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Research Article

Design of English Translation Mobile Information System Based on Recurrent Neural Network

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To solve the problem of translating lines of difference in length into English, this article presents a model of neural network recovery (RNN) English translator-based models of end-to-end encoder-decoder. This method promotes machine autonomous learning of features and transforms corpus data into word vectors by constructing end-to-end. By mapping the source language and target language directly through the recurrent neural network and selecting semantic error to construct objective function during training, the influence of each part in semantic can be well balanced, and the alignment information is fully considered, which provides powerful guidance for deep recurrent neural network training. The results of the neural network test define the standard BLEU score by 1.51–11.86. Our test scores and BLEU scores at all levels show that data in equivalence play an important role in modeling. *Summary*. the English translation model based on the neural repetitive fusion is efficient and stable.

1. Introduction

Translators are an important source of research in the field of natural language and intelligence. It is also one of the most popular services on the Internet. For example, Google Translate, Baidu Translation, and Microsoft Bing Translation provide online multilingual translation services, as shown in Figure 1. Although the translation quality of machine translation is still far behind that of professional translators, machine translation is still widely used because of its obvious advantages in translation speed in some scenes where the quality of translation is not too high or in translation tasks in specific fields [1]. Given the difficulty of machine translation and the concept of its application, both academics and industry consider this field an important area of research, making it one of the most important studies in the making of natural language. Translator is an automatic translation of a language from a native language into a computerized language. This is an interdisciplinary subject that requires the use of knowledge and skills from multiple disciplines, such as linguistics, computer science, and mathematics. The basic model of machine translation system is natural language processing system. The basic principle is the principle of element synthesis. The process of machine translation can be simply understood by the three stages: firstly, the text of the source language is decomposed into basic constituent elements, such as words, phrases, and grammatical structure. The original text is analyzed by morphological analysis, grammatical analysis, and semantic analysis to form the machine internal representation of the source language, and then the structural level conversion and ordering are carried out by using the composition law of the target language to finally generate the translation of the target language [2]. Therefore, the study of machine translation has not only become a hot topic in the field of science and technology, but also a hot topic for linguists all over the world.

2. Literature Review

Li et al. applied the perceptron algorithm, the simplest neural network. Early perceptrons did not solve linear integral problems due to their simple structure, which led to long-term research. After the 1980s, a feedback processing (BP) algorithm was introduced into a multilayer perceptron (MLP) called the feedforward neural network (FNN). Since then, the neural network led by Hinton, Lekun, and Bengio has grown. Ban et al. have solved the difficult problem of training neural networks through pretraining procedures.

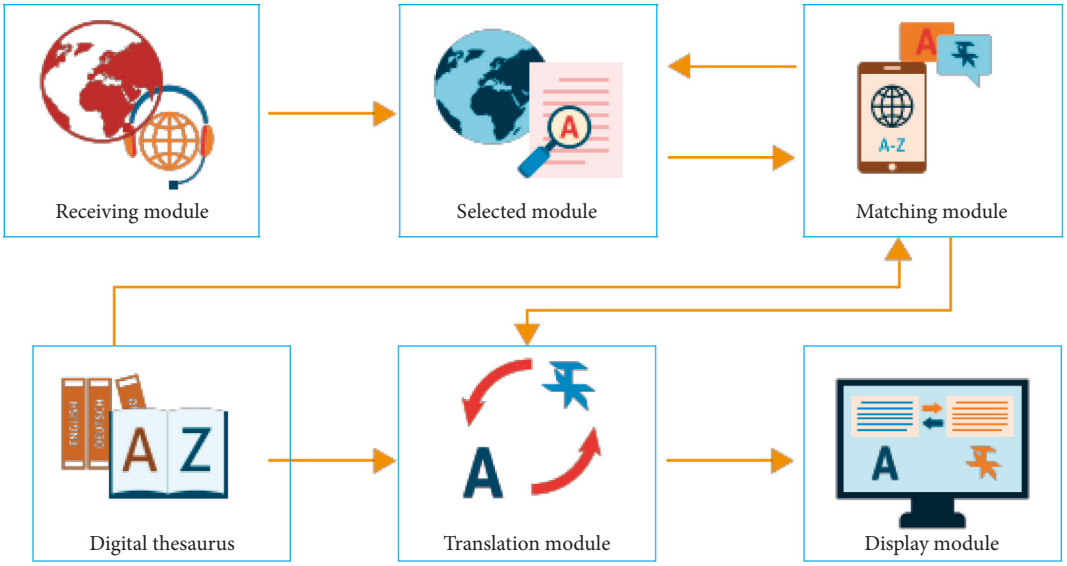

Figure 1: English translation mobile information system.

Then, due to improved computing power, such as the widespread use of communications and graphics processing (GPUs), neural networks have benefited academically and economically [3, 4]. In recent years, neural networks have made great strides in H1 and other areas of visual and speech recognition. At the same time, scientists have used this technology to create natural language, such as grammar, word representation, rhyme, and other functions, as well as support.

In translator research, neural machine translation has gradually passed through translators into many languages. Ponceles et al. have used United Nations Parallel Corps v1.0 to compare neural translators and translators in 30 languages. Neural machine translation outperformed phrase-based statistical machine translation for 27 language pairs. [5]. Poncelas et al first proposed the case-based machine translation method. This method starts from the existing translation experience and knowledge and translates new source language sentences through the principles of analogy [6]. The case-based method divides the source language sentence into phrase fragments seen in the translation knowledge, and then matches the obtained phrase fragments with the empirical knowledge through analogy and other methods to obtain the translation of the phrase fragments, and then splices the translated phrase fragments into the target language sentence. Duan et al. have reported the use of statistics-based technology. The use of statistical technology includes the relationship between mother tongue and native language as a result [7]. The statistical machine translation method regards any target language sentence as a possible translation candidate of the source language sentence, but the probability of different candidates is different. The core problem of statistical machine translation is to use statistical methods to automatically learn a translation model from the corpus, and then based on this translation model, find a target language sentence with the highest score for the input source language sentence as the translation result. At present, neural machine translation has not only attracted widespread attention in academia, but the industry is also actively exploring the commercial value of this method. Khan, H. I. et al. pointed out the end-to-end neural network machine translation, defined the encoder-decoder architecture, realized translation probability modeling, mapped the source language sentence into a continuous compact vector through the encoder, and realized the transformation of the vector into the target language sentence based on the decoder [8].

On the basis of this research, this paper proposes an English translation model based on recurrent neural network. Convolutional neural network is used to build the encoder and recurrent neural network is used to build the decoder, so as to obtain historical information and scientifically process variable-length strings. It is concluded that the English translation model based on recurrent neural network has high effectiveness and stability.

3. Research Methods

3.1. Recurrent Neural Network Analysis. In recent years, in-depth study of natural language processing technology has led to the development of various natural language processing task systems (DBN), automatic encoder (auto encoder), convolutional neural network (CNN), and recently repetitive neural network (RNN) supports functional improvement. Among them, because of its recursive connection, RNN can record and save a wider range of context information, and then model stronger correlation information, which attracts the attention and interest of researchers. A neural network device is a mathematical model for processing information using structures similar to the synaptic connections of neurons in the brain. The weight of the connection at each of the two nodes is equal to the network memory [9]. Unlike an anterior neural network, the recurring neural network is time-dynamic and can store some information. In order to follow the neural network of the brain, it is equal to the internal instantaneous memory of

repetitive neural network. Recursive networks use this internal memory to process ideas.

In-depth training of the neural network has a unique quality and plays an important role in solving a variety of problems, such as distribution, but the transmission of the neural network is limited. The classification task is only a small part of the vast computational power of the human brain. In addition to interpreting personal situations, people can determine the depth of key information in a rich description. There is also a very complicated time relationship between information, and the length of information varies.. These problems can only be solved effectively by a neural network. The key is to cover the network, which can store background data as a network version [10].

The recursive neural network model [11] is shown in Figure 2.

If the intermediate closed loop link is removed, it will be transformed into the three-layer structure previously in the feedforward neural network, namely the input layer, the hidden layer, and the output layer.

Where V_k represents k-time input, h_k represents the hidden form at time k, and W_{kD} represents k-time output [12].

If $k1$, set h_k to 0. The special counting procedure is as follows:

$$\begin{cases} r_1 = \mathrm{UV}_1 + Mh_0, \\ h_1 = f(r_1), \\ W_1 = g(Nh_1). \end{cases} \tag{1}$$

Here, f and g represent activation functions.

As time progresses, the next prediction procedure includes state memory for period 1.

$$\begin{cases} r_2 = \mathrm{UV}_2 + Mh_1, \\ h_2 = f(r_2), \\ W_2 = g(Nh_2). \end{cases} \tag{2}$$

The following formula:

$$\begin{cases} r_k = UV_k + Mh_k, \\ h_k = f(r_k), \\ W_k = g(Nh_k). \end{cases} \tag{3}$$

Recurrent neural networks are prone to gradient explosion or disappearance during training, which results in the inability of gradients to be continuously transmitted in long sequences during training, and finally makes it difficult for the model to capture long distances. In the case of gradient bursts, the initial gradient can be determined scientifically and rationally based on the training of the parameters. If the gradient exceeds the starting point, it can be stopped immediately. Scientifically initialize the weight values to ensure that all the neuron weights do not choose maximum or minimum values to avoid the vanishing range of the gradient. As with other functions, sigmoid and tanh can be replaced by relu function as activation function. The model is based on design principles, such as long-term or short-term (LSTM) or GRU [13].

3.2. Framework of English Translation Model Based on Recurrent Neural Network. The model frame of English machine translation based on recurrent neural network is shown in Figure 3.

The box layer optimizes the scalability and reliability of the developer using an organic combination of Nginx and web servers. When sending requests to multiple users, Nginx can not only transmit the request probability to the server, but also process a large number of concurrent requests based on a reasonable setting of the maximum number of visits to prevent failures. The intermediate process consists of an intermediate unit and a memory database module. It is possible to ensure the stability and efficiency of data transmission by increasing the control of the dispatch module. There are two layers of CPU decoding module and GPU decoding module. As more and more parallel models are connected, the uniformity of the models will be improved, the slow response patterns will be reduced, and all models will have higher parallelism and lower latency [14–16].

3.3. Construction of English Translation Model Based on Recurrent Neural Network

3.3.1. Model Training Framework. The English translation model realizes model construction through the concept of componentization, so that it can quickly and effectively measure the role of components in translation work, and adopt a joint training mode during training to effectively reflect the criticality of components. (O, Q) represents the sentence of the body and (o, q) represents selected sentences/phrases according to the body. To clarify words and phrases regularly, identify them with the terms O_x and o_x.

The training framework of English translation model is shown in Figure 4.

This includes selecting materials, concepts, and rules before and after writing in one or two languages, usually before and after completion. The vector data generated by the cyclic neural network involved in the training is called neural network recovery training. A number of neural network training processes are similar to the tree of origin formed by a sentence. Training includes sentence coders and grammar coders [17]. The model training framework selects the phrase or rule of each sentence by preprocessing and obtains the initial word vector representation based on the recurrent neural network. At the same time, the similarity between short words and grammar is measured in the internal material.

The English translation standard focuses on the bilingual sentence structure of the curriculum, which is divided into two sections. First, the word vector is derived from a cyclic neural network and is called a recursive neural network translation model. The second is divided into phrase encoder and rule encoder based on the translation model, and the encoder is divided into two

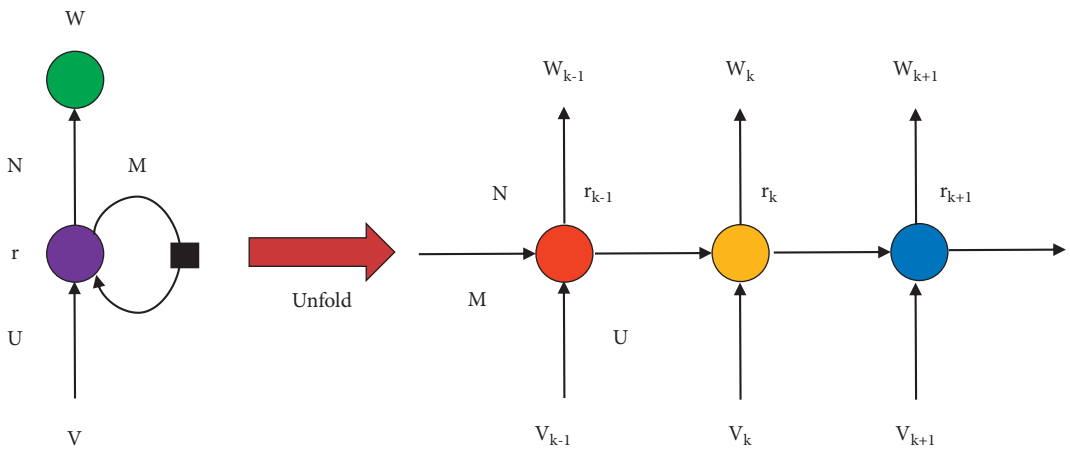

Figure 2: Recurrent neural network model.

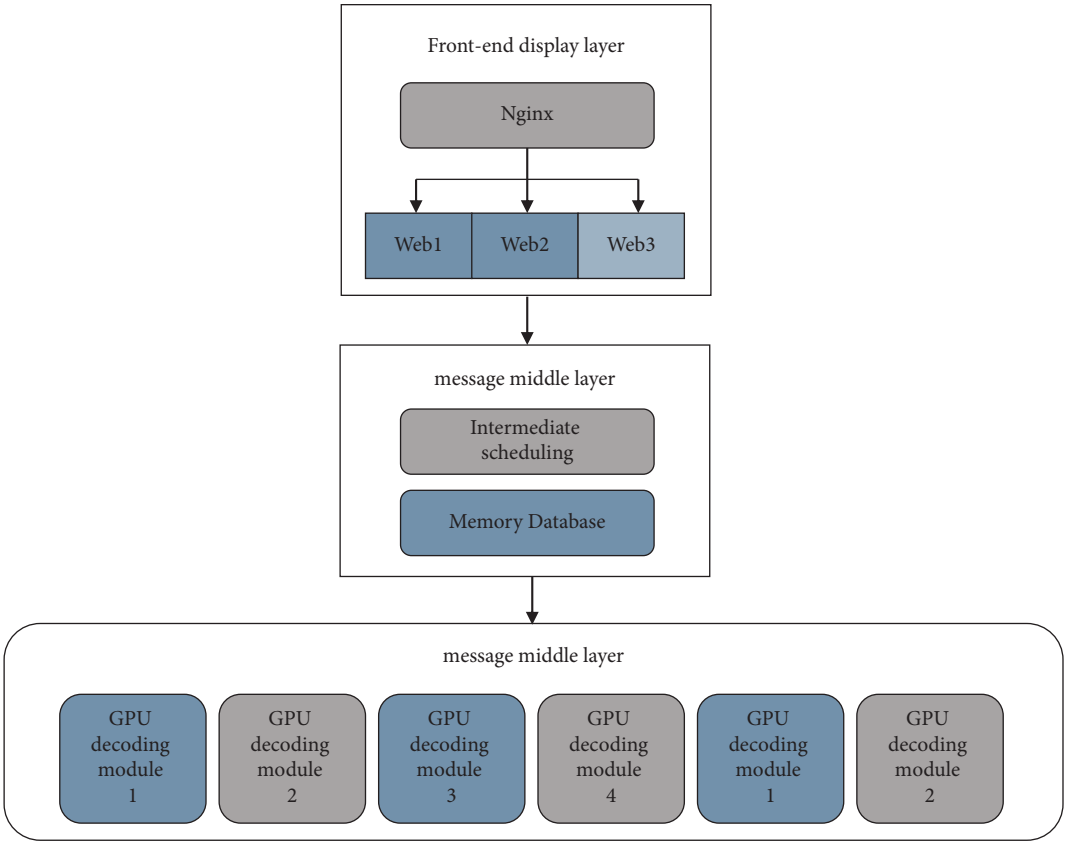

Figure 3: Model framework.

types: monolingual encoder and bilingual encoder. During the training, each language coder was prepared step-by-step, followed by two language coders. Finally, the key for each link is to follow the link [18, 19].

3.3.2. Encoder Decoder Framework. Direct mapping of natural language is achieved through recurrent neural networks. Based on an end-to-end encoder-decoder system, the model is designed directly for translation capabilities and completes all native languages so that the machine can learn on its own and to enable the machine to learn language features autonomously and directly map natural language through recurrent neural networks. In this way, translation problems move into a way of creating a simple situation that describes the specific time of the language. The English translation of the stream as a coder is based on a neural network repeater. As the end of the encoder, the input of the sequence with the beginning and end characters of the mother tongue is converted into a vector file, which

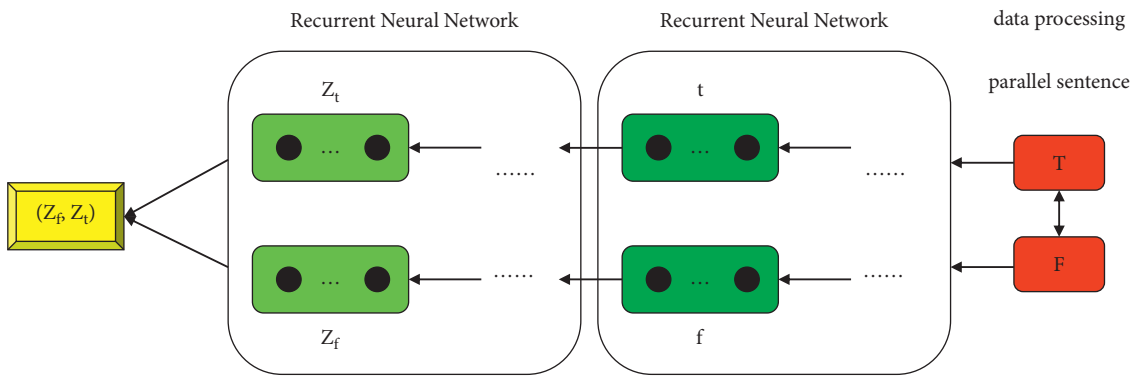

Figure 4: Model training framework.

transmits to the neural network, including the vector return of the input language file neural network. The end of the decoder, the neural network, is used as a carrier to calculate and access the target language temporarily [20].

3.3.3. Decoding Integration Analysis. The importance of the sentence/grammar at the time of determination is the result obtained by counting the numbers. In addition, sentence analysis and training sentences are required. Special vectors consist of three types of objects: similar models, such as the result of different translations, heavy words, five-letter patterns, number of words, number hierarchies, and zero suffixes. Semantic features, i.e., bilingual semantic similarity, monolingual semantic similarity, bilingual semantic sensitivity, monolingual semantic sensitivity. Sparse features, i.e., high-frequency feature number [21, 22].

4. Result Analysis

4.1. Machine Translation Settings. Based on the English translation project completed by NIST, LDC is used as the training corpus, including 1 m bilingual corpus, 32 M Chinese vocabulary, and 33 m English vocabulary. Taking the target language training model of Gigaword corpus and bilingual training corpus as the carrier, the corpus is screened by feature attenuation algorithm. In order to effectively evaluate the level and quality of translation results in real time, the five element Bleu mode is selected, and the resampling method is used to test the statistical significance of the results. Filter phrases were conducted based on the Hadoop open source system. In order to reduce the training complexity, the decoder is used to decode bilingual sentences first, and only the required phrases/rules (1.4 m phrases and 2.2 m rules) are input into the recurrent neural network for training.

4.2. Result Discussion. In order to compare the influence of semantic feature vector in the performance of translation model and the effectiveness of neural network, the baseline system is selected, that is, no semantic feature baseline is added and no recursive modeling baseline is selected. The implementation of the latter is the same as the English translation model of recurrent neural network, but the recursion of aligning phrases/rules on the side of guiding source language and target language does not need to be considered in training. The semantic vector is constructed from left to right through the source language and target language, and the baseline system of the latter also has the characteristics of bilingual semantic similarity.

In order to verify the effectiveness of features, bilingual features, namely, semantic similarity and semantic sensitivity, were added first, and then monolingual features, namely, semantic similarity and semantic sensitivity, were added. The influence of semantic features on the experimental results is shown in Table 1. The italicized characters represent that they have significant advantages under the test indexes ($P < 0.05$).

It can be seen from Table 1 that ALL represents the integration of all corpora. It can be found that the performance of not selecting recursive modeling baseline is roughly the same as that of not adding semantic features. It does not obtain semantic information and does not strengthen the translation effect. The results of recurrent neural network translation model have significantly improved the baseline BLEU score by about 1.51–1.86 BLEU scores in the three test sets and all levels, which indicates that the alignment information plays a key role in modeling. In particular, the influence of bilingual semantic features and sensitivity features is prominent, in which semantic features are more obvious, but monolingual semantic features and sensitivity features do not have a significant impact. Therefore, the recursive neural network translation model with bilingual semantic features and sensitivity features is complementary to short language translation, which shows the significance of semantic features.

One advantage of neural network model is that it can automatically learn feature representation from monolingual data through pretraining. In order to verify the effect of monolingual data pretraining, we did a comparative experiment on the basis of the above experiment. In the comparative experiment, we randomly initialize the low dimensional representation of vocabulary and vocabulary n-ary, and trained the model directly on the data. The training results are shown in Figure 5.

Table 1: Influence results of semantic features.

	Do not add semantic feature baseline	Do not select recursive modeling baseline	Translation model (bilingual semantic similarity features)	Translation model (bilingual semantic similarity/sensitivity features)	Semantic similarity/ monolingual translation model
NIST5	36.1	36.2	37.0	37.4	37.6
NIST6	34.0	34.5	36.1	35.1	35.4
NIST8	30.4	30.3	31.0	31.3	31.2
ALL	35.3	35.4	36.4	37.0	37.1

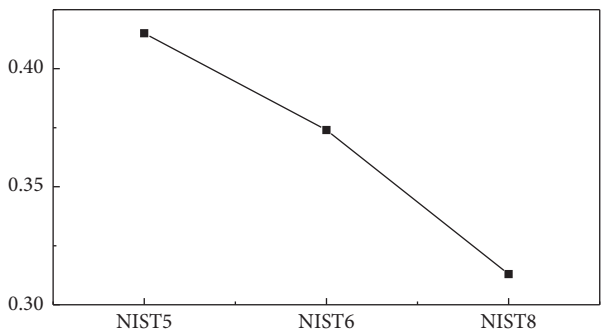

Figure 5: Shows the role of vocabulary pretraining.

The experimental results show that without pretraining, the neural network model has no significant advantages over the linear model using sparse features. We believe that this is because our neural network model adopts the low dimensional representation of vocabulary and lexical n-ary, and their number is huge. Through the training of monolingual data, we can make better use of the similarity between low-frequency n-ary and high-frequency n-ary, so as to get better results.

5. Conclusion

Artificial intelligence has contributed to the development of translation services, making it easier for people to quickly understand the meaning of languages other than their own. They do not have to rely on human interpreters for some things. Fear translator is no longer a "word for word" translator. It can better understand long sentences with full design and translate old words and languages into new words. In conclusion, a neural network has been set up to guide the translation process, and the translation process is based on English. In the course of training, the word vector with world data and data comparison between two languages is clearly stated in this document. Training organizations select representatives from more than two languages. By experimentation, the effectiveness of the model was confirmed by testing data from multiple groups. The results of the experiment concluded that the English translation model based on neural communication was very good and stable [23].

Data Availability

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

Conflicts of Interest

The author declares no conflicts of interest.

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