

## *Retraction*

# **Retracted: An Improved Machine Translation Model and its Application in Japanese Multi-Context Translation**

### **Security and Communication Networks**

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### **References**

- [1] H. Wen, "An Improved Machine Translation Model and its Application in Japanese Multi-Context Translation," *Security and Communication Networks*, vol. 2022, Article ID 8364278, 10 pages, 2022.

## Research Article

# An Improved Machine Translation Model and its Application in Japanese Multi-Context Translation

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In order to further improve the application of machine translation model in Japanese translation, analytic analysis method is adopted to optimize the original machine translation model. The improved machine translation model is used to analyze and describe Japanese translation. Finally, the optimized machine translation model is used to analyze Japanese multicontext. The relevant indexes and parameters were extracted and verified, and finally the model was verified by relevant experiments. The results show that the vector variation graph with different parameters can be divided into slow decline stage, stable change stage, and fast decline stage according to the increase of iteration number and the influence of corresponding change trend. In addition, it can be seen from the value of PE curve that the influence of parameter  $p_e$  is the least, while the influence of corresponding re parameter is the greatest. The multicontext index of Japanese has the greatest influence on Japanese fluency and the least influence on Japanese keywords, and the trend of influence is parabolic. The application curve of the optimized machine translation model to Japanese in multiple contexts shows that different parameters have different effects on Japanese, which should be represented by the positive parameter  $V$ . Finally, the accuracy of the model is verified by experimental data. The above research can provide support for the application of machine learning in different fields and also provide research ideas for the multicontext translation of Japanese.

## 1. Introduction

Machine translation models are widely used in different fields. Aiming at a series of grammatical errors in English writing, a new computational method is adopted to optimize and deal with the original machine translation model, so as to obtain a modified machine translation model [1]. The model can extract specific parameters of English words, so as to obtain the corresponding characteristic indicators, and then obtain the optimized English translation data by checking and analyzing the indicators. Finally, an experimental method is used to verify and analyze the optimized machine translation model so as to demonstrate the accuracy of the model. It is worth noting that this model can not only analyze words but also study English paragraphs and grammar. Aiming at the problems of long time and slow efficiency in French translation, RNN neural network algorithm is adopted to revise the traditional machine

translation model [2]. Thus, an optimized machine translation model can be obtained, which can carry out targeted analysis of French pronunciation, language, and grammar. This model can not only translate French but also get the optimal translation by analyzing the data. This model can provide theoretical support for French translation and popularization, thus providing ideas for the application of optimized machine translation model in other fields. Finally, a variety of data analysis methods are used to verify the model. Machine translation models are also widely used in other fields, such as deep coding information [3], language training [4], natural data [5], adversarial neural network [6], and weighted supervision [7].

The above studies mainly analyze different kinds of languages from the perspective of the original machine translation model, and the accuracy of the results obtained is relatively low. In order to further improve the accuracy of translation, analytical and analytical methods are used to

optimize the original machine translation model, so as to obtain the improved machine translation model. In order to further improve the accuracy of Japanese multicontext translation, the improved machine translation model is applied to Japanese multicontext translation, and the accuracy of the model is verified through experiments. The results of this study can provide a research idea for the translation of other languages.

## 2. Theories Related to Machine Translation Models

*2.1. The Basics of a Machine Translation Model.* Machine translation model has been widely used in various fields. In order to further analyze the application of machine translation model in Japanese multicontext, the basic content of machine translation model is first explained [8, 9]. It is worth explaining that the basic content of machine translation model mainly includes abstract semantics and neural network machine translation.

*2.1.1. Abstract Semantics.* The automatic evaluation index of abstract semantics refers to the automatic scoring of translated texts by artificial mathematical formulas, and the quality of machine translation models is evaluated according to the scoring level [10, 11]. Each node in the abstract semantics represents a semantic concept, which can be summarized into five conceptual relation types by analysis: PropBank Framesets, general semantic relation, date entity relation, list relation, and quantity relation. The advantages of automatic evaluation indicators of abstract semantics mainly include (a) more persuasive; (b) it can save costs and reduce economic pressure; (c) faster calculation. Compared with manual evaluation, automatic evaluation index is more objective and saves labor cost greatly. The common indexes for automatic evaluation of abstract semantics are accuracy ( $P$ ), recall ( $R$ ), and measure value ( $F$ ). The specific calculation formula of each indicator is given below:

$$\begin{aligned} P &= \frac{S}{M}, \\ R &= \frac{S}{N}, \\ F &= \frac{2 * P * R}{P + R}, \end{aligned} \quad (1)$$

where  $S$  represents the number of correctly matched logical triples,  $M$  represents the number of recognized logical triples, and  $N$  represents the total number of marked logical triples.

In order to further analyze the influence of different evaluation parameters on the automatic evaluation indexes of abstract semantics, the evaluation indexes change curves under different parameters are drawn, as shown in Figure 1. It can be seen from the figure that the influence curves of different parameters on evaluation indexes are different, but they can be divided into three stages according to the overall trend. To be specific, the influence of parameter  $p$  on the

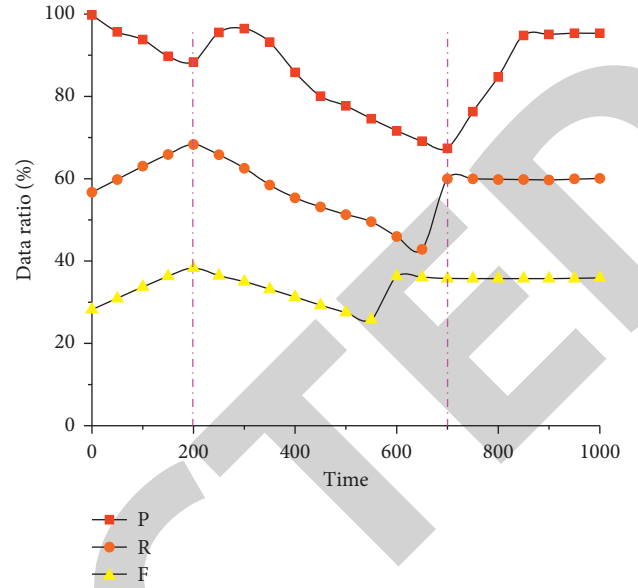


FIGURE 1: Evaluation index change diagram.

evaluation index in 0–200 time shows a gradual downward trend, and the downward trend is in line with a linear downward relationship. When the time reaches 200, with the gradual increase of time, it shows a trend of slow increase at first and then gradual decline, and the slope of this downward trend is approximately the same as the slope of the first stage. When the corresponding change time reaches 700, the curve begins to enter the third stage. In the third stage, the curve first shows a linear increase, and then gradually tends to be gentle, indicating that with the gradual increase of time. The influence of parameter  $P$  on the index curve fluctuates slowly at first, and then tends to a stable overall change. It can be seen from parameter  $R$  that the first stage of the index curve corresponding to parameter  $P$  is opposite. Parameter  $R$  shows a trend of linear increase in the first stage, and when the time exceeds 200, the corresponding curve shows a trend of gradual decline, and the slope is basically consistent with the influence of parameter  $P$ . When it reaches about 650, the curve enters the third stage. In the third stage, the change curve increases rapidly at first, and then gradually tends to be flat, which is basically consistent with the influence of parameter  $P$ . It can be seen from the influence curve of parameter  $F$  that the curve also shows a trend of gradual increase first. When the time reaches about 550, the corresponding curve enters the third stage: it also shows a rapid increase at first, and then gradually flattens out. It can be seen from the figure above that the curves of parameter  $R$  and parameter  $F$  are basically the same. The above three factors are basically the same at the time points in the first stage, but the time points in the second stage are the largest for parameter  $P$ , the second for parameter  $R$ , and the smallest for parameter  $F$ .

*2.1.2. Neural Network Machine Translation.* Machine translation model based on recurrent neural network is the earliest translation model using encoder-decoder framework

in machine translation tasks. Recurrent neural networks can capture the sequential information of sentences in machine translation tasks and are very good at processing sentences with varying length. Relevant studies show that the two algorithms using long and short memory neural network have achieved large experimental results on two data sets in abstract semantics. It shows that introducing neural networks to abstract semantic parsing tasks can improve the performance of machine translation model parsing.

In order to further analyze the influence of machine translation model on Japanese grammar, the computational flow chart of machine translation model is drawn, as shown in Figure 2. It can be seen from the figure that Japanese data is first imported into the model, and different  $X$  modules are divided into two identical modules with opposite iteration directions. Data are imported into  $X$  module, respectively, for iterative calculation. In order to extract the feature points and feature vectors of its grammar, those extracted from each module are then imported into the summary analysis module. Through further analysis of the analysis module, the machine translation model can be used for further targeted analysis of the data, and then the exported data can be brought into the  $S$  module at the top. Through further iterative analysis of the parameter, the corresponding data can be finally exported. The corresponding decoder state update formula is as follows:

$$e_{ij} = \text{match}(s_{i-1}, h_j), \quad (2)$$

$$a_{ij} = \frac{e_{ij}}{\sum_{k=1}^T e_{ik}}, \quad (3)$$

$$c_{t=i} = \sum_{j=1}^T a_{ij} h_j, \quad (4)$$

$$s_{t=i} = f(y_{t=i-1}, s_{t=i-1}, c_{t=i}), \quad (5)$$

where  $s_{i-1}$  is the hidden state of the encoder at moment  $i-1$ ;  $h_j$  is the hidden state of the encoder at moment  $j$ ;  $a_{ij}$  is the alignment weight;  $e_{ij}$  is alignment score;  $c_{t=i}$  is a vector;  $s_{t=i}$  indicates the hidden state. First, the alignment score of the hidden layer state of the encoder at moment  $j$  and the hidden layer state of the decoder at moment  $i-1$  is dynamically calculated by formula (2). Second, the alignment score of formula (3) is normalized to obtain the alignment weight. Then, formula (4) sums the states of each hidden layer of the encoder with their weights to obtain the dynamic context vector at the current moment. Finally, the hidden layer state of decoder at each time is updated by formula (5).

Through the above formula and analysis, we can see that different coefficients  $i$  and  $j$  have a great influence on decoder parameters. In order to further analyze the influence of parameters  $i$  and  $j$  on different parameters of decoder, the decoder parameter change curves under different coefficients are drawn as shown in Figure 3. It can be seen from Figure 3 that with the gradual increase of parameter  $i$ , the corresponding decoder parameters show a trend of gradual increase. However, the slope increases in the order of

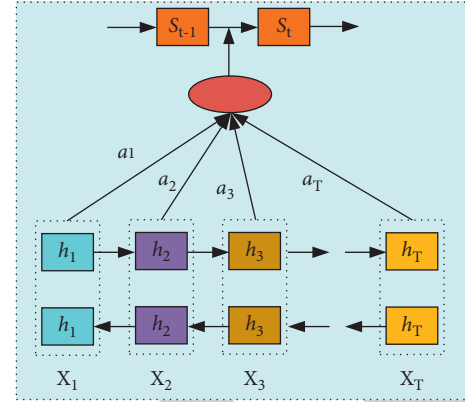


FIGURE 2: Machine translation model flow chart.

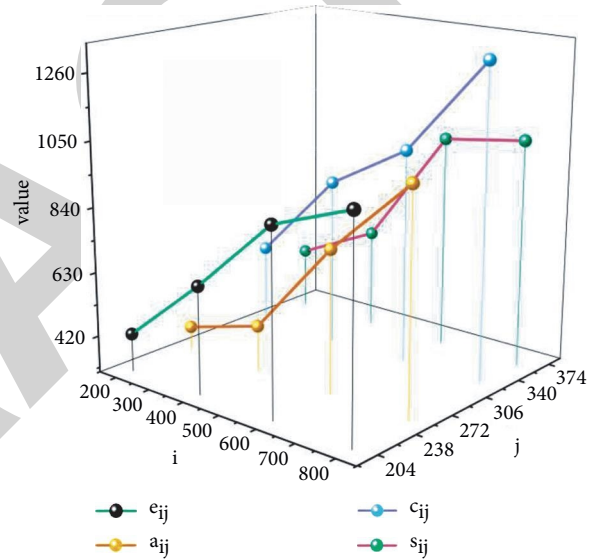


FIGURE 3: The influence curve of different coefficients  $i$  and  $j$  on decoder parameters.

$c_{ij} > s_{ij} > a_{ij} > e_{ij}$ . As can be seen from the influence of  $j$  coefficient, with the increase of  $J$  coefficient, the corresponding decoder parameters also show a trend of gradual increase. This shows that the machine translation model can show typical linear characteristics, which make the obtained results easy to analyze.

In order to further analyze the application of mechanical translation model to syntax, a framework flow chart of data processing is drawn, as shown in Figure 4. Through the analysis, we can see the specific flow chart as follows: First, the Japanese data are imported into the Chinese set, and the corresponding eigenvalues in the graph are extracted through the analysis of the Chinese set, and then the eigenvalues are cleaned and arranged to a certain extent. In this process, the annotated data need to be imported into the cleaning data cleaning module. Then, the optimized data can be imported into the machine translation model through data extraction, and the corresponding data features can be imported into the two plates of source end sentence and target end graph respectively. The data can be further

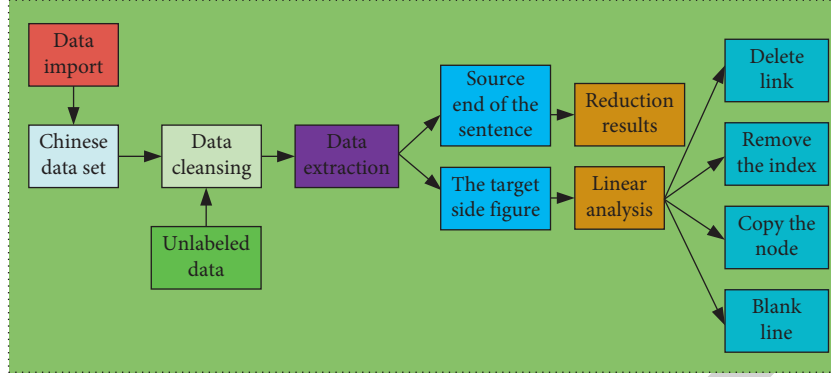


FIGURE 4: Data processing framework diagram.

analyzed through the processing of these two plates. Then, the data obtained from these two plates are imported into the reduction result and linear analysis module, respectively, and the obtained data can be further optimized through the analysis of these two plates. Finally, the Japanese translation results are exported to the corresponding module, which is mainly divided into four parts: deleting links, deleting leads, copying nodes, and space new lines. In this part, the corresponding data can be modified based on the calculation results of machine translation model, and finally the application data can be exported.

**2.2. Machine Translation Model Analysis.** The machine translation model overcomes two major problems: the low efficiency of serialized computation of traditional neural networks and the difficulty of modeling the long distance dependence of sentences in traditional neural networks, thus becoming the best Japanese translation model at present [12, 13]. The process of this method is simple and intuitive. It can be described as the source language sentences as input, which are transformed into continuous and dense feature vectors by an encoder composed of neural network. Then the vector is decoded by a decoder composed of neural network and the target language sentence is output. In the machine translation model, the encoder can generate semantic vector by modeling the logical relationship between words in the Japanese sentences at the source end, and the decoder can predict the corresponding Japanese result graph by the semantic vector extracted at the encoding end [14, 15]. As shown below, the machine translation model mainly includes two parts: input layer and location coding layer.

**2.2.1. Input Layer.** The input layer mainly completes the embedding of Japanese words, thus reducing the training time and avoiding the model falling into local optimal solution. The position vector of each participle in Japanese sentences is defined as a fixed position embedding vector based on trigonometric function. In this method, sine and cosine functions of different frequencies are used, and sine variables are added to the even positions of the word vector of each term. The cosine variable is added to every word in the odd position of the word vector. First, the segmented

words are vectorized, and the specific formula is shown as follows:

$$\begin{aligned} X &= [x_1, x_2, x_3, \dots, x_n]^T \in R^{n \times d}, \\ Y &= [y_1, y_2, y_3, \dots, y_m]^T \in R^{m \times d}, \end{aligned} \quad (6)$$

where  $x_i$  represents the word vector of the  $i$ -th word in the source sentence ( $i = 1, 2, \dots, n$ );  $n$  and  $m$  represent the number of source Japanese sentences and target Japanese word segmentation, respectively;  $d$  represents word vector dimension;  $y_j$  represents the word vector of the  $j$ -th word ( $j = 1, 2, 3, \dots, m$ ).

Through the above analysis, we can see that the corresponding curves of  $X$  and  $Y$  under different  $R$  values are different. In order to further analyze the influence and change of  $R$  value on curves  $X$  and  $Y$ , the change curves of  $X$  and  $Y$  under  $R$  value are drawn, as shown in Figure 5. As can be seen from the figure, with the gradual increase of  $R$  value, the corresponding  $X$  value shows a trend of slow increase. However, it can be seen from the increase that the slope of the curve remains constant, which indicates that  $X$  value under  $R$  value presents typical linear characteristics. Similarly, we can see that the corresponding data of  $Y$  increases rapidly with the increase of  $R$  value. By comparing the variation trend of the two parameters, we can see that  $Y$  value also belongs to typical linear characteristic change. In addition, we can see from the two curves that the slope of the  $Y$  value curve is greater than that of the  $X$  value, which indicates that the change trend of the  $Y$  value is greater than that of the  $X$  value. It also indicates that the influence of the  $Y$  value on the data is higher than that of the  $X$  value.

**2.2.2. Location Coding Layer.** In the natural language understanding task, the model understands a sentence through the meaning of the word and the position of the word in the sentence. After the word embedding technology at the input layer obtains the meaning of the word, it needs to input some position information to let the neural network know the position of the word in the sentence [16, 17]. In the machine translation model, the position vector of each participle in Japanese sentences is embedded based on trigonometric function definition, and the corresponding calculation formula is shown as follows:



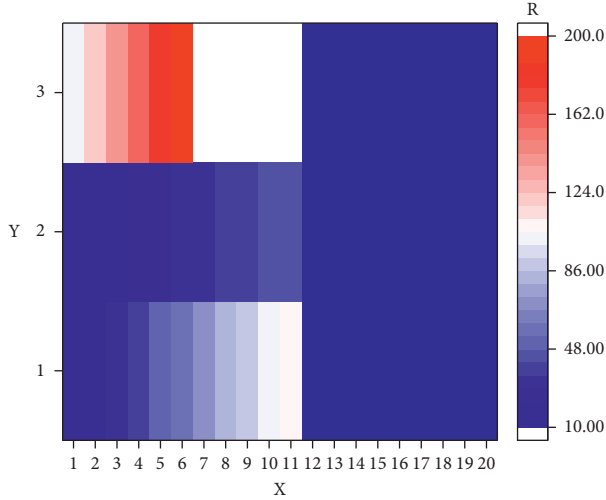


FIGURE 5: Graph of changes in X and Y at R.

$$PE(\text{pos}, 2i) = \sin\left(\frac{\text{pos}}{10000^{2i/d_{\text{model}}}}\right),$$

$$PE(\text{pos}, 2i + 1) = \cos\left(\frac{\text{pos}}{10000^{2i+1/d_{\text{model}}}}\right),$$

where  $PE(\text{pos}, 2i)$  represents the value of the machine translation model encoded in the  $2i$  dimension by the position serial number  $\text{pos}$ ;  $PE(\text{pos}, 2i + 1)$  represents the value of the machine translation model encoded in the  $2i + 1$  dimension of  $\text{pos}$  position number.  $\text{pos}$  indicates the ordinal position of the word;  $2i$  and  $2i + 1$  represent the dimension of position coding vector;  $d_{\text{model}}$  represents the length of the position encoding vector.

Therefore, the Japanese vectorization results obtained by using the machine translation model can be expressed as follows:

$$re = we + pe, \quad (8)$$

where  $we$  is the word vector in Japanese words,  $pe$  is the position vector in Japanese words,  $re$  is the multilayer vector in Japanese words.

Through the above analysis and formula, we can see that the corresponding curves of different parameter values have different variation trends with different iterations. In order to further analyze this variation trend, we drew the vector variation diagram under different parameters, as shown in Figure 6. It can be seen from Figure 6 that with the gradual increase in the number of iterations, the corresponding curve presents a nonlinear change trend. According to the parameter  $we$ , the curve can be divided into three stages. In the first stage, the curve showed a slow downward trend, and the slope of the corresponding PE curve showed a slow increase at first, and then gradually tended to 0. In the second stage, when the number of iterations is from 2000 to 6000, the corresponding curve shows a gentle trend of change, and the slope of the corresponding curve gradually approaches zero, which indicates that the number of iterations in this

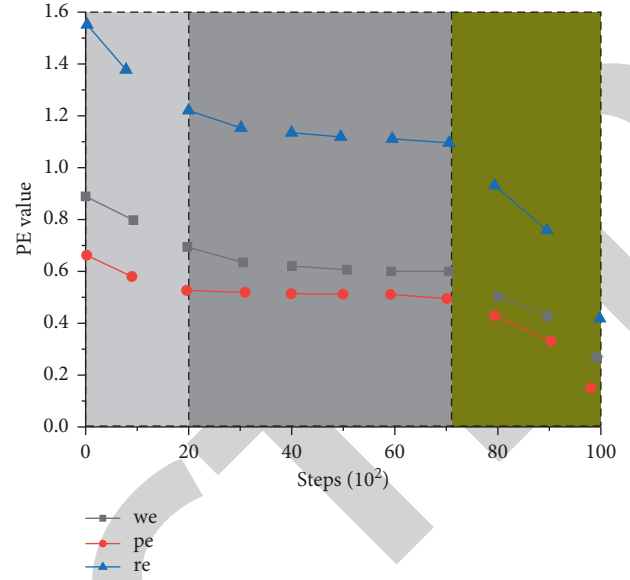


FIGURE 6: Vector variation diagram for different parameters.

stage has little influence on parameter PE. With the further increase of the number of iterations, the curve shows a rapid downward trend. The slope of the corresponding curve also drops rapidly. Among the three stages, the third stage has the greatest influence. It can be seen from the parameter  $pe$  that the slope of the curve is basically consistent with the slope of  $we$  curve. However, the value of the corresponding curve is lower than that of the  $we$  parameter. Through these two curves, we can calculate the change value of the corresponding  $re$  curve, and the data corresponding to the curve also shows a relatively obvious three-stage change trend: That is, it drops rapidly first, then gradually tends to zero, and then drops rapidly at last, which indicates that the nonlinear characteristics of this parameter are very obvious.

**2.3. Optimization of Machine Translation Models.** Machine translation models enrich the dependencies between words from multiple dimensions and make it possible to understand the syntactic and semantic structures of sentences. The optimized machine translation model consists of self-attention layer and neural network layer [18, 19].

**2.3.1. Self-Attention Layer.** Taking the Japanese self-attention calculation of encoder as an example, three vectors including query vector  $Q$ , key vector  $K$ , and value vector  $V$  are used to describe the calculation process of self-attention mechanism. In order to calculate the self-attention of Japanese sentences on encoder side, three vectors, query vector  $Q$ , key vector  $K$ , and value vector  $V$  are used to describe the calculation flow of multidirectional self-attention mechanism.  $Q$ ,  $K$ , and  $V$  vectors are obtained by multiplying the vector matrix  $X$  of each sentence with three different weight matrices  $W^Q$ ,  $W^K$ , and  $W^V$ . The corresponding formula is as follows:

$$\begin{aligned}
Q &= X \times W^Q, \\
K &= X \times W^K, \\
V &= X \times W^V,
\end{aligned} \tag{9}$$

where  $X$  is the vector matrix corresponding to Japanese sentences.

Through the above analysis, we can see that the vector indexes under different  $X$  values are different. In order to further analyze the attention of different vector indexes, the curve of parameter  $X$  changing with the vector is drawn, as shown in Figure 7. It can be seen from Figure 7 that attention value varies under different vectors, as shown below: It can be seen from parameter  $Q$  that with the gradual increase of  $X$ , the corresponding attention value shows a trend of gradual increase, and the increase of attention value shows a linear increase trend with the increase of  $X$ . According to the influence value of parameter  $K$ , it can be seen that with the increase of  $X$  value, the corresponding attention value shows a gradual decline trend, and the decline trend basically showed a linear decline, the overall decline trend remained between 25% and 35%. As can be seen from the variation of parameter  $V$ , with the gradual increase of  $X$  value, the corresponding attention value presents a gradual decreasing trend, and its decreasing trend and value are basically consistent with the variation trend of parameter  $K$ .

**2.3.2. Neural Network Layer.** According to different research contents, the machine translation model can be divided into three parts: input layer, hidden layer, and output layer [20, 21]. It can be seen from the study that different layers are connected by using Japanese data, among which the number of neurons in the input and output layers is different. The specific calculation formula of the corresponding optimization index FNN is shown in equation (10):

$$FNN(X) = \max(0, xW_1 + b_1)W_2 + b_2, \tag{10}$$

where  $x$  is a component of  $X$  vector;  $W_1$  and  $b_1$  are parameter matrices, and bias matrices of nonlinear transformation in machine translation model.  $W_2$  and  $b_2$  are parameter matrices and bias matrices of linear transformation in machine translation model, it can be seen that the dimension corresponding to  $x$  is  $[1, d_{\text{model}}]$ .

Through the above analysis, we can see that the influence of parameter matrix  $W$  and  $b$  on the network is different. In order to further analyze the changing trend of such influence, the influence diagram of parameter matrix on the network in Figure 8 is drawn. As can be seen from the figure, when the parameter  $W$  remains constant, the network influence value of the corresponding optimization index FNN shows a changing trend of linear increase with the gradual increase of the corresponding parameter  $b$ . However, when parameter  $b$  remains constant, with the gradual increase of parameter  $W$ , the network influence value of the corresponding optimization index FNN still shows a gradual increase of linear change. Therefore, through the above analysis, we can use the linear fitting method to fit and

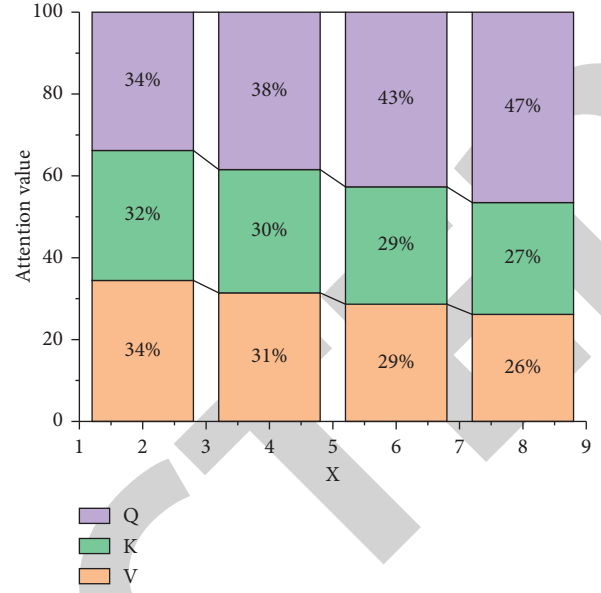


FIGURE 7: Variation diagram of different vectors.

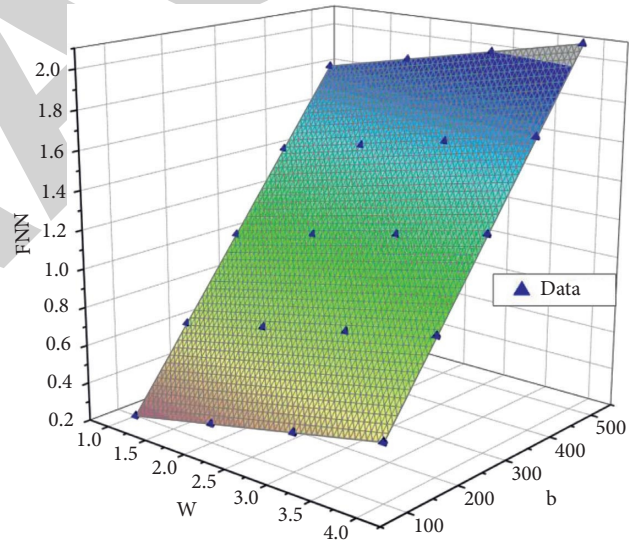


FIGURE 8: Influence diagram of parameter matrix on network.

analyze the data of optimization index FNN under two different factors. Through corresponding fitting and analysis, we can see that the influence of  $W$  and  $b$  on the optimization index FNN shows a trend of linear increase on the whole.

### 3. Application of Improved Machine Translation Model in Japanese Multicontext

**3.1. Japanese Multicontext-Related Content.** Japanese translation plays an important role in the communication between China and Japan, but there are some problems in the practical education of Japanese translation, which will restrict the development of Japanese translation to a certain extent [22]. The specific problems are as follows:

- (1) Translation is too one-sided: Through relevant investigation and analysis, it can be seen that Japanese translation is too one-sided in practical education. This problem is mainly reflected in the one-sided translation of Japanese words in the process of translation, without targeted description and translation of articles and contents, which make the translation results too single and one-sided, and cannot meet the requirements of actual translation. The main reason for this kind of problem is that the translator does not really understand and grasp the connotation of the translation, and only starts from the literal meaning to translate the article. Therefore, in practical translation, we need to pay attention to the problem of one-sided translation, adopt different translation methods to improve translation efficiency, and second, strengthen the translator's own quality, so as to obtain excellent translation results.
- (2) Outdated translation concepts: Japanese translation requires translators to keep up with the pace of The Times and carry out targeted translation. Due to the development of the Internet, many hot words and contents emerge endlessly. If the translator only relies on the book content for translation, the translation result will be quite different from the actual content, and ultimately the quality of translation will be greatly reduced. In order to better make Japanese translation results meet the needs of contemporary translators, we need to update the translation content and ideas in real time, and translators should strengthen their study and master the current popular translation content as soon as possible.
- (3) Weak innovation ability: Traditional Japanese translation only uses book knowledge for translation, which can only solve part of the translation problems, but can not provide a good solution to the relevant problems in translation. Therefore, we need to have certain innovation ability to adapt to the rapid development of the translation industry, so that we can deal with the problems in the process of translation. In order to optimize and analyze the traditional translation by using different calculation methods, the calculation results can well meet the actual requirements, and can also improve the speed and efficiency of translation so that the translation results can better meet the actual requirements.

There are a lot of content in Japanese translation, so we need to use different indicators to describe Japanese multicontext translation. For this purpose, we select six indicators from different aspects to analyze Japanese multicontext translation. The details are as follows: 1—keywords, 2—long difficult sentences, 3—smooth, 4—fluency, 5—logic, and 6—beautiful. In order to analyze the influencing factors of these six indicators on Japanese multicontext translation, we collect the data of the change of the indicators on Japanese multicontext translation.

Based on the above analysis, we can see that the machine translation model has a wide range of applications in Japanese multilingual translation, and different indicators are needed for quantitative analysis in Japanese multilingual translation. Therefore, a bar chart of the proportion of Japanese multilingual translation is drawn, as shown in Figure 9. As can be seen from the figure, the corresponding data of different indicators are different. The highest indicator is Japanese fluency, which is about 80. Followed by Japanese logic, about 60; then there is fluency in Japanese, about 50; the aesthetic score of Japanese was 30, and the analysis of long and difficult sentences was only 20. The lowest was about 10 for Japanese keywords, and through the analysis, we can see the overall performance of parabolic trend.

*3.2. Application of Machine Translation Model in Japanese Multicontext.* Machine translation model has been widely applied in different fields. In order to further improve the translation and application prospect of Japanese multicontext, this paper adopts the optimized and improved machine translation model to translate and apply Japanese multicontext. The corresponding application flow chart is shown below.

In order to have a better application of the machine translation model in Japanese, we draw a flow chart of the machine translation model in Japanese, as shown in Figure 10. It can be seen from the figure that the corresponding process is as follows: First, the numbers and words corresponding to Japanese translation are imported into the analysis model, and then feature points of Japanese multicontext are extracted through the analysis model. Then, the feature points are imported into Japanese sentences, and then the Japanese sentences are further analyzed to achieve a certain degree of coherence between sentences. Finally, the sentences with a certain degree of coherence are imported into paragraphs. Through further analysis of the paragraphs, the corresponding Japanese multicontext original text can be obtained. In order to further verify the accuracy of the original text, we adopted the method of extracting feature vectors from data for verification. In this paper, the feature vector extraction level is divided, the optimization algorithm is imported into the machine translation model, and the obtained translation data is further optimized and analyzed, so as to export the accurate results.

Through the above analysis, it can be seen that the machine translation model has certain application in Japanese translation. In order to further analyze the accuracy of the application results of the improved machine translation model in Japanese multi-context, an optimized machine translation model is used to translate and analyze Japanese in multiple contexts. Thus, the corresponding machine translation model in Japanese multicontext translation application evaluation index changes is obtained, as shown in Figure 11. It can be seen from the data changes in the figure that with the gradual increase of Japanese index factors, the data corresponding to the corresponding Q value parameter



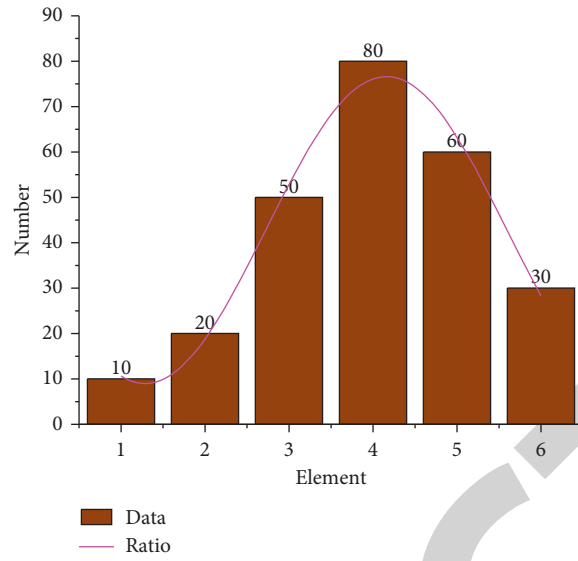


FIGURE 9: Bar chart of Japanese multicontext translation indicators.

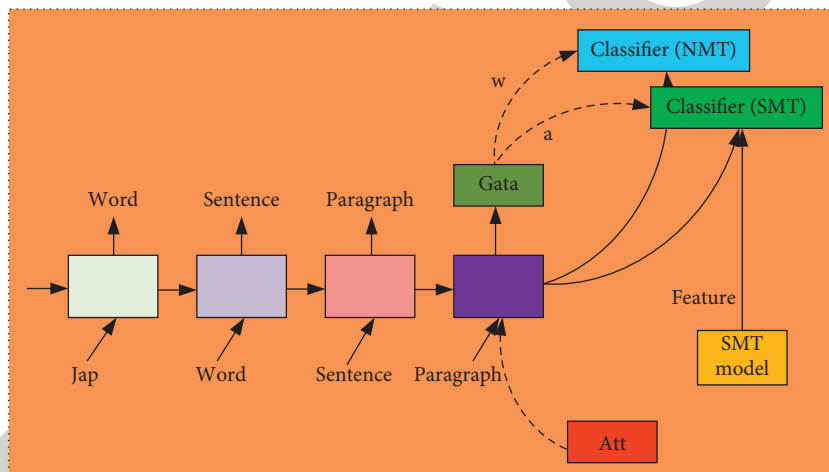


FIGURE 10: Machine translation models apply flow charts in Japanese.

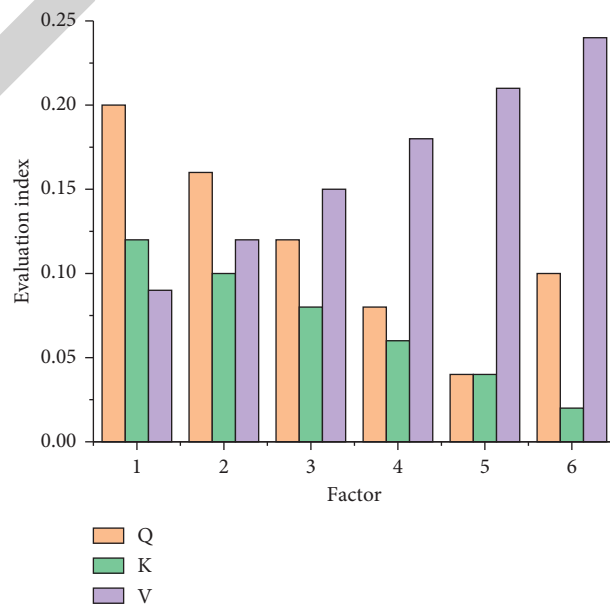


FIGURE 11: Application evaluation chart of machine translation model in Japanese multicontext translation.

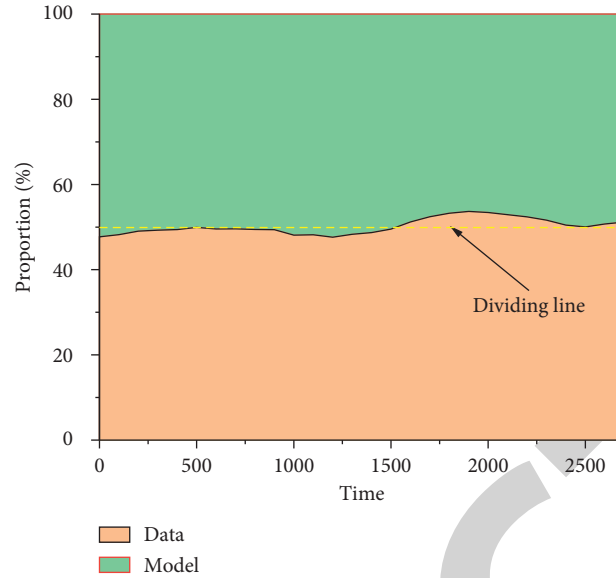


FIGURE 12: Comparison diagram of machine translation model with Japanese data.

show a fluctuating change trend of slowly increasing at first and then rising, and the change curve of the corresponding  $K$  value begins to show the overall decline. It is worth noting that this downward trend shows an approximate linear decline. With the increase of index factors, the corresponding curve of parameter  $V$  value shows a gradually increasing trend. Again, the tendency to increase is approximately linear; therefore, we can see that among the three parameters, parameter  $V$  has a positive impact on the evaluation index of Japanese multicontext. The effect of parameter  $K$  on the index is negative. Finally, the influence of parameter  $Q$  on the index is volatile.

#### 4. Discussion

The above research mainly focuses on the translation and application of Japanese multicontext from the optimization of machine translation model, which mainly includes the analysis and evaluation of machine translation model. From the above analysis, it can be seen that the MACHINE translation model has certain pertinence in the description of Japanese multicontext. In order to further analyze the accuracy of the application of the optimized machine translation model in Japanese multicontext, we draw corresponding graphs for description.

In order to further analyze and verify the accuracy of the machine translation model and the actual Japanese data, a comparison diagram between the Japanese translation data and the machine translation model is drawn, as shown in Figure 12. As can be seen from the figure, compared with the boundary line, the corresponding model index shows a fluctuation trend of first increasing, then decreasing, then increasing, and finally decreasing. The corresponding data show a decrease first, then an increase, and finally the change trend of volatility. From this trend, we can see that the cut-off point basically remains at about 50%, which indicates that the optimized machine translation model can well represent

the influence of various factors in Japanese data, so as to obtain accurate translation results.

#### 5. Conclusion

- (1) According to the overall trend, the influence curve of different parameters on the evaluation index can be divided into linear change, fluctuation change, and stable change. The variation trend of different parameters is basically the same in the first stage, indicating that parameters in this stage have little influence on the curve. The corresponding start time of the second stage showed different trends, indicating that different parameters in the second stage would have a greater impact on the curve. The parameter  $P$  has the greatest influence on the curve, while the corresponding parameter  $F$  has the least influence on the curve.
- (2) By analyzing the influence curves of different parameters  $i$  and  $j$  on the decoder, it can be seen that the influence of parameters  $i$  and  $j$  on the decoder shows a linear trend of change. By fitting the corresponding surface, it can be seen that the corresponding influence degree is  $c_{ij} > s_{ij} > a_{ij} > e_{ij}$ . Therefore, we need to use different parameters to analyze and solve the decoder in different degrees, so as to get the optimal data.
- (3) According to the curve of parameter  $X$  changing with the vector, it can be seen that parameter  $Q$  shows a trend of gradually increasing. Parameter  $K$  shows a trend of gradual decline. Parameter  $V$  presents a trend of gradual decline.
- (4) With the gradual increase of parameter matrix  $W$  and  $b$ , the influence value of the corresponding optimization index FNN network shows a change trend of linear increase. This indicates that both of

these factors can better represent the multicontext description of Japanese by machine translation model.

- (5) By analyzing the influence of  $R$  value on  $X$  and  $Y$  curves, it can be seen that with the gradual increase of  $R$  value, the corresponding  $X$  value shows a trend of slow increase. The curve corresponding to the same  $Y$  value also shows a trend of linear increase. By comparing the slope of the two curves, the influence of  $Y$  value on the data is higher than that of  $X$  value.

## Data Availability

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

## Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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