The Feasibility of the Intelligent Development of Contrastive Translation between English and Chinese based on the Development of E-commerce

Weijie Liu, M.Sc
Weijie Liu, Lecturer, Xiamen University of Technology, Xiamen, Fujian, 361000, China
Correspondence Lec Liu; wdcvxi297216698@163.com

Objectives: At present, with the rapid development and application of the Internet, the cross-border transaction of e-commerce presents a blowout development, and the demand for language is increasing. Methods: In this paper, starting from the perspective of machine intelligent translation of English and Chinese, and in view of the problem of traditional contrastive translation of machine, the algorithm of strengthening neural network was used to solve the problem of translation. In the study, the process of intelligent translation was divided into two stages: encoding and decoding. In view of the language type and word alignment, the input and output modules were formed and the algorithm was optimized, and a recurrent neural network algorithm was used to build an RNN-embed intelligent translation model of English and Chinese. Results: The model was input through the character level in English and Chinese, and then the network was trained, so as to solve the problem that it is difficult to deal with the advanced semantics in the process of strengthening the neural network calculation of text information in the cross-border transaction of e-commerce. Conclusion: It is proved by experiments that the RNN-embed translation model based on the enhanced neural network algorithm can improve the quality of the long sentence translation compared with the machine translation.

Key words: e - commerce; deep learning; intelligent translation; recursive neural network algorithm
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With the rapid development of the Internet, e-commerce has been widely used in cross-border transactions [1-3]. However, the demand of the cross-border transaction of the e-commerce platform is very large for the language, so a new round of discussion is needed in the translation technology [4-6]. It is assumed that the e-commerce platform needs a speech propaganda or online question answering function of a kind of commodity, an online translation technology is needed to achieve the real-time communications between two people in different countries [7,8]. Machine translation technology is also known as intelligent automatic translation technology in the industry, which mainly realizes the function of language conversion through computer algorithm and related programming programs [9-11]. At present, the problem of machine language translation has been recognized by the world, and it is undoubtedly a hot issue in the application of this technology. The outside world has constantly questioned the translation of machine language and questioned its practicability and feasibility, while when computer technology is used as an auxiliary tool, the practicability of machine translation is improved [12-15]. All languages have their own grammatical rules, and the grammatical password of the translation is to input the vocabularies that have been deciphered into machines and form the corresponding grammatical rules according to the human expression habits. In 1954, a machine was used to translate Russian into English for the first time in the experiment [16,17].

The general method of machine translation can be divided into two types: regular translation and corpus translation. The rule-based response method can be used for translation sentence by sentence, but it is not widely used in many common fields. Translation based on corpus can be refined as statistics and examples [18-20]. It is difficult to get a complete corpus based on the type of case, the efficiency of matching is not high, and the scope of application is limited easily, while the process of modeling can be transferred to the integration of knowledge based on statistical methods [21,22]. At present, more and more enterprise structures have launched online translation and statistics technology. Google adopts the crawler technology of online translation, which can achieve a large number of corpus of two languages [23-25]. If the common vocabulary docking can be completed by analyzing the relevant knowledge through a specific algorithm, the process of machine translation can also be completed. In recent years, algorithms based on neural network have achieved great achievements in model training and translation decoding of languages [26,27]. In this paper, a complete calculation model of intelligent translation based on neural network was established on the basis of the characteristics of the previously established neural network, and the analysis process of human natural languages was not specialized at all. By using the idea of cipher deciphering, a bilingual order of arrangement was formed, and according to the structure of the character's input model, it was no longer sorted by semantics.

Before the computer is not widely used, research on the technology of machine translation has begun. From the perspective of the overall application, it can be divided into two types: regular translation and corpus translation. The general method that researches translation based on rules is mainly aimed at language statements, and the results obtained are relatively rich, while the universality is poor. In such a state of application, a basic model of machine translation based on corpus has emerged [28,29]. Later, the method is mainly carried out by the branch example and realized by the statistical method. However, a case-based research method can only save a translation that has good statements in the corpus. Therefore, a relatively comprehensive corpus is needed as a support for technology [30-32]. In order to overcome the above technical defects, the basic method of statistics can be used to lay the foundation for the realization of the transformation of corpus into basic knowledge in the next step. In this way, it can no longer rely on parallel databases, and the basic translation function of the machine can be realized by training. At present, there are many cases that use the statistical research methods to achieve machine translation, and many Internet and software companies have launched online translation software, such as Baidu online translation. The statistical model of the level of words provides a strong technical support for machine translation, for the units of modeling built by this method are relatively small, and the resulting model will result in a poor adaptability [33,34].

Many scholars may focus their research on the method of statistical translation studies based on phrase translation, and in order to supplement the disadvantages of the accumulation of semantic information technology in China, the study of the translation has gradually shifted from the phrase translation to the sentence translation [35]. For example, some scholars have achieved the hierarchical structure of syntactic annotation system of Tibetan language based on the semi-tree model of translation. In addition to these successful applications, the basic models built for the machine translation of statistics are still being optimized [36]. The application of neural network in the translation model of languages is a great achievement, and Socher has used the neural network language in the tree-structure model of languages. Some scholars have also adjusted the sequence of the optimized language model, and used the recursive coding method to intelligentialize the expression of characteristics of adjustment of automatic learning [37]. Liu and other researchers, based on the research of neural network models, have used the code of machine translation to form the recurrent neural network and low-dimensional lexical annotation of target language. On the basis of neural network models, some other scholars even have regarded English and Chinese as the direct input parameters of network models, which is also for the accuracy of translation.

In the field of artificial intelligence of large data, a more important keyword called "deep learning" has emerged. This learning technique and method correspond to the learning method of shallow neural network, and it is another appellation of the learning method of deep network. Neural network algorithms are likely to be very important in the application of large data processing and deep learning, which has a direct relationship with the task allocation of artificial intelligence. In the field of image processing and speech recognition in artificial intelligence, the error probability of supporting the basic model of SVM is about 1.5%, while the error rate will be reduced to 0.38% after a deep learning algorithm is added [38]. In the application of speech recognition systems, the error probability of the HMM basic prototype model in the general system is about 28% in the work, while this error rate will be reduced to 19% after adding a deep learning algorithm. Because of the continuous application of the algorithm of deep learning, the application field of human natural language is constantly tried. Although the results of the application can't be compared with that of the speech recognition and image analysis technology, the principles and methods of the two are different after all [39]. The recognition of speech or image is only a storage and expression of a space vector, however, according to the characteristics of the natural language, the primary processing of the vocabulary for the input of the language is the basic difference between the two. The space vectorization of vocabulary can be used to study and model the deep-level neural network, and in addition to the translation process that is related to natural language, the recursive algorithm structure is always used.

For machine translation and question answering function system of electronic business platform, a complex algorithm expression is needed, which requires a more specific neural network structure. From the point of view of language transformation, the meaning of the word itself lies in the connection between the words that it can realize, and under such guidance, the training model of neural networks is proposed, and space vectors can be used to express vocabulary [40]. For the language algorithm model, the classical $N-Gram$ algorithm has relatively loose computing data, and the overall combination does not achieve a better calculation effect. Neural network displays the input role of vocabulary in translation system, and the training process is to calculate the vocabulary vector of the vocabulary size, and then repeat the cycle iteration for calculation the updating [41]. Although deep learning and related algorithms are more mature in the field of image recognition and speech recognition, the recognition of algorithms in text data is just beginning [42-44]. The language is more complex than the picture and sound, and the content of this paper also requires a certain amount of learning and understanding. Therefore, the higher the requirements for the algorithm and model, the more perfect the computing performance of neural network training method based on deep learning will be.

METHODS

Neural Network Translation Algorithm Based on Deep Learning

In a large number of machine translation methods and basic learning tasks, some of the characteristic values are discontinuous and may also be classified. In this paper, RNN-embed model is built based on distributed features. On the basis of distributed feature expression, the mainstream language processing method is adopted, which takes advantage of the word segmentation machine to divide the translation sentence of the whole sentence into several words. For text data with a digital type, in order to obtain better optimization results of data training, in this paper, a RNN generation model of lexical vectors (a neural network with a recurrent type) is proposed. The recursive neural network (RNN) obtains an input vector x that can change the length by calculation, and gets the output variable y by the machine loss of h in the hidden layer. After a certain calculation time (t), the calculation expression of the hidden layer of the recurrent neural network is as follows:

$$h_t = f(h_{t-1}, x_t) \tag{1}$$

In formula (1), f represents an activation function, which is expressed as a nonlinear meaning. The activation function can represent both simple *sigmoid* functions and complex network units that maintain a long-term memory. After continuous cyclic training, a kind of symbol can be obtained, and the recurrent neural network can calculate the corresponding probability distribution from learning. The expression of the activation function with a polynomial distribution is as follows:

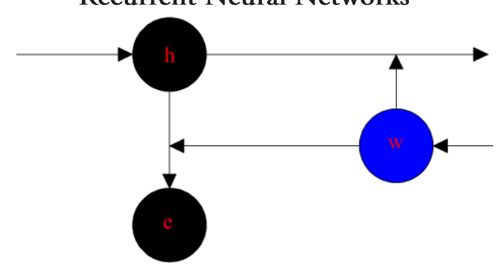
$$p(x_{t,j} = 1 | x_{t-1}, ..., x_1) = \frac{\exp(w_j h_t)}{\sum_{j'=1}^{K} \exp(w_j, h_t)} \tag{2}$$

In formula (2), w_j represents a line of weight matrix W , and by calculating the joint probability value, the basic probability value of a certain order may be calculated, and the calculation expression is as follows:

$$p(x) = \prod_{t=1}^{T} p(x_t | x_{t-1}, ..., x_l) \tag{3}$$

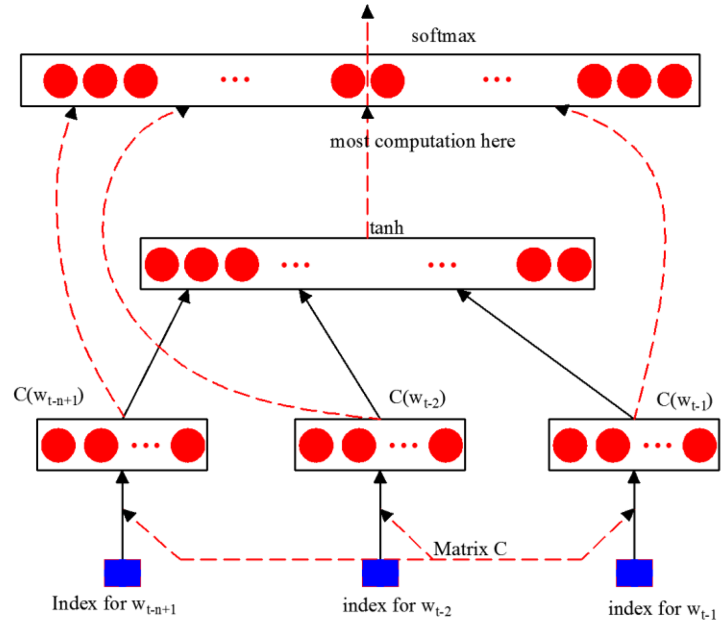
Referring to the calculation idea of recurrent neural networks, the task of the basic vector of the vocabulary can be obtained. Although the hidden layer gets the last step of h_T , the vector is a forming vector, and the vector does not represent a word vector, but a sentence vector. It is assumed that it is completely zeroed within the specified time before the next hidden layer enters, a nonlinear transformation will be obtained on the basis of $One-Hot$. The process of shearing vocabulary in natural language is the zero processing, and it is also the model input of random characters. In the neural network, a switch is defined to output the segmented vocabulary vector, and a word information can be completed in the location that has been zeroed. Figure 1 shows the generating unit of the lexical vector of a recurrent neural network.

Figure 1
Word Vector Generating Unit Based on Recurrent Neural Networks



The purpose of human research on intelligent translation is to hope that computers can understand human's natural languages and deal with basic human affairs, such as machine translation, character recognition, and so on. The human language that has been created can't be fully grasped by the simple computer algorithm at present. Figure 2 shows a NNLM model, and the aim of this model is to predict the next word by using the current $n-1$vocabulary. However, it is important to note that when the number of vocabulary is $n-1$ which will be connected to the beginning and the end, the input of the current vocabulary vector can ensure the effectiveness of the algorithm. Recurrent neural network can be used in continuous space, and besides the deep validity of the structure, the historical data that is hidden before learning can be used.

Figure 2
Schematic Diagram of NNLM Model



The structure of the generating unit of a language model is shown in Figure 3. In a specific time series, the expansion is carried out in a certain direction, and the element that is added to the hidden layer is g. The corresponding network algorithm at this stage is the best recurrent neural network, which is the addition of two different control units of r and z.

Figure 3
Language Model Generating Unit

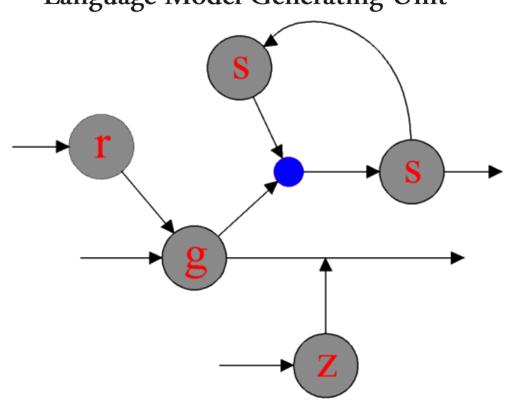
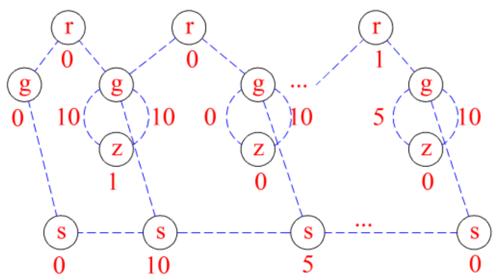


Figure 4 shows the sequence effect diagram of the language model. As shown in Figure 4, it makes a recursive neural network (RNN) which is corresponding to the lower part, and here is only an example of the base function of memory of the historical information.

Figure 4
A Sequence Effect Diagram of a Language Model



The machine translation system is sure to store two relative natural languages, and through the encoder of GRU bidirectional optimization, the sequence s of the hidden layer can be obtained. At the same time, the structure of decoding module s' is similar to the structure of the bidirectional optimization decoder. In the calculation process of the decoding module, the basic information c of the module is added, and the specific generation process algorithm of the language model in the decoder is as follows:

$$z_i = \sigma(W_z e_{i-1}^y + U_z s_{i-1}' + C_z c_i) \tag{4}$$

$$r_i = \sigma(W_r e_{i-1}^y + U_r s_{i-1}' + C_r c_i) \tag{5}$$

$$s_i' = (1-z_i)^0 s_{i-1}' + z_i{}^0 s_i' \tag{6}$$

e_i^y in formula (4-6) needs an embedded vector of the translation language, and the dimension of the vocabulary is m; o represents the calculation method of point multiplication; C_z, C_r, C_s represents the weight matrix, and it satisfies $s_o' = ranh(V_s s_1)$ at the same time.

The Experiment of Algorithm of Bilingual Intelligent Translation Between English And Chinese Based on E-Commerce

BGD batch gradient descent algorithm requires a reverse relaying each time, and the data error of the calculation training is relatively large. In the course of this training, it is unrealistic to use such a large amount of data. However, the reverse propagation of SGD gradient descent algorithm will generate errors while calculating, but the data string is more obvious and the use efficiency of the hardware is too low. In the pattern process, SGD gradient descent algorithm is used for parameterized learning, and when each gradient is updated, the updating process can be calculated as follows:

$$x_{t+1} = x_t + \Delta x_t \tag{7}$$

$$\Delta x_t = -\eta g_t \tag{8}$$

t in formula (7) and (8) represents the time series, the training parameter is x, η represents the learning efficiency, and g represents the gradient.

The algorithm is used to adjust the automatic learning rate, and the calculation formula is as follows:

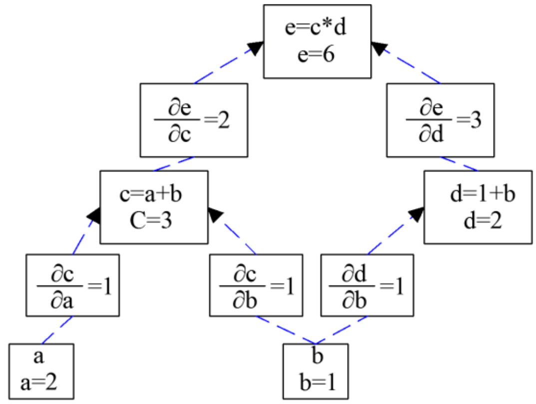
$$\Delta x_t = -\frac{RMS[\Delta x]_{t-1}}{RMS[G]_t} g_t \tag{9}$$

$$RMS[g]_t = \sqrt{E[g^2]_t + \in} \tag{10}$$

$$E[g]_t = \rho E[g^2]_{t-1} + (1-\rho) g_t^2 \tag{11}$$

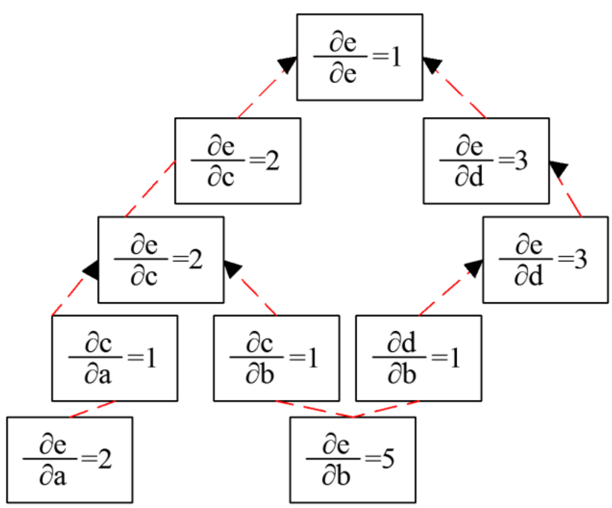
For the recursive part of the network, BPTT algorithm is used to reverse the anti-propagation of errors, as shown in Figure 5. In the derivation graph model of Figure 5, it is assumed that the value of a is 2 and the value of b is 1, and the edge tag is the result of the derivation for the connected input node, then the derivation gets grad function that is carried.

Figure 5
Derivation Graph Model



According to the method of backward propagation of link rules, the chain derivation process as shown in Figure 6 can be obtained. The above process can be expressed as a process of finding the point path, and for example, the expression of $\frac{\partial e}{\partial b}$ can be divided into two paths.

Figure 6
Chain Derivation Process



RESULTS

In order to objectively reflect the performance of the translation system and ensure the timely judgment in the process of frequently adjusting models, some intelligent evaluation algorithms are needed in the process of executing tasks of machine translation. In the past research, it has been mentioned for many times, and the mainstream evaluation method is $BLEU$, which can be used as an objective criterion for the quality of the translated text as well as the basic criteria for the automatic evaluation of the translation system. The calculation expression of the evaluation of $BLEU$ is as follows:

$$BLEU = BP \times \exp(\sum_{n=1}^{N}(w_n \log p_n)) \quad (12)$$

In the computational expression, w_n represents the corresponding weight of n tuple, p_n represents the accuracy of n tuple, and the penalty factor based on the length is BP. Firstly, it is necessary for the designer to calculate the basic probability of the matching of n tuple, which is expressed by p_n. The statistical translation text corresponds to n tuple of different values of n, and the total number of the corresponding reference matching is used as the basic reference for the translation. Finally, the results of $BLEU$ are calculated according to formula (12). In the course of the experiment, bilingual sample data are selected in the bilingual database. The level of the corpus is ten million, the number of bilingual data is 2 million pairs, and the number of training sets is 5000. Since the length of the sequence is closely related to the quality of the translation, as shown in Table 1, the basic training for the level and character level of the word is achieved, and the test data and the language themselves also obtain the results of the length statistics. Moreover, the difficulty in modeling the characters of the data itself is very high.

Table 1
Word Level Data Length Analysis

Sequence length	1~9	10~19	20~29	30~39	40~49	50~59
Train/en	1270522	520850	4921	3137	541	29
Test/zh	1366950	432225	820	5		
Train/en	144438	54549	574	381	56	2
Test/zh	153835	46077	88			

Table 1 shows the result of the calculation of different models. Table 2 shows the optimal structural framework obtained in the translation of existing statistical results, and in order to complete the basic requirements of the experiment, a system platform for response is configured in the system. The input data in the model can complete the process of segmenting the words, and there is a certain difference in the translation atom of the character.

Table 2
Comparison Results of Model Evaluation

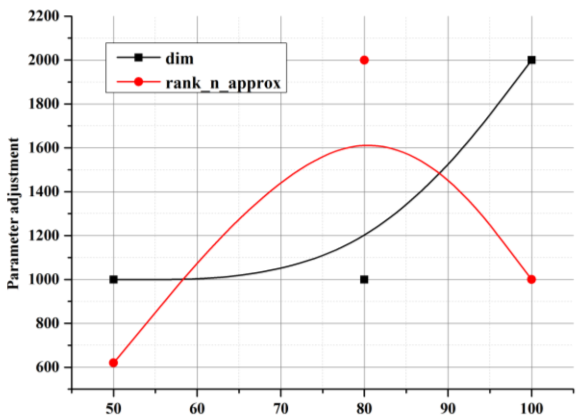
Model	Moses	RNN-search	RNN-embed
BLEU	26.59	25.21	25.29
BP	0.980	0.814	1
P1	55.6	58.4	42.4
P2	32.7	36.5	29.0
P3	21.4	25.6	21.2
P4	13.9	16.8	15.7

The second column in Table 2 represents the results of measurement of BLEU method, and BP is the penalty factor for the whole calculation length. Then, according to the actual situation, the precision matching of 1 tuple to 4 tuple is allocated. Among the matching results, *Moses* has the highest scores, for *Moses* itself has a higher mark. The translation model algorithm proposed in this paper is still in a relatively primary stage, and there is a relatively large space for optimization. Table 3 shows the process of adjusting the parameters of RNN-embed model. What can be seen from Table 3 and Figure 7 is that the main focus is to adjust the parameters of the second column and the third column, while results of parameter adjustment in the seventh line of Table 3 have already been greatly improved. When the score of the training set is more than 25 points, the fitting effect of the fitting degree of the model is not good. The result of the training model is still improving, while the process is relatively slow.

Table 3
The Process of Adjusting the Parameters of The RNN-Embed Model

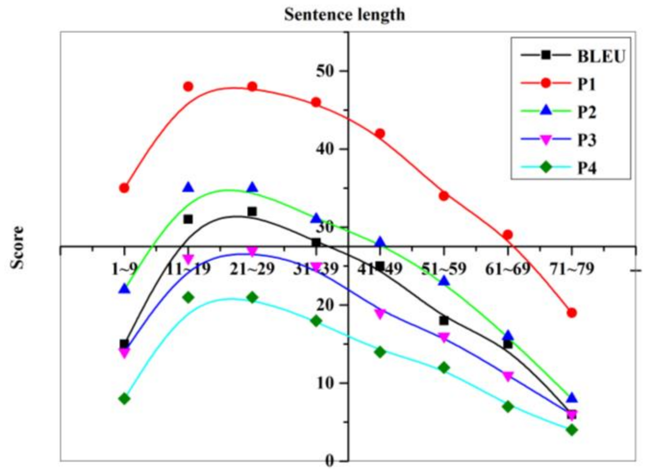
Seqlen	50	80	80	100	80	80
dim	1000	1000	1000	2000	2000	2000
Rank_n_approx	620	1000	2000	1000	1500	1000
BLEU	22.97	23.83	23.40	23.89	24.36	25.29

Figure 7
Schematic Diagram of Parameter Adjustment and Change



In order to further analyze the test results of the model, according to the length of the sentences of "1-9", "11-19"... "101-109" that are in different categories, tests and specific analysis results of testing are shown in Figure 7. The average length of the word sentence is "7", and the average length of the character length is "32". The analysis of the score data that is shown in Figure 7 shows that the score of the length of "11-19" is the best. Therefore, the computation model still needs to deal with long sentences, especially when the character level is input, the average length of sentences has increased to a large level. This paper focuses on the generation of data sets in Chinese and English, and model training methods are used to verify the algorithm. Through the training of the model and the specific setting of the parameter, the score of English corpus of the e-commerce platform is compared based on RNN-embed algorithm and *Moses* algorithm proposed in this paper, so as to verify advantages of this algorithm.

Figure 8
Classification of Test Results According to Sentence Length



DISCUSSION

In the Internet era, the data resources of the business platform show an explosive growth, and promote the development of cross-border transactions. With the rapid development of data mining and machine learning algorithms, it is difficult for the traditional algorithm to solve many problems. The classic machine translation method sets up a relatively independent module for the alignment of words and the process of phrase extractions. However, in this paper, the algorithm of deep neural network was used to cover the whole process of the system translation. Machine translation optimizes the output modules and generates algorithms and language models, which also establishes the RNN-embed model of the deep neural network. The bilingual translation of the e-commerce platform does not divide the vocabulary, and the bilingual translation only enters the network according to the character level, and the semantic problem of the text is also solved. Through simulation experiments, it can be seen that although RNN-embed translation algorithm model solves the problem of segmentation of words to some extent, it still haven't surpassed the mature *Moses* algorithm. In this paper, the embedding method of RNN recurrent neural network was optimized, and the input of the data was in the form of characters, and the language model was also simplified. However, the translation sequence of the sentence would be increased. Therefore, it is necessary to further improve the translation process of long sentences in the later period.

Human Subjects Approval Statement

This paper did not include human subjects.

Conflict of Interest Disclosure Statement

None declared.

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