Hindawi
Mobile Information Systems
Volume 2022, Article ID 2086486, 10 pages
https://doi.org/10.1155/2022/2086486

Research Article

An English Translation Quality Evaluation Model Integrating Knowledge Transfer and Wireless Network

Xiaojing Li

Foreign Language Department, Henan University of Chinese Medicine, Zhengzhou 450000, Henan, China

Correspondence should be addressed to Xiaojing Li; lixiaojing@hactcm.edu.cn

Received 28 December 2021; Accepted 25 January 2022; Published 12 March 2022

Academic Editor: Hasan Ali Khattak

Machine translation is to automatically translate one natural language text into another. It is one of the important applications of natural language processing. The research of machine translation is closely related to machine translation evaluation technology. Therefore, with the progress of machine translation technology in recent years, researchers are also committed to designing more reasonable evaluation methods. Manual evaluation is costly, time-consuming, and subjective, so it has been difficult to provide practical help for the development of machine translation systems. Finding a feasible automatic machine translation evaluation method has been a hot spot in machine translation evaluation research in recent years. Based on this, this paper proposes an English translation quality evaluation model integrating knowledge transfer and wireless network. Firstly, wireless network technology is used to coordinate multitasks, and then knowledge transfer optimization technology is used to construct an English translation quality evaluation model. In this paper, simulation experiments are designed to verify the effectiveness of the model. The experimental results show that the accuracy of the evaluation method based on fusion technology is significantly improved compared with the existing evaluation methods.

1. Introduction

Machine translation, as the name implies, is automatically translating one natural language text into another natural language text. And it is also one of the important applications of natural language processing. The ultimate goal of machine translation is to generate translations without any mistakes so that ordinary people can also read smoothly, and its research and application are designed to reduce communication barriers among people from different cultures and regions [1]. The rapid development of the Internet has brought great changes to the spread of information and knowledge and more frequent communication between different languages, which brings broad demand for machine translation, as an important application technology in natural language processing, involves many basic studies in the field, such as word segmentation, syntactic analysis, semantic analysis, named entity recognition, and semantic disambiguation, which will also have an important impact on the development of these basic technologies [2].

There has been more and more research on machine translation, and machine translation technology has made great progress. The research of machine translation is closely related to machine translation evaluation technology [3]. On the one hand, the evaluation technology can promote the development of machine translation, and on the other hand, the progress of machine translation will also be subject to the specific evaluation technology [4]. An evaluation method that cannot correctly measure the quality of the translation also cannot truly reflect the performance of the system, and it cannot timely reflect the impact of the change of the model on the translation results [5]. Therefore, along with the progress of machine translation technology in recent years, researchers are also committed to designing more reasonable evaluation methods. Machine translation evaluation is a complex and challenging research topic. Unlike a natural language processing task such as speech recognition, there is no unique correct answer for translation. If different translators translate the same sentence, they give several different answers. Even for a short sentence, the evaluators have little consistent translation [6]. Therefore, how to take the diversification of translation into account in the evaluation is also an important issue in the evaluation research.

When evaluating the quality of the translation, a common method is to manually check whether the translation output of the system is correct. Obviously, bilingual assessors who master both the source and target language are the best suitable to make such an evaluation, but such people do not always appear in the evaluation task [7]. Therefore, the usual method is to evaluate the machine translation given a reference translation with the help of monolingual evaluators who can understand the target language. Usually, such an evaluation is conducted sentence by sentence. However, manual evaluation has a big drawback, which is time-consuming. If the evaluator wants to be paid accordingly, then the manual evaluation will also be costly. Researchers in machine translation systems have limited funding and have relatively frequent system updates, usually testing the effect of the system in different configurations multiple times in a day [8]. Therefore, machine translation research prefers automatic evaluation. Ideally, the automated evaluation method should quickly give whether a system produces better translation results after a change.

In recent years, automatic evaluation of machine translation has made great progress, so researchers of machine translation system trust automatic evaluation and improve their system according to the level of automatic evaluation. In translation system, automatic evaluation is mainly used in two important aspects: model parameter estimation and translation quality evaluation. Model parameter estimation refers to the use of developed corpus to determine the parameter values in the translation model [9]. The main method to determine the parameters is to recycle the two processes of translation and evaluation to find the parameter setting with high translation quality. Translation quality evaluation is the main function of the automatic evaluation method, that is, to determine the quality of translation given by the translation system or the relative quality between translations [10]. Although automatic evaluations have been widely used, they have been a topic of discussion, and their ability to distinguish systems between good and bad is often questioned, so the research of automatic evaluation methods has received more and more attention [11].

Therefore, this paper proposes an English translation quality evaluation model integrating knowledge transfer and wireless network, which mainly lies in using wireless network technology to achieve multitask coordination and then using knowledge transfer optimization technology to construct an English translation quality evaluation model.

2. Related Work

Machine translation has high efficiency and low cost. With the development of artificial intelligence technology, it has been widely used. At the same time, people have higher and higher demands for translation quality, and the quality of a translation depends on whether it is faithful to the source language and the grammatical and semantic errors of the target language. In order to achieve the accuracy and authenticity of the translation, translation evaluation analyzes the inherent or potential influencing factors in machine translation, grasps the distortion of the translation and its similarity with the original text, and then formulates the evaluation index system and evaluation model. The overall process of translation evaluation is shown in Figure 1.

2.1. Existing Translation Evaluation Models. Translation evaluation is similar to machine translation, requiring decoding and recoding of works and reasonable scientific evaluation of work translation quality through fusion and training. Intelligent translation evaluation system needs an algorithm or model to complete the characterization of the characteristics of text variables [12], then constructs the evaluation weight set through rules, and finally realizes the evaluation and translation analysis with a matching model.

Experts have now begun to explore qualitative or quantitative translation quality evaluation methods. Experts have now begun to explore qualitative or quantitative translation quality evaluation methods. Zhao Tie-Jun from Harbin Institute of Technology was the first to put forward manual evaluation and automatic evaluation ideas and to evaluate the translation quality of the EBMT system with sentence similarity [13]. Later, Zhou Guo-dong of Soochow University summarized the three aspects of automatic evaluation, including linguistics detection points, string matching, and machine learning [14]. Sun and Zhou of Xiamen University proposed a quantitative evaluation of machine translation quality by hierarchical analysis and fuzzy mathematical model [15]. Ma et al. of the Chinese Academy of Sciences proposed fusion strategies and multiangle comprehensive evaluation methods, for example, on Blend, comparing the two machine algorithms of SVM and FFNN [16]. Liu et al. from Beijing Jiao Tong University proposed to use the cross-sentence attention mechanism to construct a BP restatement recognition model to improve translation accuracy [17].

2.2. Current Situation of Optimization Algorithm. In the field of machine learning, Multitask Learning has been widely concerned by researchers in the past two decades, and related technologies and researches have also been greatly developed [18]. The basic idea of multitask learning is to improve the performance of each task by learning multiple related tasks at the same time and sharing the useful information obtained from each task. Similarly, in the field of intelligent optimization, many optimization problems are interrelated. However, unlike the booming development of multitasking learning, the concept of intelligent optimization of multitasking was not put forward by Gupta et al. until 2016 [19]. Similar to multitask learning, the basic idea of multitask intelligent optimization is to improve the optimization performance of each task by solving multiple different optimization problems at the same time and transferring and sharing the useful knowledge obtained by each task in the process of multitask optimization.

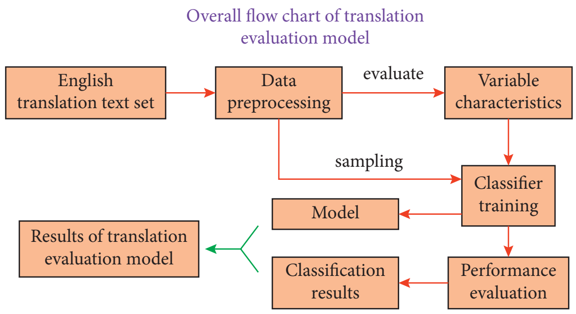

Figure 1: The overall process of translation evaluation.

Multifactorial Optimization is the first algorithm framework for multitask intelligent optimization. The model suggests that the complex characteristics of offspring formation are coinfluenced by genetic and cultural factors [20]. In order to better explain the excellent performance of multitask optimization, researchers have conducted in-depth research on the internal mechanism of multitask optimization. Da B designed a random individual assignment strategy, randomly assigning offspring individuals generated through knowledge transfer to any task for evaluation [21]. Gupta A verified that the performance improvement of MFEA compared with the single-task optimization algorithm was due to knowledge transfer between tasks rather than the increase of diversity caused by the optimization of different populations in a unified search space [22]. Regardless of the difficulty of the task, all tasks enjoy the same computing resources. Wen and Ting improved the resource allocation strategy, which is based on the observation that simple tasks have faster convergence [23]. Recently, Hashimoto divided the individuals in the population into subpopulations according to the corresponding tasks and established an island model to analyze the performance [24].

Because of the performance advantage of the multitask optimization algorithm over the single-task algorithm, there are a lot of research works on applying a multitask optimization algorithm to solve specific problems. Chandra et al. applied the multitask optimization algorithm to the training of neural networks [25]. Tang et al. proposed a multitask optimization algorithm for training multiple extreme learning machines with different numbers of hidden neurons to solve the classification problem [26]. It can be seen that the emergence stage models take the knowledge transfer between tasks as the starting point to carry out the design and research of high-performance multitask intelligent optimization algorithm.

3. English Translation Quality Evaluation Model

3.1. Wireless Network Technology. Wireless network is the basic network architecture of mobile Internet. It combines the advantages of wireless LAN and wireless ad hoc network, supports multipoint to multipoint mesh structure, and is a wireless broadband access network with large network capacity, high transmission rate, and wide coverage, which can provide high-quality wireless broadband access services for a large number of users at the same time [27]. However, the traditional scheduling method aiming at maximizing the system throughput does not take into account the fairness between users. If the quality of a user channel is poor for a long time, the oriented scheduling method will make the system unable to provide a service guarantee for such users [28]. Therefore, this section proposes a packet fair scheduling mechanism based on network coding perception, which combines network coding and scheduling algorithm in wireless networks to provide fair access and error correction services for multiple users, ensuring that the throughput of each user is improved.

The FSNC mechanism includes two core algorithm modules: scheduling algorithm and encoding algorithm. The scheduling algorithm focuses on scheduling objective function and mainly solves the fairness problem of algorithm. The main steps of the algorithm are as follows:

Step 1: short-term fairness control. Considering the compensation problem of short-term fairness in the special environment of wireless networks, the compensation method for backlog connections is mainly to reserve system resources or sacrifice some services with lower priority. However, the above compensation methods are actually unfair. Those who should really bear the responsibility for compensation are those who have been served. Based on this idea, this paper achieves the purpose of controlling short-term fairness by compensating between the scheduled code set and the unscheduled users.

Step 2: schedule the target function settings. The mechanism selects the encoding set service with efficient use, high credit, low transmission cost, and low system service time requirements from the already constructed alternative coding set by setting the scheduling target function and maximizing the throughput of the encoding set.

Step 3: encryption algorithm. The coding algorithm of the mechanism includes three subalgorithms: coding queue control algorithm, coding member selection algorithm, and network coding algorithm. The three algorithms complement each other, and the design of each one further emphasizes the relationship between scheduling algorithms for maintaining fairness and encoding algorithms that improve the throughput rate.

Step 4: cohort control algorithm. In addition to the fairness of service time, fairness also guarantees the fairness of the user decoding rate after the introduction of network coding. The source maintains a data frame queue, and if the network coding is not introduced, the source needs to cache the raw data frame queue on the network coding to be encoded. Therefore, this paper changes the previous queue management idea of discarding data frames after user decoding, but after the user perceives the data frames.

Step 5: source cohort analysis of the encoding set. The physical queue length of the source maintenance reflects the overhead of the source to cache data frames to be encoded while improving network performance and ensuring fairness. The following compares the length of decoding: the physical cache queue under the two queue management ideas. For the two queue management ideas, the difference is mainly reflected in the relationship between physical and virtual queues, which are the same under the two schemes. Assume that the size of the encoding finite domain can guarantee that the encoding frame is novel. The conceptual diagram of the algorithm is shown in Figure 2.

3.2. Optimization Algorithm Based on Knowledge Transfer. In this section, knowledge transfer in a multifactor evolutionary algorithm is studied, and an adaptive knowledge transfer method is proposed. Compared with traditional evolutionary algorithms that solve one optimization problem at a time, multifactor optimization solves multiple optimization tasks simultaneously. The research in this section is based on MFO and MFEA, which involves a lot of MFO definition and MFEA algorithm content. Therefore, this section will briefly introduce the concept and definition of MFO and the algorithm flow of MFEA.

MFEA is a specific implementation of MFO based on a genetic algorithm. Specifically, MFEA first initializes a population in which each individual adopts a unified coding method. Next, each individual will evaluate all current tasks to calculate their corresponding factor overhead. Then, a progeny population is generated by performing selective mating on the current population. Then, a progeny population is generated by performing selective mating on the current population. Finally, the scalar fitness of all individuals of the parent population and the offspring population is updated, and the individuals with the optimal scalar fitness are selected to form the next generation population. The above process will be repeated until the preset termination conditions are met. Crossover operation is a way to exchange genetic information between individuals. This paper will introduce several common crossover operators for continuous optimization problems.

3.2.1. Discrete Crossover Operator. In this category, each dimension of the offspring accurately inherits knowledge from a parent, as shown in Figure 3.

Two-point crossover operator: randomly select two positions $i, j \in \{1, 2, \ldots, n\}\,(i < j)$, and then exchange the i to j segments of two parent individuals to obtain two offspring individuals.

$$\begin{aligned} c_1 &= \left(p_1^1, p_1^2, \ldots, p_2^i, p_2^{i+1}, \ldots, p_2^j, p_1^{j+1}, \ldots, p_1^n\right),\\ c_2 &= \left(p_2^1, p_2^2, \ldots, p_1^i, p_1^{i+1}, \ldots, p_1^j, p_2^{j+1}, \ldots, p_2^n\right). \end{aligned} \tag{1}$$

Then, the value of each dimension of the offspring is randomly selected from the corresponding positions of the two parent individuals with equal probability.

$$c_1^i\left(or\, c_2^i\right) = \begin{cases} p_1^i, & \text{if } \mu = 0,\\ p_2^i, & \text{if } \mu = 1. \end{cases} \tag{2}$$

Aggregation-based crossover operators pass the mixed knowledge of two parents to their children through an aggregation function. When the aggregation function is determined, the offspring obtained from the parent is also determined, so its corresponding knowledge transfer has certain determinism. Therefore, this paper takes arithmetic crossover and geometric crossover operators as representatives to study in experiments, and their definitions are as follows. The arithmetic crossover operator represents that the value of each dimension of the descendant is a linear combination of the corresponding position values of the two parent individuals. The mathematical expression is

$$\begin{aligned} c_1^i &= \lambda \cdot p_1^i + (1-\lambda)\cdot p_2^i,\\ c_2^i &= \lambda \cdot p_2^i + (1-\lambda)\cdot p_1^i. \end{aligned} \tag{3}$$

The value of each dimension represented by the geometric crossover operator is the exponential combination of the corresponding position values of two parent individuals.

$$\begin{aligned} c_1^i &= p_1^{i\omega} \cdot p_2^{i^{1-\omega}},\\ c_2^i &= p_2^{i\omega} \cdot p_1^{i^{1-\omega}}. \end{aligned} \tag{4}$$

In this class, the interval formed by the values of the same dimension of two parent individuals is defined as the neighborhood. Crossover operators belonging to this class acquire the knowledge of the neighborhood and pass it on to their offspring according to a predefined probability distribution model. Therefore, the crossover operators of this group will produce more changes when generating offspring. In particular, crossover operators adopt uniform and exponential probability distribution models, respectively, as shown in Figure 4.

Further, for simplicity, this study reconstructs the input before denoising through a single-layer mapping. The reconstructed data needs to minimize the following mean-square reconstruction error:

$$\mathscr{L}_{sq}(M) = \frac{1}{2N}\sum_{i=1}^{N} q_i - Mp_i^{\,2}. \tag{5}$$

To simplify the symbolic representation, a constant feature is added to the input vector. Therefore, the error function in equation (5) can be transformed into a matrix form:

$$\mathscr{L}_{sq}(M) = \frac{1}{2N} tr\left[(Q - MP)^T (Q - MP)\right]. \tag{6}$$

The solution of equation (6) can be expressed as a common closed solution by the least square method, which is given in the following formula:

$$M = \left(QP^T\right)\left(PP^T\right)^{-1}. \tag{7}$$

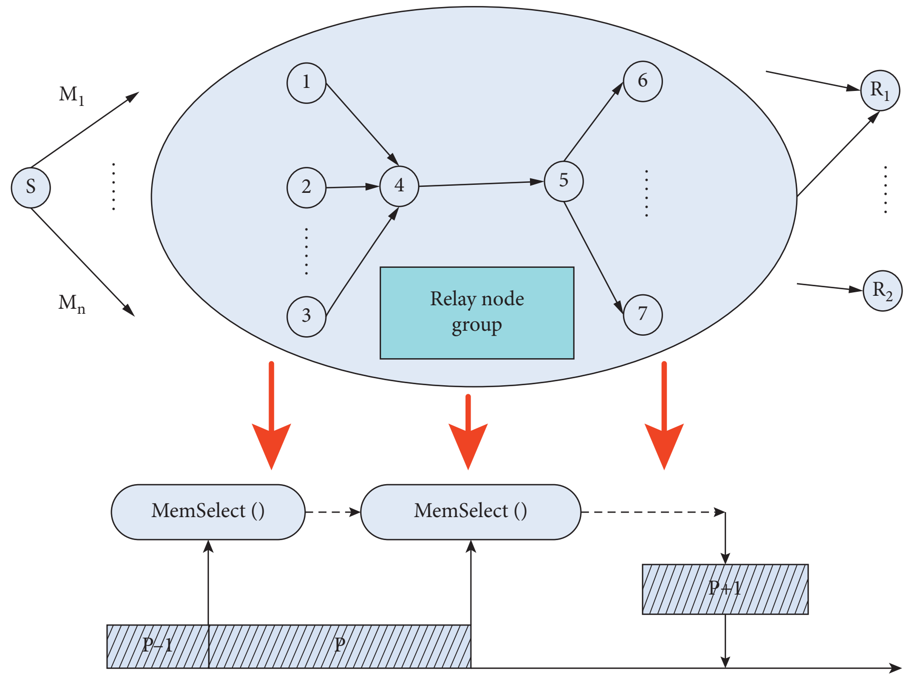

Figure 2: The conceptual diagram of the algorithm.

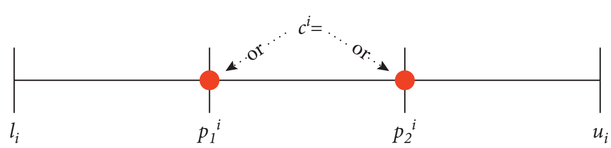

Figure 3: Each dimension of the offspring inherits the exact knowledge from one of the parents.

It can be seen that the closed solution obtained by learning can be used for the mapping between problems. It can be seen that the algorithm uses two different evolutionary solvers based on independent population. Next, in order to establish the association between tasks, the algorithm uniformly and independently samples a set of solutions from the search space, takes them as the input and output of the noise reduction automatic encoder, and then obtains the mapping matrix between the two tasks.

Because it is extremely expensive to evaluate each individual in the search process on all tasks, in EMA, each individual is only evaluated on a task that may have good performance. The offspring produced by the mutation operation will be evaluated directly on the tasks corresponding to their parent's skill factors. In addition, the child individual will perform a local search with a given probability, and its factor overhead on all unevaluated tasks will be set to infinity, transforming the individual from a unified search space to a feasible solution on the task. In order to realize adaptive knowledge transfer, each individual is randomly assigned a crossover factor in the initialization stage. Next, in the adaptive selection mating step, the crossover operator is selected from the available crossover operators according to the crossover factor for knowledge transfer. Finally, the crossover factor of each individual will be updated according to the information collected in the evolutionary search process. The basic flowchart of the algorithm is shown in Figure 5.

Most of the existing multifactor evolutionary algorithms only use a single crossover operator for knowledge transfer in the whole optimization process. In this paper, the effects of different crossover operators on the performance of multifactor evolutionary algorithms are studied. It is observed that different crossover operators can perform well in different multitask optimization problems, but no crossover operator can achieve good results in all problems. The denoising autoencoder technology in machine learning is used to realize explicit knowledge transfer in the form of explicit transfer of feasible solutions between tasks. In addition, multiple tasks are allowed to be optimized by different evolutionary algorithms to make full use of their respective advantages. Finally, more efficient optimization performance is obtained than traditional MFEA based on implicit knowledge transfer.

3.3. Process of Evaluation Model Construction. Because machine learning can use any feature that can be expressed digitally, there are many valid features available beyond combining existing methods. However, more features does not make machine learning better because as the number of features increases the mutual restriction and influence will increase, and the cost of training and evaluation will also increase. This section will introduce feature types and feature combination utility. The contribution of each feature may vary in different tasks. This paper suggests that the following two aspects should be considered in feature selection: (1) features based on deep linguistics can effectively improve the evaluation effect, such as the help of retelling features to

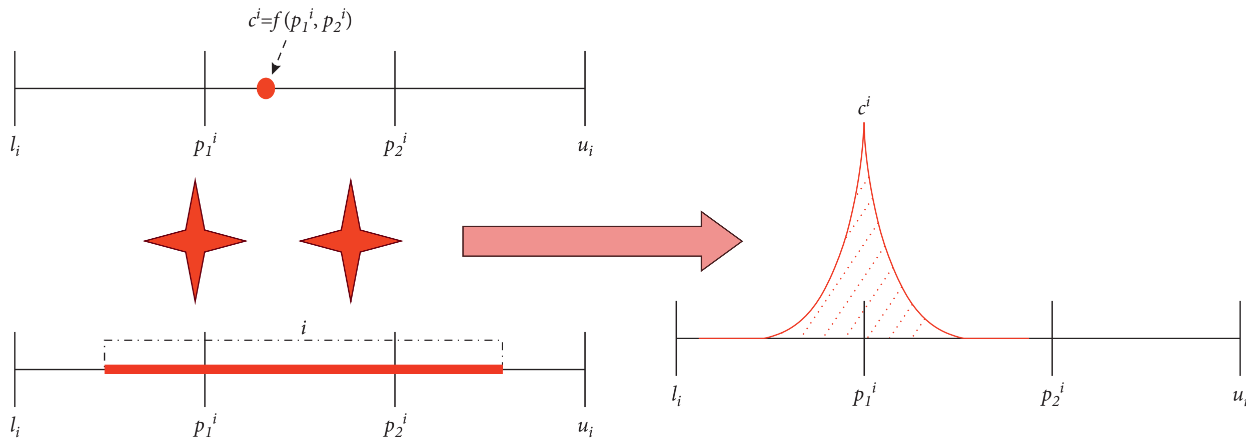

Figure 4: Schematic diagram of extracting information in neighborhood.

evaluation; (2) blindly combining features does not necessarily produce good reviews. Some simple and intuitive features contribute more than others. Evaluation without reference is often called quality estimation. At present, the effect of nonreference translation evaluation is not very satisfactory, but it can be used in a wide range and has strong practical value, such as filtering translation for manual editing or selecting the best translation. The construction of the evaluation model proposed in this paper is shown in Figure 6.

Next, we use an image example to express the fusion idea of evaluation methods. The translation system is like an English major student, and the evaluation method is like an English evaluation expert. Therefore, the integration of evaluation methods can be regarded as the so-called "excellent, medium, and poor" evaluation of an English translation by English evaluation experts. Of course, due to the different evaluation experience of each expert, their evaluation angles and concepts are different, so their evaluation results are also different. However, an evaluation expert makes his original evaluation results of the student's translated sentences change to varying degrees through mutual communication with each other. With the deepening of the communication between evaluation experts, finally, an agreement can be reached.

4. Experiments and Results

4.1. Data Set and Experimental Description. The data set in this paper is the XNLI data set, that is, the data set on cross-language tasks. XNLI also uses crowdsourcing to build a multitype natural language inference corpus. It collects and verifies 750 new instances for the multitype NLI corpus from 10 text sources, with a total of 7500 instances. Based on these data, XNLI hired some professional translators to translate these examples into 10 target languages so as to create a complete XNLI corpus. After being tested in the target language, the accuracy of the generated cross semantic vector still lags behind that of the source language. Therefore, this paper believes that there is room for improvement under this task.

Named entity recognition refers to the recognition of special objects in the text. The semantic categories of these objects are usually predefined before recognition, such as person, address, and organization. The supervised named entity recognition task relies on annotation data. It is a named entity recognition data set with multiple English. These two sets of data sets are also selected in this paper. Named entity recognition can use the ability of deep learning to deal with nonlinear mapping relationships to establish a nonlinear mapping from input to output. Tag decoding is the last step in the named entity recognition model. After obtaining the vector representation of the word and converting it into context-sensitive representation, the tag decoding module takes it as the input and predicts the corresponding tag sequence for the input of the whole model. Using this structure, the named entity recognition model can be regarded as a multitype classification problem. At this stage, the label of each word is predicted independently according to the input context semantic representation, rather than relying on adjacent words.

4.2. Data Analysis and Experimental Results. In multitask training, NLI prediction was taken as task 1, named entity recognition as task 2, and sentence alignment using parallel corpus as task 3. All three tasks shared the same encoder. The data are passed into the encoders with shared parameters, respectively, and the loss function results on their respective tasks are calculated, respectively. Combined with classification, sequence tagging, and machine translation, all sentences share the sentence level coding layer. In one round of training, the loss functions of three tasks are calculated and backpropagated. After five rounds of training, the F value in the named entity recognition task, the accuracy in English-Chinese translation, and the accuracy in Chinese-English translation were compared. The experimental results are shown in Table 1.

As the number of training rounds increases, the accuracy of named entity recognition and English-Chinese translation increases, but the accuracy of Chinese-English translation decreases. The reason is that, under the setting of multitask

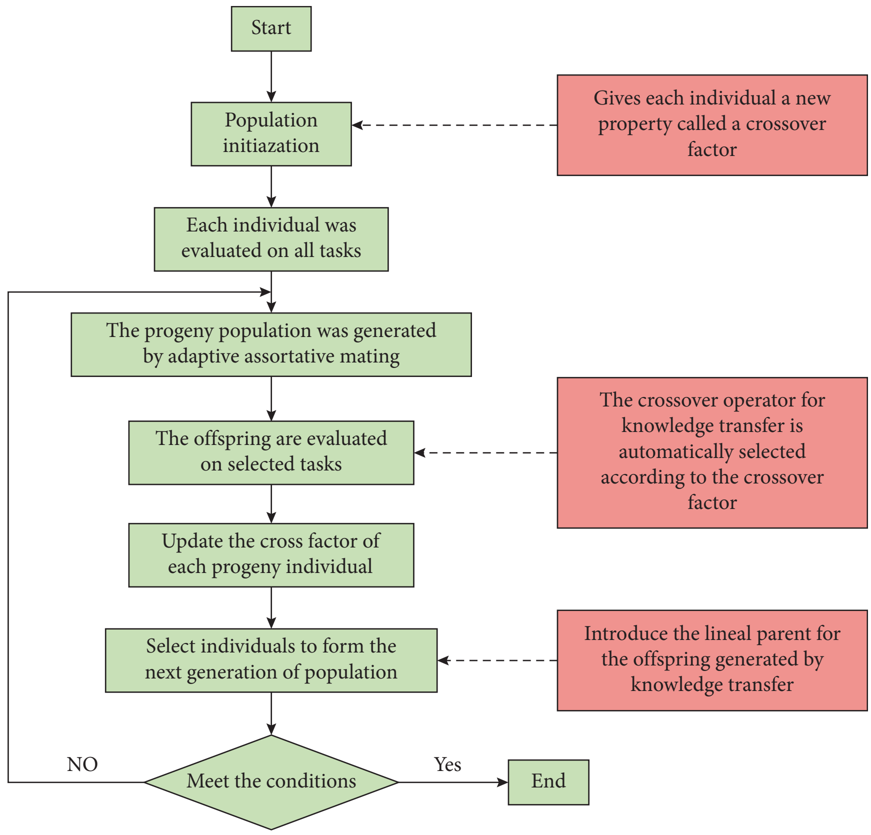

Figure 5: The basic flowchart of the algorithm.

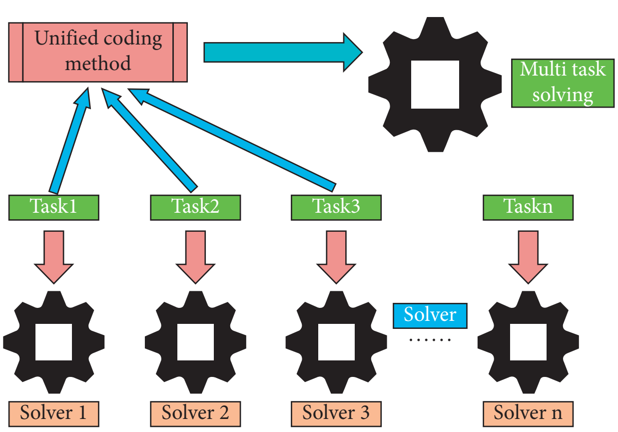

Figure 6: The construction of the evaluation model proposed in this paper.

learning, since the three tasks share encoder parameters, with the deepening of training, the named entity recognition task and natural language understanding task are improved, but the performance of the aligned encoder is reduced. The semantic vector experiment is followed, and the experimental results are shown in Table 2.

Based on the experimental data, two LCA values of all parameters on transformer model, unidirectional model combined with semantic vector, and bidirectional model combined with semantic vector are calculated, respectively. This paper calculates the LCA value in the training process to compare the contribution of each parameter to loss in the training process. It can also compare whether the newly introduced parameters have a positive or negative effect on the reduction of loss. Compared with the machine translation and the baseline data, the semantic vector in this paper is able to translate the training data and express stronger results. This paper will compare the effects of sentence coding with different structures, use the best structure to conduct experiments on cross-language tasks as the baseline model, and then further improve the performance of the encoder through multitask learning. Finally, the performance of the semantic vector obtained by cross-language unsupervised learning is close to that of the source language obtained by supervised learning. The parameter accumulation histogram of the LCA calculation method is shown in Figure 7.

4.3. Comparison of Experimental Results. By studying the advantages of the knowledge transfer method in this paper, the classification results and classification error rate are obtained. Then, the evaluation value of translation quality is obtained from the model. After the training sample set of the English translation is preprocessed by the toolkit, the text feature data is obtained. N samples are extracted from the corresponding training set through bootstrap, the classification results and classification error rate are obtained through majority voting, and the evaluation value of translation quality is obtained through hierarchical

Table 1: Experimental results on data sets and named entity recognition.

Epoch	F	English-Chinese translation	Chinese-English translation
1	46.21	87.65	77.75
2	50.05	91.21	75.76
3	51.26	91.43	76.92
4	51.12	91.54	76.12
5	52.03	91.6	76.92

Table 2: Results of the semantic vector experiments.

	Transformer	Sentence embedding
En-emb	1.3	1
De-emb	2.4	2
De-out	1.1	1
En1	75.4	75
En2	46	44
En3	45	44
En4	41	36

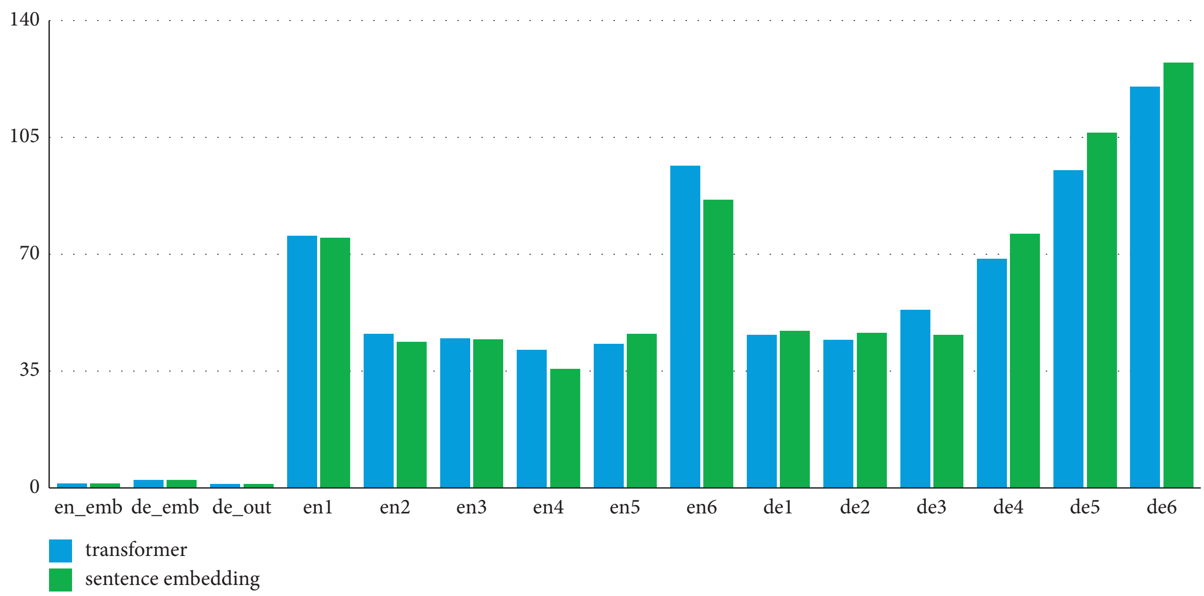

Figure 7: Parameter cumulative bar graph for the LCA calculation method.

correlation calculation. Calculate the performance index error rate of output classification results, respectively, as shown in Table 3 and Figure 8. Comparing the classification error rates of various model algorithms in a different number of translation sets, the classification error rate decreases significantly with the increase of iteration times. And when the number of iterations is stable to about 200, the classification error rate tends to be stable. Therefore, for the selected experimental samples, 200 is determined to be the optimal number of iterations.

In this paper, the single direction and two-way machine translation experiments combined with semantic vector are carried out, respectively. Compared with the baseline model transformer model, the Bleu value has been improved. In addition, the two-way translation system can make full use of the semantic information on both sides of the source language and the target language, so the result is better than the one-way model. Comparing the classification error rate of various translation sets under the same number of iterations of 200, the classification error rate of the algorithm in this paper is the lowest, the random-RF algorithm is the second, the original RF algorithm is the highest, and the error rate of manual translation is less than that of the other four online machines. The evaluation results are consistent with the actual translation situation, which shows that the

Table 3: Results of the semantic vector experiments.

	System	BLEU
Baseline	GNMT [29]	38.95
	Convs2s [30]	40.51
	Transformer [31]	43.2
Our work	One direction	43.4
	Two directions	43.7

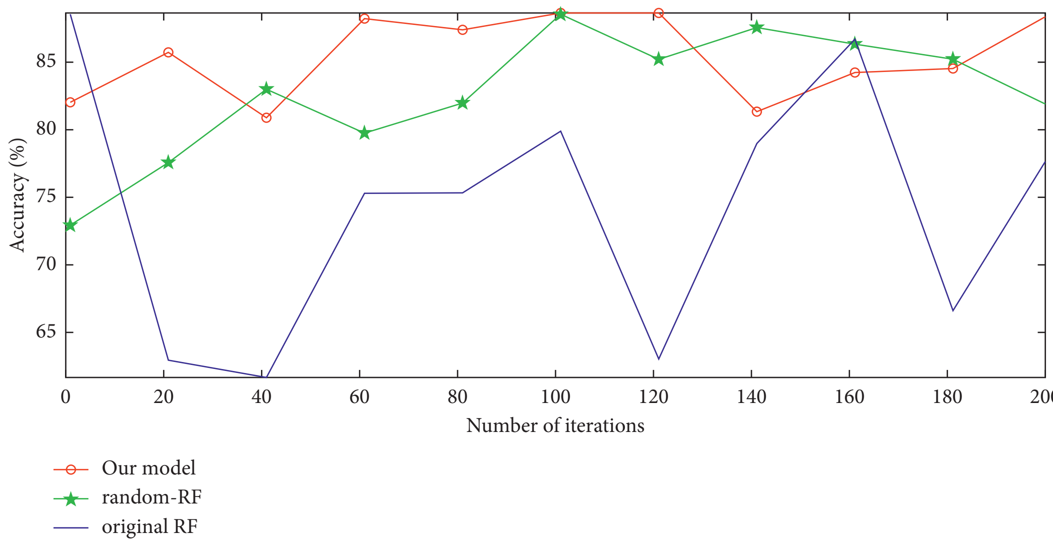

Figure 8: Error rate results of the algorithm.

translation evaluation method proposed in the text is feasible. As far as this paper knows, this is the first time to apply the semantic vector trained by easily available data to the machine translation task. In the process of machine translation, in order to make full use of the semantic vectors at the source language end and the target language end, this paper will train a two-way machine translation system at the same time, that is, from the source language to the target language and from the target language to the source language.

5. Conclusion

Because the research and development of the automatic machine translation system are very complex and need a lot of time and money, the machine translation system is very expensive. The evaluation of the machine translation system can effectively analyze and guide the rational development of the translation system. Therefore, the research on the evaluation of machine translation system is of great significance. In the field of machine translation evaluation, this paper makes a more in-depth research and practice around the following aspects.

Firstly, based on the existing machine translation evaluation methods, this paper studies the feasibility of the application of these evaluation methods in the quality evaluation of English-Chinese machine translation and discusses the special problems caused by the influence of Chinese language characteristics when they are applied in the evaluation of English-Chinese machine translation. The results show that various methods can evaluate the quality of the English-Chinese translation system to a certain extent, but their accuracy is not high compared with manual evaluation. Secondly, in order to improve the accuracy of the existing automatic evaluation methods, this paper introduces the fusion technology, makes a simple modification and improvement on the basis of the fusion technology, and applies it to the fusion of machine translation evaluation methods. An automatic evaluation method based on fusion technology is proposed, and the effectiveness of the method is verified by experiments. Then, some problems encountered in the process of design and implementation are analyzed, and the solutions are discussed. The practice shows that the accuracy of the evaluation method based on fusion technology is significantly improved compared with the existing evaluation methods.

Although this paper has achieved the above-phased research results and achieved the expected objectives, the work of this paper can be further discussed and studied in the following two aspects: (1) Although the accuracy of the evaluation method of fusion technology has been significantly improved compared with the existing evaluation methods, we can also try to apply other advanced fusion technologies to compare and analyze the evaluation results, to improve the accuracy of evaluation. (2) Consider fusing more existing evaluation methods to further improve the fusion effect and accelerate the convergence speed of fusion.

Data Availability

The data sets used during the current study are available from the author upon reasonable request.

Conflicts of Interest

The author declares that he has no conflicts of interest.

Acknowledgments

This work was supported by the Training Plan for Young Backbone Teachers in Colleges of Henan Province, Research on Construction and Application of Bilingual Knowledge Base of Metaphorical Discourse in Traditional Chinese Medicine Classics (Project no. 2019GGJS114). This work was also supported by the Ministry of Education Industry University Cooperation Collaborative Education Project, Construction and Application of Bilingual Parallel Corpus of Traditional Chinese Medicine (Project no. 202002242007).

References

[1] N. Mathur, T. Baldwin, and T. Cohn, "Putting evaluation in context: contextual embeddings improve machine translation evaluation," in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 2799–2808, Florence, Italy, July 2019.

[2] Y. Graham, B. Haddow, and P. Koehn, "Statistical power and translationese in machine translation evaluation," in *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 72–81, November 2020.

[3] C. Han and X. Lu, "Can automated machine translation evaluation metrics be used to assess students' interpretation in the language learning classroom?" *Computer Assisted Language Learning*, pp. 1–24, 2021.

[4] A. Toral and A. Way, "What level of quality can neural machine translation attain on literary text?" *Machine Translation: Technologies and Applications*, Springer, Berlin, Germany, 2018.

[5] M. Yamada, "The impact of Google neural machine translation on post-editing by student translators," *The Journal of Specialised Translation*, vol. 31, pp. 87–106, 2019.

[6] A. Mukherjee, H. Ala, M. Shrivastava, and D. M. Sharma, "MEE: an automatic metric for evaluation using embeddings for machine translation," in *Proceedings of the IEEE 7th International Conference on Data Science and Advanced Analytics (DSAA)*, pp. 292–299, IEEE, Sydney, NSW, Australia, October 2020.

[7] M. Munk and D. Munkova, "Detecting errors in machine translation using residuals and metrics of automatic evaluation," *Journal of Intelligent and Fuzzy Systems*, vol. 34, no. 5, pp. 3211–3223, 2018.

[8] I. Rivera-Trigueros, "Machine translation systems and quality assessment: a systematic review," *Language Resources and Evaluation*, pp. 1–27, 2021.

[9] B. Dorr, J. Olive, and J. McCary, "Machine translation evaluation and optimization," *Handbook of Natural Language Processing and Machine Translation*, Springer, New York, NY, USA, 2011.

[10] C. Callison-Burch, M. Osborne, and P. Koehn, "Re-evaluating the role of BLEU in machine translation research," in *Proceedings of the 11th Conference of the European Chapter of the Association of Computational Linguistics*, pp. 249–256, Trento, Italy, April 2006.

[11] J. Pei, K. Zhong, J. Li, J. Xu, and X. Wang, "ECNN: evaluating a cluster-neural network model for city innovation capability," *Neural Computing & Applications*, 2021.

[12] X. Zhao, D. Wang, and Z. Zhao, "A neural topic model with word vectors and entity vectors for short texts," *Information Processing & Management*, vol. 58, no. 2, pp. 2082–2086, Article ID 102455, 2021.

[13] J.-M. Yao, M. Zhou, and T.-J. Zhao, "Machine translation evaluation method and its effectiveness analysis," *Computer Research and Development*, vol. 41, no. 7, pp. 1258–1265, 2004.

[14] L. Liang-You, G. Zheng-Xian, and G.-D. Zhou, "A review of automatic evaluation of machine translation," *Journal of Chinese Information Science*, vol. 28, no. 3, pp. 81–91, 2014.

[15] Y.-Q. Sun and M.-K. Zhou, "Research on comprehensive Evaluation method of machine translation Quality," *China science & technology translation*, vol. 30, no. 2, pp. 20–24, 2017.

[16] Q.-S. Ma, Z. Jin-Chao, and Q. Liu, "Automatic evaluation method for Machine translation based on fusion strategy," *Journal of Chinese information science*, vol. 32, no. 9, pp. 11–19, 2018.

[17] M.-T. Liu, Y.-J. Zhang, and J.-A. Xu, "Neural network retelling recognition model based on syntactic structure," *Journal of Peking University*, vol. 56, no. 1, p. 4552, 2020.

[18] R. Caruana, "Multitask learning," *Machine Learning*, vol. 28, no. 1, pp. 41–75, 1997.

[19] A. Gupta, Y. S. Ong, and L. Feng, "Multifactorial evolution: toward evolutionary multitasking," *IEEE Transactions on Evolutionary Computation*, vol. 20, no. 3, pp. 343–357, 2016.

[20] J. O. Rice, C. R. Cloninger, and T. H. Reich, "Multifactorial inheritance with cultural transmission and assortative mating. I. Description and basic properties of the unitary models," *The American Journal of Human Genetics*, vol. 30, no. 6, p. 618, 1978.

[21] B. Da, A. Gupta, Y. S. Ong, and L. Feng, "The boon of gene-culture interaction for effective evolutionary multitasking," in *Proceedings of the Australasian Conference on Artificial Life and Computational Intelligence*, pp. 54–65, Canberra, ACT, Australia, February 2016.

[22] A. Gupta and Y. S. Ong, "Genetic transfer or population diversification? Deciphering the secret ingredients of evolutionary multitask optimization," in *Proceedings of the IEEE Symposium Series on Computational Intelligence (SSCI)*, pp. 1–7, Athens, Greece, December 2016.

[23] Y. W. Wen and C. K. Ting, "Parting ways and reallocating resources in evolutionary multitasking," in *Proceedings of the IEEE Congress on Evolutionary Computation (CEC)*, pp. 2404–2411, Donostia, Spain, June 2017.

[24] R. Hashimoto, H. Ishibuchi, N. Masuyama, and Y. Nojima, "Analysis of evolutionary multi-tasking as an island model," in *Proceedings of the Genetic and Evolutionary Computation Conference*, pp. 1894–1897, Kyoto, Japan, July 2018.

[25] R. Chandra, A. Gupta, Y. S. Ong, and C. K. Goh, "Evolutionary multi-task learning for modular training of feedforward neural networks," in *Proceedings of the International Conference on Neural Information Processing*, pp. 37–46, Guangzhou, China, November 2016.

[26] Z. Tang, M. Gong, and M. Zhang, "Evolutionary multi-task learning for modular extremal learning machine," in *Proceedings of the IEEE Congress on Evolutionary Computation (CEC)*, pp. 474–479, Donostia, Spain, June 2017.

[27] S. Li, R. Yeung, and N. Cai, "Linear network coding," *IEEE Transactions on Information Theory*, vol. 49, no. 2, pp. 371–381, 2003.

[28] S. Katti, H. Rahul, W. Hu, D. Katabi, M. Medard, and J. Crowcroft, "XORs in the air: practical wireless network coding," *IEEE/ACM Transactions on Networking*, vol. 16, no. 3, pp. 497–510, 2008.

[29] Y. Wu, M. Schuster, Z. Chen et al., "Google's neural machine translation system: bridging the gap between human and machine translation," 2016, https://arxiv.org/abs/1609.08144.

[30] G. Tiwari, A. Sharma, A. Sahotra, and R. Kapoor, "English-Hindi neural machine translation-LSTM seq2seq and ConvS2S," in *Proceedings of the International Conference on Communication and Signal Processing (ICCSP)*, pp. 871–875, IEEE, Chennai, India, July 2020.

[31] Y. Xia, T. He, X. Tan, F. Tian, D. He, and T. Qin, "Tied transformers: neural machine translation with shared encoder and decoder," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, no. 1, pp. 5466–5473, Honolulu Hawaii USA, January 2019.