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Human-machine Translation Model based on Artificial Intelligence Translation

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Abstract

The development of artificial intelligence (AI), cloud computing, Big data, and other technologies have promoted the rapid evolution of the data centre industry. As a new human-computer interaction mode, human-computer translation is essential in information transmission. However, many translation systems have certain defects, such as high error rates and low accuracy rates, and cannot meet personalized needs. This article, taking AI translation as the research object, analyzed attention mechanisms and other related technical methods, summarized and explored the limitations of traditional translation methods, and constructed a human-machine translation model based on AI translation, which had a clearer understanding of translation quality differences between various methods. It provides a reference for further improving translation models and exploring the application of AI in translation. The comprehensive automation and manual evaluation methods have proven that AI-based human-machine translation effectively improves the insufficient matching between text and context, enhances the accuracy of intelligent recognition and semantic expression, and sets a subjective evaluation score of 1-10 for users, with a score of 6 or above as qualified. The results showed that the language fluency score has increased from about 4.9667 for traditional Statistical Machine Translation (SMT) to about 6.6333 for AI-based human-computer translation. The AI-based human-computer translation model can improve the efficiency and accuracy of language input, enhance the correlation between intelligent recognition semantic features and text, and promote the development of AI recognition functions, thus providing users with accurate, efficient, and high-quality services and achieving automatic processing natural language understanding and output.

Keywords: Artificial Intelligence, Attention mechanism, Human-computer Interaction, Statistical Machine Translation

1. Introduction

Human-machine translation combines Machine Translation (MT) technology with human translation. It uses computer computing power and Big data processing capabilities, aiming to improve the efficiency and quality of language users by assisting or replacing the process of human translation through automation. Human-machine translation has been widely used in various languages such as English, French, Japanese, German, etc.

However, due to the lack of personalized text processing technology for different languages, it cannot solve semantic understanding problems in complex scenarios. The emergence of AI translation has broken this dilemma. It is based on machine learning and deep learning, which can quickly construct corresponding text models and make appropriate adjustments according to actual situations. At the same time, it also has a strong self-evolution ability, which can analyze, judge, and predict natural language to some extent, helping users better understand the meaning they want to express. Based on this, this article explores the construction process of a human-machine translation model from the perspective of human-machine interaction, combining the automation power of AI with the professional knowledge and judgment of human translators, which helps to improve translation quality and promote cross-language communication and understanding.

Translation is essential for disseminating information, knowledge, and ideas. MT only directly translates words to words; only manual translation can achieve understanding [1]. The existing translation shows the potential of large-scale multilingual MT by training a single model that can translate between any pair of languages [2]. MT is a technology that uses computers to translate human language automatically. At the same time, it has many other applications in translation and academic research and occupies an essential position in the circle of natural language processing [3]-[5].

Neural Machine Translation (NMT) has made a breakthrough in translation performance by simulating the direct mapping between the source and target languages through deep neural networks. It has become a de facto model of MT [6]. Building an NMT system for multilingual participation spaces promotes multilingual communication among speakers in consultative democracy [7]. Some analysts suggest that Google Translate should be used to convert all texts into English before starting analysis, create a real multi-to-multi-language translation model, and evaluate the effectiveness of MT on the Bag-of-Words model, such as the Topic Model [8]. Artificial translation and MT have similar features, which can assist users in completing complex tasks, such as word recognition, automatic sentence generation, and contextual reasoning.

In the context of globalization, language barriers remain obstacles to obtaining information. Sometimes, relying solely on manual translation is impossible to meet translation needs [9]. Although inter-sequence attention NMT has made significant progress over the past years, it still faces two challenges: learning the optimal model parameters for long parallel sentences and using various contexts well. Applying attention models to capture context between and within clauses for translation prediction can improve parameter learning and effectively explore different translation contexts [10].

Due to the rapid development of artificial intelligence, MT has emerged as the most widely used new form, known as NMT, which provides the potential for its widespread application in foreign language learning [11]. Syntactic knowledge can effectively improve the performance of NMT. Using a syntax-aware encoder to extend sequences to dependency frameworks, both source and target dependency structures can enhance the quality of translation [12]. A deep attention model based on low-level attention information can automatically determine what should be transmitted or suppressed from the corresponding encoder layer to make distributed representations suitable for high-level attention and translation and improve the fidelity of system translation [13]. The development and progress of AI translation technology can help solve language understanding problems and lay the foundation for cross-cultural communication.

Traditional translation methods and models lack a deep understanding of language rules and semantics. For issues such as complex context processing, the use of deep learning and neural network technologies in AI can construct intelligent translation models that are more in line with corpus characteristics, to some extent overcoming the various difficulties faced by existing methods in solving complex contexts, and providing more accurate, smooth, and flexible translations [14]-[15]. Compared with other translation methods, this new model can transform textual information into machine-recognizable knowledge and present it to users more intuitive, vivid, and interactive, enhancing the user experience.

2. Development and Importance of Artificial Intelligence Translation Models

Language is the carrier of cultural communication. In the context of globalization, people need to communicate with people from other languages and cultural backgrounds. AI has produced an important effect on various industries, including the translation industry, and improved efficiency and accuracy, and it is affecting the transformation of translation, education, and teaching. [16]. AI translation models are a bridge to promote cross-cultural communication by translating texts and spoken language from different languages. Therefore, developing AI translation models can help individuals and organizations communicate across language barriers.

With the rapid development of AI technology, computer vision, pattern recognition, and other disciplines, more and more intelligent translation machines are being applied in practical translation work. The AI translation model based on neural networks and deep learning technology is one of the more mature ones, which can effectively solve the problems in traditional English sentence expressions [17]. However, due to a lack of systematic and comprehensive theoretical guidance and corresponding technical support, the AI translation model is still in its early stages, so it is necessary to conduct an in-depth analysis.

From the existing scientific research achievements, the research on machine recognition mainly focuses on voice understanding and natural language processing. With the continuous progress of technology, people have begun to focus on combining various advanced technologies with manual labour to improve work efficiency and quality while promoting the development and application of AI translation methods. Through continuous optimization, the conversion between simple text and complex semantic information has been achieved, providing powerful translation tools and services for individual users, enterprises, and society. It is crucial to achieve accurate and efficient cross-language communication.

3. Limitations of Traditional Translation Models

The purpose of translation is to help readers understand and master the original text, and under different cultural backgrounds, the translation exhibits other characteristics [18]-[19]. The traditional manual translation mode mainly relies on the translator to achieve accurate, clear, and natural conversion between the original work and the target translation through various means to better convey the author's intended information. This requires translators to grasp text features, analyze content, and integrate their language knowledge into the work to achieve the expected results. The introduction of traditional translation methods and their benchmark models is shown in Table 1.

Table 1 Limitations of traditional translation models

	Accuracy	Fluency	Naturalness	Limitation
The statistical machine translation model	–	↓	↓	Difficulty dealing with long texts and domain-specific terminology
Neural network translation model	↑	↑	↑	Difficulty dealing with long-distance dependencies and rare vocabulary
Pre-trained language models	↑	↑	↑	Poor handling of scarce languages and specific domains

Note: "-" indicates moderate, " ↑ " indicates high, and " ↓ " indicates low.

SMT usually utilizes vocabulary, syntactic knowledge, and logical reasoning to construct a corpus suitable for computer processing. After in-depth analysis and derivation of sentences, it obtains the semantic relationships and grammatical features between words or phrases in different languages. Then, it provides corresponding translated texts on this basis [20]. The translation accuracy of this model has reached a moderate level in some language pairs. Still, its fluency and naturalness are relatively low due to its reliance on statistical methods, which only consider the degree of interconnectedness between vocabulary and ignore the correlation between semantics.

Neural network translation and pre-trained language models have high translation accuracy, fluency, and naturalness, which can better capture contextual information and grammatical structure. However, this traditional translation model cannot meet the intelligent translation needs of rare vocabulary and scarce language due to limitations such as time and cognition. Therefore, with automation and machine learning technology, highly parallel translation processing can be achieved with AI translation model-based human-machine translation, significantly improving translation speed and efficiency [21].

4. Human-machine Translation Model Based on Artificial Intelligence Translation

The AI-based human-machine translation model used in this article is an end-to-end system, including key modules such as input processing, encoding, and decoding. These modules work together to enable the model to convert input source language text into target-language text automatically. High-quality translation effects can be achieved by introducing deep learning algorithms, statistical modeling, and attention mechanisms, as shown in Fig.1.

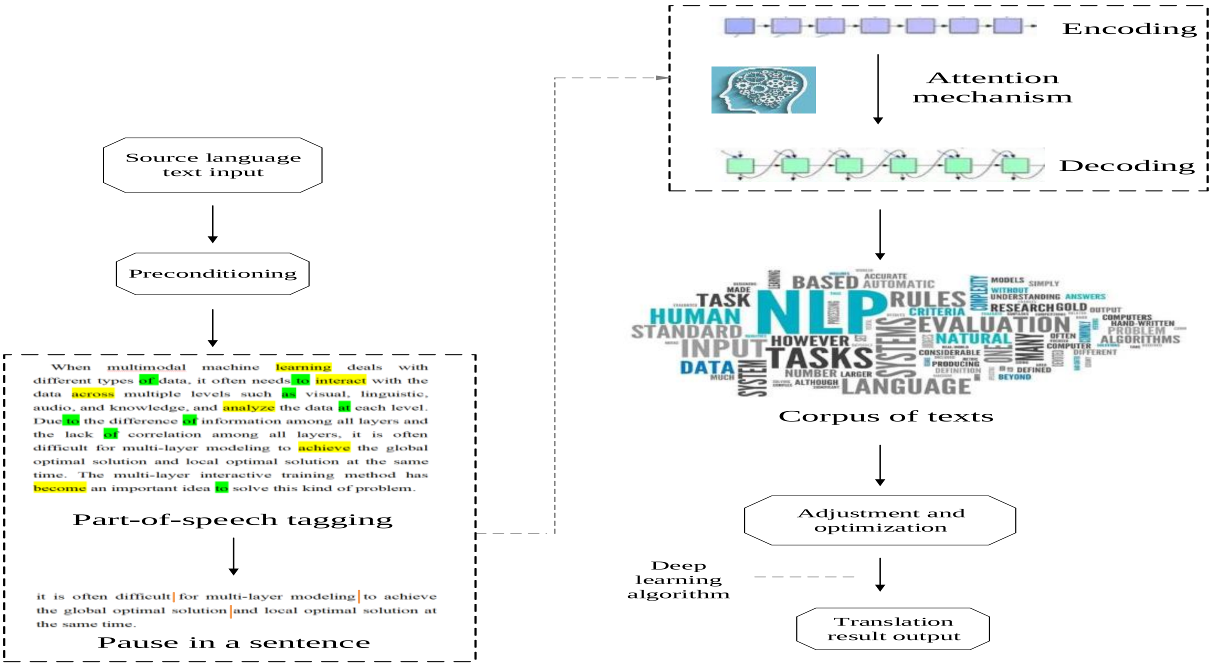

Fig.1 A human-machine translation model based on AI translation

When a source language text is input into the model, preprocessing operations such as word segmentation, part-of-speech tagging, and sentence segmentation are first required to help the system better understand the structure and syntax of the input text [23]. The attention mechanism encodes the input sequence's vocabulary, context, and semantic information to convert the preprocessed source language text into a continuous vector representation. Then, the decoder generates the translation results by predicting the conditional probability distribution of each target vocabulary. The corpus is the core component of the model, which includes a corpus of all possible vocabulary and related phrases from the source and target languages to meet the personalized requirements of users with different needs for specific vocabulary or phrases.

In addition, adjusting model parameters and optimizing training strategies are also crucial, especially for some complex and difficult-to-explain words or sentences. It is necessary to reasonably select appropriate matching methods according to the actual situation, which relates to machine learning algorithms' performance and accuracy and affects the final translation's quality.

In the above model, the attention mechanism is widely used in encoder and decoder modules. Assuming a source language translation dataset Q, where a and b are any set of data in the dataset, Q can be represented as:

Using as the representation of J=1 sentence pair in the text, the definition of translation probability is as follows:

$$P\left(b^{(1)},\ldots,b^{(J)}\middle|a^{(1)},\ldots,a^{(J)};\ \rho\right)=\prod_{J=1}^{J}P\left(b^{(J)}\middle|A_{<j},B_{<j},a^{(j)};\ \rho\right)$$

is the source sequence of the first $J-1$ sentences in the source language text and is the output sequence, with the expressions:

$$A_{<j}=\left(a^{(1)},\ldots,a^{(j-1)}\right)$$

$$B_{<j}=\left(a^{(1)},\ldots,a^{(j-1)}\right)$$

$a^{(J)}$ is a sentence in the source language text and $a^{(J)}=\left(a_1^J,\ldots,a_m^J\right)$ is represented in vector form as:

$$W_a=\left[W\left(a_1^J;\ \ldots;a_m^J\right)\right]$$

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Among them, m is the length of the sentence. In the encoder module, three matrices, R, S, and T, are assigned weights to translated sentences, obtaining feature vectors. The attention mechanism function is treated as a mapping relationship, which can be expressed as:

$$\mathrm{Attention}(\mathrm{R},\mathrm{S},\mathrm{T}) = \mathrm{softmax}(\frac{\mathrm{RS}^{\mathrm{K}}}{\sqrt{\mathrm{d_S}}})\mathrm{T}$$

In the field of AI translation, the introduction of attention mechanisms can help models handle long sentences and complex structures, capture the correspondence between input and output, and improve the overall intelligence level of human-machine translation [24]-[25].

5. Evaluation and Implementation of Human-machine Translation Based on Artificial Intelligence Translation

Experimental Design

In order to ensure sufficient scale and representativeness of the dataset, this article obtains sentence pairs containing source and target languages from the open dataset WMT (Workshop on Machine Translation) and runs AI translation-based human-machine translation models and traditional SMT models respectively to translate source language sentences into target language ones. This article describes the human-machine translation model based on AI translation as Model 1 and the traditional SMT model as Model 2. The results obtained are compared from automatic and manual evaluations to verify the advantages of the AI translation model.

Data Analysis

Automatic Evaluation

Five sets of sentence pairs are selected as samples to explore the translation results of Model 1 and Model 2 from three aspects: BLEU (Bilingual Evaluation Understudy), METROR (Metric for Evaluation of Translation with Explicit Ordering), TER (Translation Error Rate). The values of these indicators usually range from 0 to 1. Among them, the closer the values of BLEU and METR are to 1, and the closer the values of TER are to 0, indicating better translation quality. The results are shown in Figure 2.

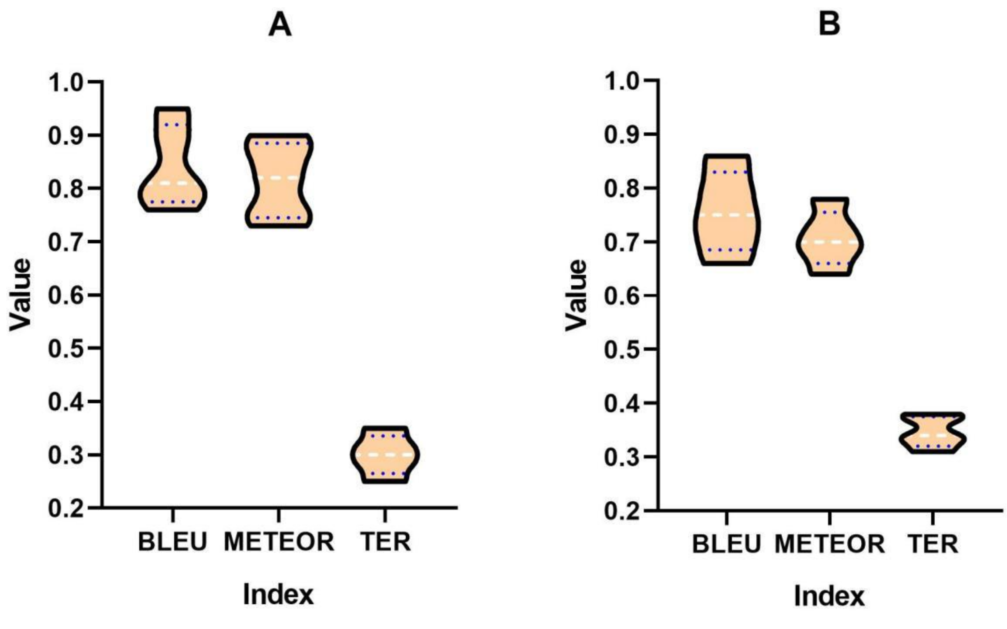

Fig.2 Comparison of automated evaluation results between two translation models

Fig. 2A: Model 1 Automation Evaluation Results

Fig. 2B: Model 2 Automation Evaluation Results

The horizontal coordinates of the two figures in Figures 2A and 2B represent the BLEU, METR, and TER indicators, respectively. In contrast, the vertical axis represents the values of the indicator evaluation results. The values of BLEU and METEOR obtained from the model 1 operation are between 0.7 and 1, with BLEU reaching the highest or even above 0.9. The BLEU and METEOR values obtained from the model 2 operation range from 0.6 to 0.9, and the maximum value does not exceed 0.9, which is lower than model 1. It can be seen that Model 1 can fully utilize existing resources, better understand and utilize contextual information, and thus produce more accurate translation results. In addition, the TER values of Model 1 are between 0.2 and 0.4, while those of Model 2 are 0.3 and above. The TER values of Model 2 are higher than those of Model 1, so Model 1 can provide more accurate and fluent translation results, significantly reducing error rates and ambiguity.

Manual Evaluation

The same source language text was selected and translated using two different models to obtain two translation results. Subjective evaluations of 30 users on the appropriateness of their translation style, the accuracy of language expression, the flexibility of translation skills, and language fluency were collected. The score is set to 1-10 points, with a maximum score of 10. A score of 6 or above is considered qualified, and the specific evaluation results are shown in Figure 3

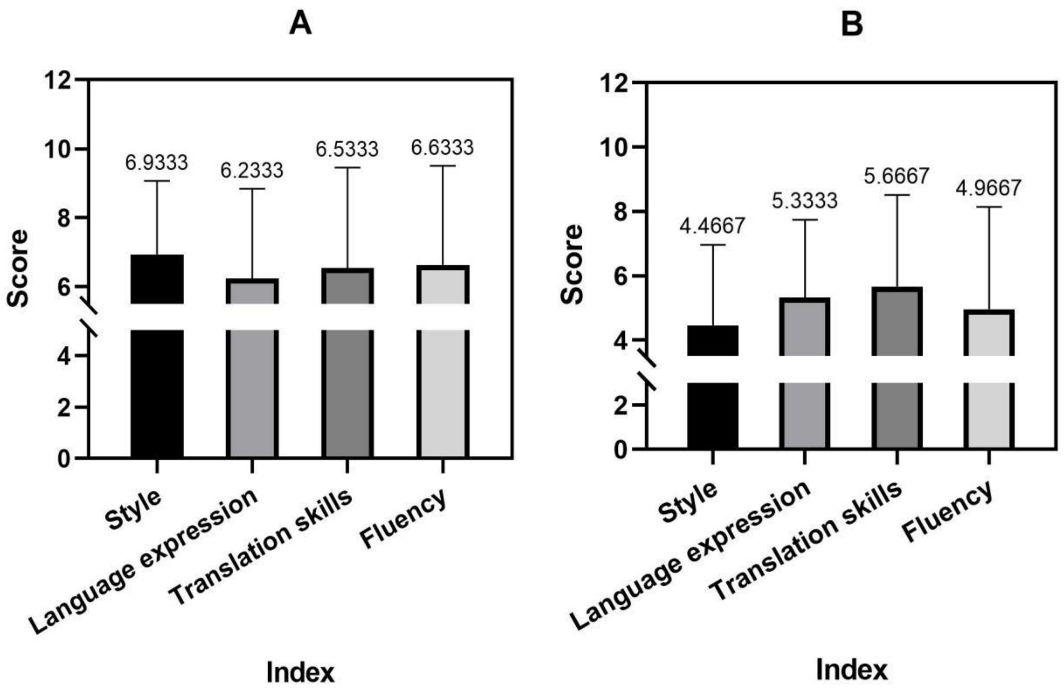

Fig.3 Comparison of manual evaluation results between two translation models

Fig. 3A: Model 1 manual evaluation results

Fig. 3B: Model 2 manual evaluation results

Fig. 3 shows the comparison of manual evaluation scores between two translation models, with Fig. 3A showing the manual evaluation results of Model 1 and Fig. 3B displaying the manual evaluation results of Model 2. The horizontal axis represents four evaluation indicators, while the vertical axis represents the average score size. After calculation, it can be seen that in terms of translation style, the average score of Model 1 is around 6.9333 points, while Model 2 is around 4.4667 points. Model 1 has a more proficient translation style and may only have a small number of stylistic and register features that do not match the target language, which has a relatively small marketing impact on the overall translation effect. However, the translation style of Model 2 is not very prominent, and errors may affect users' understanding or even change the original meaning. The gap between the two has been narrowed to a certain extent regarding language expression and translation skills. However, the wording of Model 2 is still not as accurate as Model 1 and may not be able to solve translation problems well.

Regarding language fluency, the average score of Model 1 is around 6.6333 points, while Model 2 is around 4.9667 points. Model 1 is closer to the usage habits of the target language and can be flexibly adjusted according to actual situations to achieve natural softness. Based on the evaluation of the above indicators, it can be concluded that Model 1 achieves a qualified level in each indicator's rating, has good decoding quality, and contributes to improving the user experience.

In summary, AI-based human-machine translation models have significant advantages over traditional SMT models regarding context understanding, accuracy, real-time translation, and flexibility. These advantages make AI-based translation models the mainstream method in the current MT field and provide a broad space for further translation technology development and application.

6. CONCLUSION

As a new and intricate language phenomenon, human-machine translation breaks people's understanding of language barriers and cultural differences in traditional language communication methods. It compensates for the inherent shortcomings and drawbacks of conventional manual translation.

The human-machine translation model based on AI translation can better reflect the characteristics of intelligence and automation in intelligent translation, effectively realizing dialogue between humans and computers, changing how humans and machines communicate to a certain extent, and promoting the process of the information technology revolution. Starting from analyzing the importance of AI translation, this article elaborated on the limitations and solutions of traditional translation methods and models. Combining the advantages of AI technology, a human-machine translation model was constructed. By describing and verifying the functions of the model, the aim was to improve translation efficiency and reduce error probability.

Integrating the advantages of AI and human translation, human-computer translation provides vital technical support for achieving more accurate and efficient cross-language communication. At the same time, AI-based human-machine translation offers a broader and deeper knowledge background and cultural resource management for human society, and further research is needed with the development of translation technologies.

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