

Research on English Translation Language Based on Bi-GRU Network

Fucong Lai^{*}, Chunhong Zeng

Ganzhou Teachers College, Ganzhou, Jiangxi, 341000, China

^{*}Corresponding author.

Abstract:

The use of neural machine algorithms to translate English is a hot research topic at present. Using the traditional sequential neural framework for English translation has its own limitations in capturing long-distance information. Aiming at the shortcomings of traditional machine translation algorithms, this paper establishes an attention encoding and decoding model, and combines the attention mechanism with the GRU neural network framework, which proves that the performance of the proposed algorithm model is significantly improved compared to the traditional model. Selecting the semantic error to construct the objective function during training can well balance the influence of each part of the semantics, and fully consider the alignment information, providing powerful guidance for the training of deep recurrent neural networks. Experiments show that the English translation model based on recurrent neural network has high effectiveness and stability.

Keywords: English translation; neural network; GRU.

I. INTRODUCTION

With the rapid development of the economy and the rapid development of the Internet industry, the status of English translation in world trade has gradually increased. Machine translation technology can overcome various problems in human translation and reduce the economic and time consumption of manual translation. In the current era of high informationization, people's requirements for English translation are gradually increasing, and the need for computers to understand and translate the English language is becoming more and more urgent [1-4]. The computer's English translation ability directly affects the translation [5]. The application effect of the results is closely related to people's economic activities. However, the English translation results will have grammatical errors, which will cause deviations in the computer translation results and affect the output and judgment of the English translation results [6-8]. Therefore, in previous studies, a large number of experts and scholars have proposed automatic identification methods for machine English translation errors, in an effort to reduce the impact of English translation errors on economic activities.

Zhang Nan et al. used the neural machine translation method to predict the translation results of Chinese and English, and completed the identification of translation errors in the process of prediction [9].

As a research direction in the field of natural language processing and artificial intelligence, machine translation mainly uses computers to realize the mutual conversion between different languages [10-13]. At present, many Internet companies provide multilingual online translation services, such as Google Translate, Microsoft Bing Translator, Baidu Translator, etc., but there is still a big difference between the quality of machine translation and professional translation, especially in the translation of some long sentences. The word order difference between the source language and the target language is difficult to describe accurately [14]. In order to solve the problem of long-distance sequencing, related scholars have carried out various researches [8-10]. For example, the ordering model based on maximum entropy completes the accurate translation of sentences through the relationship between different words in the sentence [11]; some scholars implant the source language syntactic information into the translation model, which effectively improves the accuracy of the description of long-distance ordering. However, it is easy to cause the problem of prolonged translation and decoding time [12].

The above-mentioned traditional decoding-decoding algorithm framework focuses on single-sentence translation, that is, focusing on specific sentences for translation. Using the constructed algorithm model to translate word by word will create a sense of separation between sentences. This is not conducive to the translation of the text, and will cause the semantic discontinuity between the text and sentences, and the overall translation is not smooth. In addition, translating only a single sentence has the problem that the sentence may be ambiguous. The recognition speed of this method is relatively high, but the recognition accuracy and effectiveness are poor. To this end, using multi-feature fusion technology, a new automatic recognition method for machine English translation errors is designed. In order to ensure that this method has application value after the design is completed, a corresponding experimental link is constructed to verify it to ensure that this method has research significance.

II. MODEL

In traditional natural language processing systems, vocabulary is usually regarded as high-dimensional sparse features [13-15]. On the basis of related research, in order to improve the promotion ability of high-dimensional vocabulary, this paper realizes the low-dimensional dense transformation of high-dimensional vocabulary by establishing a neural network model, and uses the mapping relationship to convert similar vocabulary into low-dimensional vocabulary. Similar points, a negative sampling fast learning algorithm is established, as shown in Figure 1.

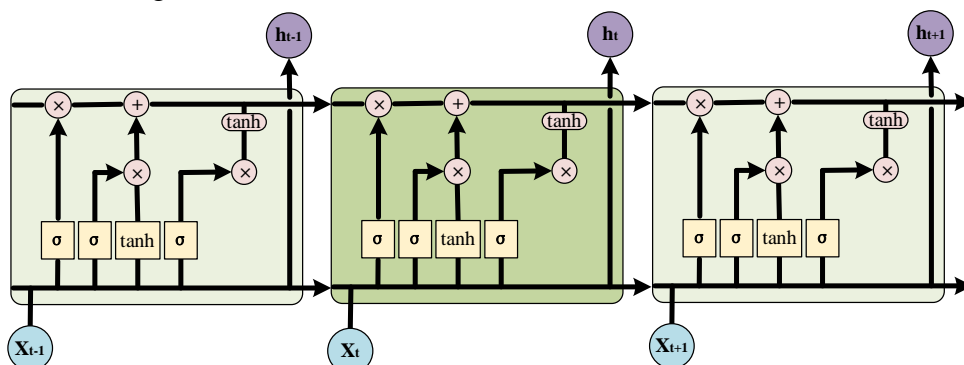


Fig. 1 GRU neural network

2.1 Autoencoder

This paper proposes a neural network reservoir resettlement sustainable development evaluation model based on the Encoder-Decoder structure. Then, the extremely deep architecture is shown and the parameter learning algorithm is given. First, we assume that there are N input-output training data pairs $\{x^{(m)}, y^{(m)}\}_{m=1}^N$, $x^{(m)} = [x_1^{(m)}, x_2^{(m)}, \dots, x_n^{(m)}]^T \in R^n$ where is the input part with input variables, and is the output part with only one output variable. An autoencoder is an unsupervised neural network consisting of three layers, an input layer, a hidden layer and an output layer [16]. It tries to mine a limited number of representations to reconstruct its input, the target output is equal to the input of the model. Figure 2 shows the structure of an autoencoder with L hidden nodes.

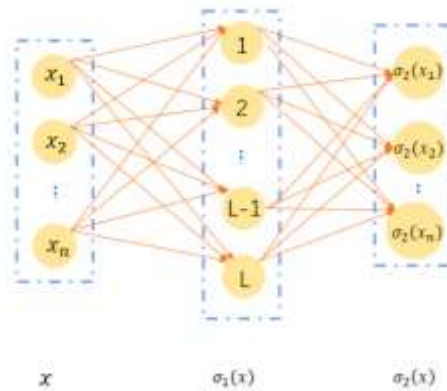


Fig.2 Autoencoder

2.2 Extreme Stacked Autoencoder

To predict energy consumption, we propose a deep learning method named extreme SAE, and the proposed encoding structure is shown in Figure 3. In this approach, the input is fed into the SAE part, and then the fully connected layers are trained by the ELM. The SAE part is used to extract building energy consumption features, while the ELM part is used as a predictor to obtain accurate prediction results.

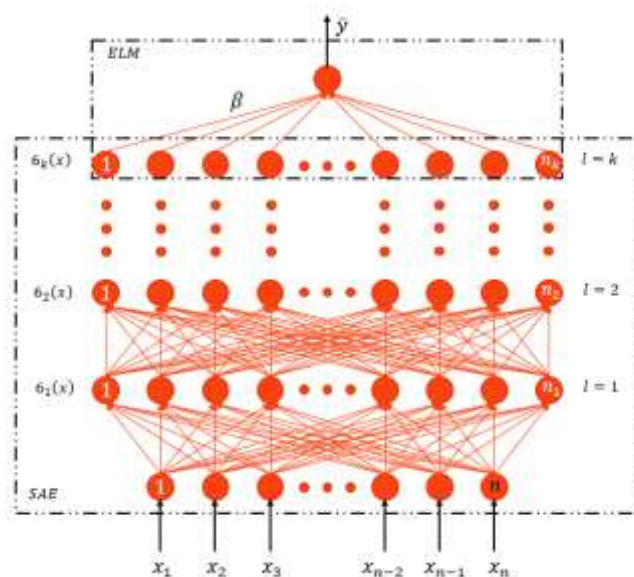


Fig.3 Structure with k hidden layers.

To design a well-performing network, the optimal parameters should be chosen, including the parameters in the SAE part and the ELM part should be determined first. In this study, we used two steps to determine these parameters. In the first step, we pretrain the parameters. Then, in the second step, we use the least squares method to find the parameters in the ELM.

III. Experiment

In order to confirm that the automatic recognition method of machine English translation based on GRU neural network proposed in this study has application value, an experiment was constructed to analyze the application effect of this method.

3.1 Experimental environment

In the process of this experiment, the experimental platform is set as the windows and linux systems, in which the collection and processing of the original translation information and extended information are completed, and the experimental part will be completed in the linux system [17-20]. During the experiment, JAVA is used as the experimental control language, and the processing of files and the output of experimental results are controlled by this language. At the same time, set the rules for merging experimental results, process the experimental results, and output the results.

3.2 Experimental results

We have conducted comparative experiments in the password sets mentioned above. We respectively

input the test set passwords in the CDS password set, Rosg password set, Tianya password set and Yahoo password set into DNN-HM, LSTM-CTC and the model of this paper. The word error rates of are shown in Table 2.

TABLE 2 Experimental results on four data sets

Dataset	model	word error rate (%)
CDS	DNN-HM	20.8
	LSTM-CTC	20.7
	Our method	19.8
Rosg	DNN-HM	21.9
	LSTM-CTC	20.9
	Our method	19.5
Yah	DNN-HM	20.5
	LSTM-CTC	20.3
	Our method	19.4

IV. CONCLUSION

Aiming at the current English translation results, this paper proposes a new method for automatic recognition of translation errors, which has been proved to have certain practical effects through experiments. This time, the focus of the research is based on the accuracy of recognition, and there is no optimization for other fields. In order to solve the shortcomings of inaccurate translation and incomplete semantics in the traditional decoding-decoding algorithm translation model, this paper proposes to combine the attention mechanism and the recurrent neural network model to establish an English-Chinese translation model with an improved attention mechanism. The model can improve the contextual semantic connection and parallel computing performance, and then effectively improve the translation quality of long sentences. The experimental results show that the translation performance of the method proposed in this paper is significantly better than the traditional translation model. In the long sentence translation test, the translation performance of the improved attention mechanism translation model is also ideal.

REFERENCES

- [1] Chen Rui. Research on English Machine Translation Based on LSTM Attention Embedding [J]. Automation and Instrumentation, 2021(10):140-143.DOI:10.14016/j.cnki.1001-9227.2021.10.140.
- [2] Cheng Xiaojiao. Research on automatic recognition of machine English translation errors based on multi-feature fusion [J]. Journal of Heilongjiang Institute of Technology (Comprehensive Edition), 2021, 21(10): 66-71. DOI: 10.16792/j.cnki.1672 -6758.2021.10.014.
- [3] Song Xiaohuan, Liang Jinwei, Liu Xiaolian. Design of an intelligent recognition model for English translation based on improved GLR algorithm [J]. Electronic Design Engineering, 2021, 29(19): 64-68. DOI: 10.14022/j.issn1674-6236.2021.19.013 .

- [4] Wang Jing, Zhao Cai. Research on neural machine English translation method based on parallel corpus [J]. Automation and Instrumentation, 2021(08):5-8.DOI:10.14016/j.cnki.1001-9227.2021.08.005 .
- [5] Chen Min. Research on Neural Machine English Translation Based on Syntax [J]. Electronic Design Engineering, 2021, 29(10): 24-27. DOI: 10.14022/j.issn1674-6236.2021.10.006.
- [6] Zhao Jiayu. Research on exposure bias in neural machine translation [D]. University of Electronic Science and Technology of China, 2021. DOI: 10.27005/d.cnki.gdzku.2021.004757.
- [7] Wang Qiao, Yan Lei. English translation method based on recurrent neural network [J]. Automation Technology and Application, 2020,39(11):37-40+70.
- [8] Zheng Meng. Research on intelligent English translation method based on improved attention mechanism model [J]. Electronic Science and Technology, 2020, 33(11): 84-87. DOI: 10.16180/j.cnki.issn1007-7820.2020.11.016.
- [9] Sun Ying, Wang Jing. English translation of neural network algorithm based on particle swarm optimization [J]. Science Technology and Engineering, 2020, 20(18): 7331-7335.
- [10] Tan Min. Research on neural machine translation under low resource conditions [D]. Soochow University, 2020. DOI: 10.27351/d.cnki.gszhu.2020.002722.
- [11] Li Zhen. Research on end-to-end neural network machine translation technology [D]. Strategic Support Forces Information Engineering University, 2020. DOI: 10.27188/d.cnki.gzjxu.2020.000065.
- [12] Yin Jinfang. The Machine Translation Based on Neural Networks from the Example of Technical English Translation [J]. Journal of Nanchang Normal University, 2019, 40(06): 58-61.
- [13] Wang Yijun. Research on Neural Machine Translation Methods for Limited Parallel Corpus Resources [D]. University of Science and Technology of China, 2019. DOI: 10.27517/d.cnki.gzkju.2019.000035.
- [14] Li Qike. Research on Indian English-Chinese Neural Machine Translation with Integrated Language Features [D]. Strategic Support Forces Information Engineering University, 2019. DOI: 10.27188/d.cnki.gzjxu.2019.000048.
- [15] Li Xiangyu. Computer textbook Neural Networks for Pattern Recognition (Chapter 1) English-Chinese translation practice report [D]. Heilongjiang University, 2018.
- [16] Li Qiang. Research on machine translation methods based on multi-level knowledge [D]. Northeastern University, 2018. DOI: 10.27007/d.cnki.gdbeu.2018.000610.
- [17] Luo Xusheng. Entity linking of cross-language web forms [D]. Shanghai Jiaotong University, 2018. DOI: 10.27307/d.cnki.gsjtu.2018.002176.
- [18] Tang Ze. Research and Design of Chinese College Students' English Translation Computer Scoring [D]. University of Science and Technology of China, 2015.
- [19] Wang Jianjia, Zhang Xu. Chinglish translation from the perspective of connectionism [J]. Writer, 2013(16): 169-170.
- [20] Bu Yukun. Research on the Chinese translation of scientific and technological English metaphors from a cognitive perspective [D]. Northeast Normal University, 2011.