# A MACHINE INTELLIGENCE EVALUATION SYSTEM BASED ON INTERNET AUTOMATION TECHNOLOGY AND DEEP LEARNING

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Abstract. To realize the machine intelligence evaluation system, a method based on Internet automation technology is proposed. Firstly, then extracted and optimized, and finally combined with each other. A BP neural machine evaluation system is designed to compare the results of machine evaluation with the average value of teachers' independent evaluation by selecting 20 students' test paper translation samples from a class randomly. The test results show that by selecting a random class of 20 students, the comparison of machine evaluation results and teacher independent evaluation shows that the error range of the evaluation results of 20 samples is-5.6% -6.7%, which is within the allowable range of translation evaluation and meets the requirements of teaching evaluation. It is proved that the Chinese-English machine translation evaluation system based on Internet automation technology has excellent performance, which can improve the reliability and accuracy of the evaluation and reduce the degree of human intervention and misjudgment rate of the Chinese translation evaluation.

Key words: Internet, automation, evaluation system, translation, misjudgment rate, Intelligent evaluation system

**1.** Introduction. Intelligent characteristics are one of the important characteristics of intelligent systems. Qualitative evaluation of the intelligent characteristics of intelligent systems is a challenge and a new issue. Because, firstly, people's definition of the concept of intelligent characteristics itself is not clear enough. Secondly, the evaluation of intelligent characteristics is related to the environment, era, and conditions. Therefore, this evaluation has relativity, correlation, and time effects. In addition, there is very little specialized research and communication on this evaluation. And the theory and application of intelligent control continue to develop. It is necessary to conduct specialized research on the evaluation of intelligent characteristics in a timely manner, as various products and systems with the term "intelligent" are constantly entering the market. This is not only an academic need, but also an application need. Intelligent system is a system with anthropomorphic intelligence.anthropomorphic intelligence is the intelligent characteristic of simulating, extending and expanding human. Such as: self-learning, self-adaptation, self-organization, self-optimization, self-stabilization, self-identification, white planning, self-coordination, self-repair, self-reproduction, etc. Because the intelligence of human body control system is multi-level and multi-faceted, the intelligence of anthropomorphic system is also divided into different levels and different aspects such as high level, middle level and basic level. In order to realize the intelligent characteristics in the system, the commonly used intelligent methods include expert system, artificial neural network, fuzzy control and so on. With the development of the Internet and the advent of the era of economic globalization, the need to overcome language barriers and realize free communication across languages has become increasingly prominent [1]. The language barrier severely restricts the breadth, depth and speed that most users can obtain information from the Internet [2]. However, the development of advanced machine translation technology and the realization of large-scale application of machine translation products pose new challenges to the machine translation technology.

With the increasing progress and development of modern science and technology such as "Internet +" and artificial intelligence, people's work, study and life have been closely related to the modern information technology, and people rely on intelligent technology and tools increasingly [3]. Computer-aided translation means that translators can improve translation efficiency and control translation costs effectively by scientifically selecting language translation tools based on Internet, artificial intelligence and big data technologies. The computer translation technology emerged at the end of the 20th century, providing a technical support for

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people's scientific research activities, work and life, and promoting the cross-language communication [4,5].

In foreign countries, the research on this technique can only provide some reference for translators. Due to the limitation of the algorithm level, early computer translation is difficult to form a smooth and reasonable translation text. In the context of the rapid development of the Internet, big data and artificial intelligence provide strong support for the development of this technology and promote CAT technology to achieve great progress. Many translation websites and platforms based on CAT technology provide convenience for translators and relieve the pressure of translation work. CAT technology has been further developed with the help of translation memory libraries. Based on a brief review of the history of machine translation, the research discusses the existing methods of machine translation, and then discusses the challenges and technical routes of Internet machine translation.

2. Literature Review. Broadly speaking, machine translation involves all aspects of natural language processing technology, and almost all the research results of natural language processing can be directly or indirectly applied to machine translation. In a narrow sense, machine translation methods can generally be divided into three categories: rule-based machine translation, case-based machine translation and statistical machine translation, of which the latter two methods can be collectively referred to as corp-based methods [6]. The rule-based translation approach, which holds that the process of translation needs to analyze the source language and express the meaning of the source language, and then regenerate into an equivalent target language, has been dominant in the field of machine translation from the mid-1970s to the late 1980s. A large-scale rule-based commercial machine translation system should not only solve the problem of machine translation methodology, but also organize the system from the perspective of knowledge engineering and software engineering, in which the rules are often multi-level and fine-grained. The refinement of rule level and knowledge granularity can control the interaction and conflict between rules effectively, and make the rule system have good expansibility.

The essence of case-based machine translation is "machine translation based on translation instance and similarity principle". Translation instances can be stored in their natural form without any processing, or they can be represented in a completely structured form. Recent researches show that semi-structured translation instance representation approaches strike a good balance between the difficulty of preprocessing translation instances, the temporal and spatial efficiency of translation and the quality of translation. Another on the principle is very similar with case-based machine translation technology is translation memory, which is a computer-aided. It is a kind of auxiliary translation in essence. It retrieves similar translation instances from the instance library and submits them to users in a friendly form, thus achieving the purpose of assisting users in translation [7]. In recent years, translation memory technology is increasingly integrating various automatic translation technologies [8]. Statistical machine translation is also based on bilingual corpus, but unlike the casebased method, which directly uses translation examples in the translation process. Statistical method abstracts the translation knowledge implied in bilingual corpus into statistical model through prior training process. The translation process is usually a decoding process based on these statistical models. Statistical models used in statistical machine translation usually include translation model and language model [9]. Compared with language model and decoding, translation model is currently the most involved content in statistical machine translation research [10]. Generally, translation models can be divided into three types: word-based model, phrase-based model and grammar-based model. At present, phrase-based and grammar-based models have significantly better performance than word-based models. Although statistical methods are valued for their good mathematical model, unguided learning ability and robustness, rule methods are also valuable for their good generalization and description of language rules and instance methods for the accurate translation of similar sentences. In fact, the combination of multiple methods is becoming an important direction in the development of machine translation, such as the combination of rules and statistical methods, case-based methods and statistical methods, phrase-based and syntactic statistical translation methods.

On the basis of the current research, a machine translation evaluation system for TCSL based on Internet automation technology is proposed in the research. Firstly, then extracted and optimized, and finally combined with each other. A BP neural machine evaluation system is designed to compare the results of machine evaluation with the average value of teachers' independent evaluation by selecting 20 students' test paper translation samples from a class randomly. The test results show that by selecting a random class of 20 students,

Stacking

**BP** neural machine

evaluation model

Result

Evaluation

results

The statement	Number of	Number of	Scores	Number of
text	translation	statement text	range	sentence patterns
1	1650	10	0-3	8
2	1825	10	0-3	8
3	1756	6	0-3	4
4	1622	6	0-3	4
Fe		Decision e	valuation	

Integrated lear

Calculate weights

Table 3.1: Description of statement set information

Fig. 3.1: Basic framework of ETSS system (high-end)

Lexical quality characteristics - GBRT

Sentence gracefulness - CNN Statement correlation feature - LSTM

the comparison of machine evaluation results and teacher independent evaluation shows that the error range of the evaluation results of 20 samples is -6.7%, which is within the allowable range of translation evaluation and meets the requirements of teaching evaluation.

### 3. Research Methods.

LDA Word2Vec

**Original** text

**Original statement** 

text set

Filtered text vector

**3.1. The development and design of ETSS system.** In the research, the Chinese translation texts of the university Chinese (1-4) courses of a university in 2019 are selected. The sentence translation texts include the sub-texts of the four courses, with a corresponding number of translation sentences [10, 10, 6, 6]. More than one thousand students answer the translation sentences under each sub-text, and the score of each sentence ranges from 0 to 3. The details are shown in Table 3.1.

**3.1.1. Basic system framework.** The basic framework of ETSS(English Translation Scoring System) is shown in Figure 3.1. The main functions of the system are divided into three core modules: text feature extraction, weight calculation and decision evaluation [11]. System uses the annotated corpus, i.e., nearly 8 years of text translation for libraries of a university, as well as Chinese corpus, structures, vocabulary quality evaluation model, the beautiful statement and statement relevance evaluation model, evaluation model. Then the input text sets are evaluated separately, and then integrated with BP neural machine model for comprehensive evaluation [12].

**3.1.2. Extraction of ETSS feature vectors.** Figure 3.1 shows the ETSS feature text library [13]. As can be seen from the system structure diagram in Figure 3.1, the text library W of ETSS system needs to establish the text library h [T] for vocabulary quality evaluation, the text library g [T] for sentence elegance evaluation and the text library l [T] for sentence relevance evaluation. According to the comprehensive summary, the basic characteristics of sentence text judgment include 11 items, such as word accuracy, average word length, number of high-frequency words, number of advanced words, proportion of nouns, adjectives or verbs, number of connectives, number of word blocks, advanced sentence patterns, specialty of key words, word granularity and sentence granularity, etc [14]. There is a progressive relationship between different levels of the system, so the system database design first needs to analyze and integrate different types of text data, and obtain the text feature vector. In order to extract feature vectors quickly, the extraction standards and numbers are

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The text	Number	ber Feature		Specificity	Weight
IIbrary			description		
		Word	of words that	0% - 100%	$\mathbf{v}$
	$T_1$	word	or words that	$0/_0 \sim 100/_0$	$\Lambda_1$
		accuracy	are spened		
	$T_{c}$	Avoraço	Obtained by		
		word	modian or	2.20	V.
	12	length	standard deviation	2-20	$\Lambda_2$
		lengen	standard deviation		
h [T] for		Number of	Commonly		
vocabulary	$T_3$	high-frequency	used unmarked	$1\sim 8$	$X_3$
quality		words	words		
evaluation		Number of	Commonly		
	$T_4$	advanced	used marker	$1\sim 5$	$X_4$
		words	words		
		The proportion	Average the		
		of nouns,	proportion of the	$0 \sim 100\%$	$X_5$
	$T_5$	adjectives and	number of words in		
		verbs	different parts		
			of speech		
g[T]			Including phrases		
for	$T_6$	Number of	such as turning point,	$1 \sim 3$	$X_6$
sentence	-0	connectives	connectives juxtaposition, choice,		0
elegance		cause and effect			
evaluation			Including phrasal		
	Ŧ	Number of	verbs, prepositional		17
	$T_7$	word blocks	phrases, adverb	$1 \sim 5$	$X_7$
			phrases, adjective		
			phrases and so on		
	$T_8$	A	Including emphasis		
		Advanced	inversion contoneos	V/N	$\mathbf{v}$
		patterne	humothatic sontoneos	1/1	A8
		patterns	and so on		
		Specialty	The rank of key		
	$T_{0}$	of key	words in the	$1 \sim 5$	Xo
	19	words	reference answer	1.10	219
1 [T]		Wordb	Describe the		
for	$T_10$	Word	relatedness		
		granularity	characteristics	$0 \sim 100\%$	$X_10$
relevance		8	of words		
evaluation		Specialty	Describe the		
	$T_{1}1$	Sentence	semantic dispersion	0 10007	V 1
		granularity	characteristics of	$0 \sim 100\%$	$X_1 1$
			statements		

Table 3.2: The feature text database W [i] of ETSS system

formulated specially, as shown in Table 3.2. In order to ensure that the system data query, modification and update can be saved in advance, it is necessary to adjust the text library system, which is not only conducive to data management, but also convenient for the system to modify the stored procedure of the required data according to the actual demand, and improve the portability of the system source code [15].

After the establishment of ETSS system feature text database W [i], the filtering extraction method of

selected text features is studied. Word2Vec tool model and K-means clustering method are used to filter and extract the word quality features (T1-T5). According to the text library h [T], the text is mapped from the statement text to the feature vector of fixed dimensions, and the text words are encoded. The feature degree and feature base weight are obtained according to the feature description of the text base [16,17]. The feature base weights obtained through experiments (X1~ X5) can be adjusted by modifying the feature degree in practical application to actively adapt to Chinese translated texts of different stages and difficulties. The research is also applicable to the calculation of other weights or weight coefficients later [18,19].

Extraction of feature vectors of sentence elegance is as follows [20]. Elegant Chinese sentences need to integrate advanced lexical blocks, sentence patterns and ingenious rhetorical devices. The identification of elegant Chinese sentences can also be treated as a text classification problem. Doc2Vec tool is used to filter and obtain the text feature information, and then the feature of sentence elegance (T6-T7) is filtered and extracted. According to the text library g [T], the feature base weight (x6-x8) is obtained from the given text label classification training. Due to the influence of language features, cultural background, oral expression and other factors, the feature and degree of sentence elegance are difficult to grasp. Convolutional neural network CNN can be used for modeling feature extraction, and its advantage lies in automatic feature selection and combination, which is used in the subsequent text elegance evaluation in the research [21].

Extraction of sentence relevance feature vectors is as follows. The judgment of sentence relevance is subjective and difficult to be judged by machine, which requires the integration of meaning, sentence meaning and vocabulary. Therefore, the judgment of Chinese sentence relevance needs to combine the above extraction features to comprehensively analyze word granularity, sentence granularity and sentence theme. Here, LDA model is used to read text feature information, and then sentence relevance features (T9-T11) are extracted. According to the text library L [T], subject probability distribution of text is obtained through Bayesian network learning and training, and then feature base weight (x9-x11) is obtained [22].

**3.1.3. Feature extraction algorithm.** The symbol used to identify or distinguish text is feature. In the research, VSM method of vector space model is used to filter and extract feature information in text. A feature vector is used to represent a Chinese sentence text, which consists of feature terms and weights. The feature vector extracted from the text directly represents the original text, and the extracted optimized feature vector is one of the key factors affecting the results of system evaluation [23]. In VSM model, Chinese text uses space vector  $(T_2, X_1; T_2, X_2; ...; T_j, X_j)$ .  $T_j$  is the feature item, and  $X_j$  is the corresponding basic weight of the feature item, which is used to define the importance of the feature item in the description statement text. In order to improve the accuracy and speed of feature item acquisition, Doc2Vec method, NLTK and StanfordParser toolkit are used for text filtering and extraction processing (including counting, part of speech tagging, average, local maximum and minimum, word frequency weighting, position weighting, syntax analysis, etc.). The text encoding and text feature degree are obtained [24].

Feature vector filtering and extraction methods: Text vector features are obtained through Doc2Vec text parsing. Feature details are obtained through NLTK and Stanford Parser tool package sampling. The second level decomposition is the same, with more detailed space division. It can not only rely on one filtering to extract degree of text feature. And filtering should be continuously repeated several times in order to avoid misoperation accident conditions. By using the wavelet transform and short time Fourier analysis mathematical tools, sentence text features are processed again. Equation 3.1 is used to obtain the square mean root value of the feature degree in the ith time window at the j node, which can achieve better feature discrimination effect [25].

$$X_{j,i} = \left(\frac{1}{N}\sum_{n=1}^{N}K_{j,n}^{2}\right)^{\frac{1}{2}}$$
(3.1)

In Equation 3.1,  $X_{j,i}$  is the square mean root value of the feature degree in the ith time window at the j node.  $K_{j,n}$  is the nth coefficient at the j node. N is the total number of coefficients of j node.

In order to judge the weight of feature degree, the basic assignment table corresponding to feature degree of Chinese sentences is first established, as shown in Table 3.3. Then, based on Chinese sentence rules and translation characteristics, a simulation model of feature weight assignment is established, as shown in Equation

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Feature	Assignment x							
Ti	1	1.5	2	2.5	3			
$T_1$	$10\% \sim 20\%$	$21\%{\sim}40\%$	$41\% \sim 60\%$	$61\% \sim 80\%$	$81\% \sim 100\%$			
$T_2$	$2 \sim 5$	$17 \sim 20$	6~8	$14 \sim 16$	$9 \sim 13$			
$T_3$	1	2	$3 \sim 4$	$7 \sim 8$	$5 \sim 6$			
$T_4$	1	2	3	5	4			
$T_5$	$1\% \sim 10\%$ or $91\% \sim 100\%$	$11\% \sim 30\%$	$31\% \sim 50\%$	$51\% \sim 70\%$	$71\%{\sim}90\%$			
$T_6$	1	-	2	-	3			
$T_7$	1	2	3	4	5			
$T_8$	Ν	-	-	-	Υ			
$T_9$	5	4	3	2	1			
$T_10$	$10\% \sim 20\%$	$21\%{\sim}40\%$	$41\% \sim 60\%$	$61\%{\sim}80\%$	$81\%{\sim}100\%$			
$T_11$	$10\% \sim 20\%$	$21\%{\sim}40\%$	$41\%{\sim}60\%$	$61\%{\sim}80\%$	$81\%{\sim}100\%$			

Table 3.3: Chinese sentence feature assignment

3.2. The maximum and minimum values of feature weights are obtained by using reference answers and random answers of translation sentences, and the coefficient changes after wavelet transform are used as the basis of the model. Taking the 5-layer wavelet packet decomposition method as an example, the node importance ratio  $\lambda$  is used, and the ratio of importance between 2 to 5 nodes and the importance of 1 node in Equation 3.3 is taken as the effective weight of feature quantity. The threshold value is set as 0.025, and 11 feature degrees are calculated continuously. In a preset period, the weight of feature quantity is obtained through this simulation model.

$$\frac{1}{g}\frac{dg}{dt} = \frac{1}{\tau}(\frac{x_j^2}{x_c^2} - 1) \tag{3.2}$$

$$\lambda_{j,i} = \frac{E}{E_1} = \frac{\sum_{r=2}^{r=j} \sum |u_r(n)|^2}{\sum |u_1(n)|^2}$$
(3.3)

In Equation 3.2 and 3.3, g is the derivative value of the characteristic quantity.  $\tau$  is a time constant;  $x_j$  is base weight assignment.  $x_c$  is weight assignment coefficient.  $\lambda_{j,i}$  is the weight of feature quantity. E is the sum of importance between node 2 and node 5. E1 is the importance of 1 node.  $u_1(n)$  is the reconstruction coefficient of 1 node.  $u_r(n)$  is reconstruction coefficient of r node.

## 3.2. Application of ETSS system.

**3.2.1. Comprehensive evaluation of sentence text.** The previously extracted sentence text feature vectors are then input into the trained BP neural machine evaluation model for interactive fusion promotion regression verification after stacking learning by sentence vocabulary quality evaluation model GBRT, sentence elegance evaluation model CNN and sentence relevance evaluation model LSTM, respectively. The final score of the sentence text is obtained, and the process of comprehensive evaluation is shown in Figure 3.2.

**3.2.2. BP neural machine evaluation method.** The proposed ETSS system is based on BP neural network algorithm and machine learning to automatically judge the results of Chinese sentence translation. This evaluation method can consider the language factors of Chinese sentences and judge the correctness of sentence translation relatively accurately. ETSS system introduces the translation result evaluation into BP neural machine algorithm to ensure that input vector and output vector meet nonlinear mapping, which can greatly improve the accuracy of system evaluation results. Based on the above simulation model of feature weight assignment, the weight of feature quantity and the weight coefficient, which affect the translation quality, are regarded as the input layer of BP neural machine, and the output layer ix of BP neural machine is the judgment value of the system after the decomposition of 5-layer wavelet packet and the calculation of 312 subdivision consecutively within one period.

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Fig. 3.2: Flow chart of comprehensive evaluation

4. Result Analysis. In the research, the English-Chinese translation questions of the final examination of College Chinese courses in a certain university are selected as the evaluation sample, and the score features, feature degree and feature assignment of English-Chinese translation questions are integrated and provided to the examination evaluation team members for understanding and familiarity. Experts in the field of Chinese translation and linguistics are invited to form an evaluation team, and the feature base assignment x is given according to the text features and feature degree, as shown in Table 4.1. And the feature assignment coefficient xc is given according to the features and difficulty of the actual translation topics. Through MAT-LAB software input Equation 3.1-3.3 and text feature weight, machine learning is carried out in a preset period to obtain the evaluation score ix. BP neural machine algorithm can carry out self-diagnosis and detection, and finally modify machine learning according to the evaluation results and manual correction, so as to meet the needs of teaching effect evaluation. If the error of the output result is less than the set , or the number of training learning exceeds the set maximum, the algorithm ends and starts the next text automatically. If the criteria are not met, the retraining is required from Equation 3.1. The software operation rules are as follows:

Output001: IF(results fit well); THEN(go to the next text to learn); Output002: IF(result coincidence is general); THEN(adjust the weight assignment coefficient); Output003: IF(the result is relatively poor); THEN(returns to the previous stage to adjust the feature degree and base weight assignment).

The operation of the BP neural machine learning rules mentioned above should also be based on the classification of Chinese course translation. With the help of this system, translation evaluation teachers set evaluation criteria of different levels according to the difficulty of Chinese translation at different stages of university, so as to meet the ultimate goal of examination scoring. Figure 4.1 shows the results of a specific example. By selecting test paper translation samples of 20 students in a class randomly, the comparison between the machine evaluation results and the average value of teachers' independent evaluation shows that the error range of the evaluation results of the 20 samples is -5.6%-6.7%, which is within the allowed range of translation evaluation and meets the requirements of teaching evaluation.

5. Conclusion. In the research, an automatic judgment algorithm for Chinese sentence text was proposed. The algorithm first splits and filters sentences, then extracts and optimizes them, and finally combines them



Fig. 4.1: Comparison of evaluation results

with each other. The recognition and extraction of text feature vectors, as well as the fusion and interaction of feature weights, play a crucial role in determining the correctness of the results. A basic framework for evaluating Chinese sentence translation has been designed. By comparing the results of machine validation and manual evaluation, the ETSS system has excellent performance and high evaluation reliability and accuracy. Developed a BP neural machine evaluation model, completed automatic processing of natural language and evaluation of Chinese translated sentences. By selecting test paper translation samples of 20 students in a class randomly, the comparison between the machine evaluation results and the average value of teachers' independent evaluation shows that the error range of the evaluation results of the 20 samples is -5.6%-6.7%, which is within the allowed range of translation evaluation and meets the requirements of teaching evaluation. Artificial intelligence and computer technology have promoted the development of intelligent assisted teaching methods, reducing human intervention in Chinese translation evaluation.

This article has achieved certain results in the above aspects, but there are still many shortcomings. The main problem is the quantity and quality of user feedback. It is difficult to collect large-scale user feedback in laboratory environments. At the same time, there is a large amount of noise in user feedback. This article uses corresponding quality control strategies to remove some of the noise. However, overall, larger scale user feedback experiments are needed to further confirm the experimental conclusions of this article. At the same time, there are still shortcomings in the noise processing work of this article.

In future research work, we should explore using large-scale user feedback data to confirm the conclusions of this article. The work of this article reveals the contribution of several user behavior features to automatic translation evaluation, and the processing and utilization of overall user feedback information is still quite limited. Therefore, future work should explore more diverse user behavior features and other feature selection and fusion methods on this basis for automatic translation evaluation.

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