpus technology. Although it has the advantages of fast translation speed and high efficiency, the translation quality is mediocre and can only meet general reading needs. For texts with rich emotions, such as literary works, the translation quality is obviously insufficient. Combined with the three principles of Skopos Theory and the evaluation system of machine translation quality, the author finds that the current machine translation literary translation has the following typical problems:

4.1. It Is Not Eloquent and Has Low Intelligibility. For translators, they can find or choose the most appropriate translation by looking up dictionaries, searching online resources, or according to the content before and after the text. However, for machine translation, the only criterion for machine selection is the translation version in the selected termbase. There is a greater possibility of a mistranslation of special nouns representing people, place names, and things. These proper nouns may be far from the background of the text, and the term library producer did not add the entry to the library or is it that some people's names or place names have a conventional translation method, and machine translation adopts literal translation or transliteration, resulting in errors.

4.2. Logical Confusion and Poor Organization. Whether it is machine translation or manual translation, it is a permanent standard to achieve the logic of sentence translation, enable readers to correctly understand the meaning of the translation, and meet the "localized" expression in the target language environment. However, at present, machine translation has not reached such an "intelligent" stage. Its translation method is to follow the program to perform the mechanical transformation of vocabulary, grammar, and semantics, which has not risen to the level of "emotion" and context matching.

Based on the established semantic ontology optimization model, this study optimizes and improves the transformation layer, which includes the forward neural network layer, residual connection layer, and standardization layer. The transformation layer is used to realize syntax transformation, realize literary intelligent translation, and improve the translation effect.

5. Conclusion

With the rapid development of the Internet, machine translation has become an important research part in the field of artificial intelligence. It studies the intelligent translation of literature based on the improved optimization model. Based on the establishment of the semantic ontology optimization model, by adding a conversion layer to the encoder and decoder of the model, an improved optimization model is established to realize the intelligent translation of literary works. Experiments have verified that this method has high effectiveness. However, this study did not conduct an in-depth analysis of the ideographic ability of literary words and lacked verification of the emotion of translated literary sentences. Accurate and intelligent translation of literary sentences can be realized. In the future, the amount of training data should be further used to optimize the structure of the recurrent neural network, and various efficient methods should be integrated to improve the effect of intelligent literary translation, accurately express the emotions of literary works by analyzing the ideographic ability of literary words, and further promote the translation and dissemination of Chinese literature.

Data Availability

The data used to support the findings of the study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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