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Application and Effect Evaluation of Translators and Equipment Collaborative Translation in the Era of Large Language Model

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Abstract: With the development of large language model, man and machine collaborative translation system has become an important means to improve the efficiency and quality of translation. In this study, we analyzed the application effect of human and machine collaborative translation system in different languages and fields, and comprehensively evaluated the quality of translation by using evaluation indicators such as BLEU, TER and review. It is found that compared with the traditional translation tools, human and machine collaborative translation can significantly improve the accuracy and fluency of translation, especially in the professional domain content and the translation of a few language pairs. In addition, the study also explored the optimal strategy of human-computer collaboration and the tuning guide of machine translation system, which provides certain theoretical support and practical guidance for realizing more efficient human-computer collaborative translation under different translation scenarios in the future.

1. Introduction

This study explores ways to get people and computers to translate languages together. As the world becomes more connected, language differences become a big problem. Translation is a bridge to help people in different languages communicate, but the traditional translation method is often slow and prone to make mistakes. Therefore, researchers began to study how to use computers to help translation and make it faster and more accurate. We did a lot of experiments and found that people working with computers did very well in translation tasks, especially in special areas and less commonly used languages. We also explored how to make people work most effectively with computers and gave suggestions. The purpose of this study is to let people know how to better translate languages by computers and to help people communicate better in the future.

2. Overview of the human and machine collaborative translation system

2.1 Development background and trend of large language model

2.1.1 Development background and trend of large language model

In recent years, the rapid development of large language models (Large Language Models, LLM) has revolutionized the field of natural language processing (NLP)[1]. Early language models such as n-gram and statistical machine translation (SMT) -based systems had limitations in dealing with complex language phenomena and long-distance dependencies. With the improvement of computational power and deep learning techniques, especially the wide application of neural networks, models are able to better capture contextual information and complex semantic relationships. Neural machine translation (NMT) technology is emerging rapidly, gradually replacing the traditional SMT system with its efficient translation ability.

In 2018, the GPT-2 of OpenAI attracted much attention, surpassing many previous models in tasks like text generation, translation, and question and answer. Subsequently, the BERT model released by Google has greatly improved the ability of natural language understanding by introducing a bidirectional encoder structure. These breakthroughs mark the development of large language models towards high-precision, multi-function and widely application. With its powerful language generation and understanding ability, the large language model shows excellent performance in the translation tasks.

The development of these models cannot be without the support of large data sets and powerful computational resources. Large language models often require training on large-scale corpora to capture rich language patterns and knowledge. This large-scale training not only improves the generalization ability of the model, but also enables it to perform well when dealing with texts in different languages and fields. For example, BERT and GPT series models were successfully applied to multilingual translation through multilingual pre-training, which significantly improved the translation quality of a few language pairs[2].

With the continuous improvement of large language models, the popularization of open access pre-training models and open source platforms also provides rich resources for academia and industry. On the one hand, researchers can customize the tuning based on these pre-trained models to adapt to the specific translation task requirements. On the other hand, the active atmosphere of the open source community promotes the rapid iteration and popularization and application of the technology.

The development of large language models has become an important driving force in the field of natural language processing. By combining deep learning, massive data and powerful computing resources, the large language model not only improves the quality and efficiency of machine translation, but also provides a solid technical foundation and broad application prospects for the human and machine collaborative translation system.

2.2 Working principle of human and machine collaborative translation system

The working principle of human and machine collaborative translation system mainly involves the effective combination and coordination of large language model and artificial translation. Large language model, based on neural network and deep learning technology, has the ability of large-scale corpus learning and language generation, and can produce high-quality preliminary translation results in a short time. The human and machine collaborative translation system achieves further improvement of translation quality by giving these preliminary results to the artificial interpreter for refinement.

In this process, the system uses the large language model to initially translate the source text and generate the machine translation version. Subsequently, the human and machine reviewed and revised the machine translation results, focusing on the coherence of context, the accuracy of professional terms and cultural adaptability. The information interaction between the translators and the system facilitates the translators to feedback and adjust the model output during the translation process, so as to optimize the overall quality of the translation.

The system also has the characteristics of real-time learning and self-optimization, which further improves the accuracy and applicability of machine translation models by continuously accumulating feedback and revision data in translation practice. This human and machine collaboration mode not only improves the translation efficiency, but also ensures the high quality translation effectively reduces the labor cost.

2.3 Comparative analysis of human and machine collaborative translation and traditional translation tools

Human and machine collaborative translation system has significant advantages over traditional translation tools. Traditional tools mainly rely on fixed algorithms and rule libraries, and have limited performance when handling complex contexts and cross-domain content. Human and machine collaborative translation combines the deep learning ability of the large language model with the professional knowledge of human translators, which can provide higher accuracy and fluency in the translation process. It not only improves efficiency, but also performs particularly well in professional expertise and a few language pairs, significantly reducing errors and ambiguities.

3. Experimental analysis of the application effect of man-machine collaborative translation

3.1 Case analysis of text translation in different languages and fields

The application effect of human and machine collaborative translation system in different languages and fields has been deeply analyzed through specific cases. In the language dimension, there are various languages, including English, Chinese, French, German, Spanish, and others.

In terms of fields, it covers scientific and technological literature, medical reports, legal documents, literary works and other professional fields and types. During the analysis, the same source text was used for the translation comparison to ensure that the results were comparable.

The translation results of legal documents in English and Chinese show that the human and machine collaborative translation system can effectively deal with professional terms and complex sentence patterns. This not only improves the accuracy of the translation, but also retains the rigor and legitimacy of the legal language. In the translation of medical reports, especially when involving complex medical terms and medical records, human and machine collaborative translation shows high professionalism and stability, which can accurately convey these manifestations of clinical patients and the doctors' diagnostic opinions[3].

When translating scientific and technological literature, especially involving cutting-edge technology and academic papers, the human and machine collaborative translation system shows good adaptability. By combining the rapid information processing ability of machine with manual background knowledge and experience, the translation quality is significantly improved, ensuring the accurate translation of terms and coherent expression of content. In the translation process of cross-language literary works, the advantage of human and machine collaborative translation lies in the delicate emotional expression and the retention of cultural background, especially in the translation of poetry and fiction, which is particularly obvious.

From the case analysis of different languages and fields, it can be seen that the human and machine collaborative translation system not only significantly improves the accuracy of translation, but also performs well in fluency and nature. When applied to the translation scenarios of a few language pairs, the human and machine collaborative translation system shows strong adaptability and tuning potential, which is of great significance for promoting multilingual communication and cultural communication.

3.2 Methods and indicators of translation quality assessment

Assessment of translation quality is crucial when studying the effect of human and machine collaborative translation. Generally, assessment methods and indicators include automated assessment indicators and review. BLEU (Bilingual Evaluation Understudy) and TER (Translation Edit Rate) are widely used in automated assessments. BLEU evaluates the accuracy of translation by calculating the n-group coincidence rate between reference and machine translations. TER evaluates the fluency and accuracy of the translation by calculating the number of editing operations requiring a machine translation. The advantages of BLEU and TE are that the former is intuitive and suitable for large-scale evaluation; The latter has advantages in fine granularity and can effectively reflect the subtle differences in translation.

These methods of review are equally important, usually qualitatively evaluated by linguistic experts based on a series of criteria. Review criteria often include accuracy, fluency, consistency, and word appropriateness[4]. In the manual review, the reviewers will score the translation and make detailed notes on its various dimensions. The advantages of this approach are its flexibility and meticulous qualitative analysis, helping to reveal problems that are difficult to detect in automated assessment. Scoring consistency between different reviewers is often a challenge, and assessment reliability can be improved by reviewing multiple reviewers together.

The comprehensive use of automated evaluation and manual review methods can provide a comprehensive assessment of translation quality, ensuring that the evaluation results have high objectivity and detail. In this way, the performance of human and machine collaborative translation system can be more comprehensively measured, and provide data support and theoretical basis for future optimization and improvement.

3.3 Experimental design and results of the evaluation of human and machine collaborative translation effect

To evaluate the effect of the human and machine collaborative translation system, the experimental design includes the task of translating multilingual and multi-domain text. The experiment uses BLEU, TER and manual review to compare the performance of human and machine collaborative translation and traditional translation tools. The experimental results show that human and machine collaborative translation has significant advantages in the translation of professional fields and of a few language pairs. The BLEU score improved significantly, the TER value decreased, and the manual review results were also better than the traditional methods in terms of accuracy and fluency[5]. The experimental data show that human and machine collaborative translation has high application value in diversified translation scenarios.

4. Optimization and practice guidance of human and machine collaborative translation

4.1 Discussion on the optimal strategy of man-machine collaboration

In the human and machine collaborative translation system, it is crucial to find the optimal strategy to maximize the translation efficiency and quality. Based on experiment and practice, several strategies can improve the effect of human and machine cooperation[6].

Task division is one of the core strategies of human and machine collaborative translation. In the process of translation, the machine translation system is responsible for the initial translation, especially when processing large quantities of text, the computing speed of machine and automatic processing ability can greatly reduce the manual workload. On the other hand, focus on more complex and precise understanding of context, especially context-sensitive, culturally profound or highly professional content. Such a division of tasks can not only speed up the overall translation progress, but also ensure the unity and accuracy of translation quality.

Dynamic adjustment of the translation process is also an effective strategy to improve the effect of human and machine collaborative translation. According to the complexity of translation, the urgency of translation task, the professional expertise of translators and other factors, the working mode of man-machine cooperation is flexibly adjusted. For example, for relatively simple daily dialogue texts, machine translation is supplemented by manual proofreading, however, further human and machine collaboration may be required by machine translation and manual revision. Through dynamic adjustment, the advantages of manual labor and machine can be fully utilized to achieve the optimal cooperation effect[7].

Context modeling is also an important strategy in human and machine collaboration. When dealing with long text or continuous conversations, machine translation systems often can only see local sentences and cannot grasp the global context information. At this point, by introducing the context modeling mechanism, the machine translation system can better understand the context relationship and avoid word meaning and grammatical errors. For example, translation memory and terminology database can be used to enhance the recognition of machine of proper nouns and common phrases, thus reducing the workload of manual proofreading. The human interpreter is responsible for building and maintaining these databases and constantly improving them during the translation process[8].

Enhancing the feedback mechanism is also an important way to improve the efficiency of human and Machine collaboration. By building a good reverse feedback system, the interpreter can adjust and optimize the machine translation results in time, and feedback the optimization suggestions to the machine translation system to promote its iterative improvement. This continuous feedback can not only gradually improve the accuracy and fluency of machine translation, but also provide data support for the long-term optimization of human and machine collaborative translation.

Regular training and evaluation are also indispensable strategies. Interpreters need to constantly learn and adapt to the latest machine translation technologies, and machine translation systems also need regular performance evaluation and update. In this process, through the introduction of automated assessment tools and manual assessment, the quality of translation is comprehensively tested, and problems are found and solved in time[9].

The optimal strategy of human and machine collaborative translation is not fixed, but needs to be continuously optimized and adjusted according to specific tasks and application scenarios. Flexible task division, dynamic adjustment of translation process, effective context modeling, enhanced feedback mechanism, and regular training and evaluation are all important means to achieve the best human and machine collaborative translation effect. The effective implementation of these strategies will further promote the application and development of human and machine collaborative translation, demonstrating its great potential in a wider range of application scenarios in the future[10].

4.2 Tuning techniques and methods of machine translation system

The tuning of the machine translation system is a key step to improve the quality of human and machine collaborative translation. The accuracy and versatility of the system can be significantly improved by optimizing the training data. Choosing a high-quality and diverse training corpus helps to improve the performance of the model when dealing with different domains and complex sentence patterns. Adjusting the hyperparameters, such as learning rate, batch size, and layers, can further enhance the stability and accuracy of the model.

Using data enhancement techniques, the robustness of the model can be increased. For example, through data augmentation and noise injection, we can effectively address the problem of grammatical variation and lexical diversity. Using domain adaptive training, it can help to improve the quality of translation of professional domain texts. A post-editing feedback mechanism was introduced with manual modification based on the translation results to guide the continuous optimization of the model. Through these methods, the overall performance of the machine translation system can be significantly improved, providing more efficient support for human and machine collaborative translation.

5. Conclusion

This paper studies the use and effect of human and machine collaborative translation in the era of artificial intelligence. The performance of the human and machine collaborative system is explored in different languages and professional fields. The study found that this system not only improved the quality of translation, but especially performed well in professional fields and some less used languages, making an important contribution to the development of the translation industry. The paper makes the evaluation more accurate by using a variety of methods to evaluate the quality of the translation. However, the study also indicates that in some very complex situations, the translation effect should be improved. This suggests that the current system still has limitations in understanding deep meaning and different cultural contexts. Future research will focus more on how machines and people can cooperate better, especially in deeper aspects of semantic understanding and adaptation to different cultures. In addition, with technological progress and increasing translation requirements, exploring more collaborative modes adapted to various scenarios is also an important direction for future research. These research results not only expand the application scope of human and machine collaborative translation, but also provide a reference for future relevant research. It is hoped that in the future, human and machine collaborative translation can provide more accurate and efficient translation in more fields, and help the communication and information sharing between different cultures.

References

[1] Lin Ying. On Translation teaching in the Era of Machine Translation [J]. Modernization of Education, 2019,6 (76).

[2] Li Feiyu, Zhao Yahui, Cui Rongyi, Yang Feiyang. Sino-Korean machine translation study based on reinforcement learning and machine translation quality assessment [J]. Computer Application Research, 2021, 38 (08): 2288-2292.

[3] Huang Jiayue, Xiong Deyi. Improve the translation performance of neural machine translation systems by using collaborative training [J]. Journal of Xiamen University: Natural Science Edition, 2019, 58 (02): 176-183.

[4] Ma Minghao. Quality assessment of machine translation analysis [J]. Journal of Ningbo Institute of Education, 2019, 21 (06): 76-78.

[5] Zeng Wenhao, Zhang Yongbing, Yu Zhengtao, Lai Hua. A neural machine translation method in the legal field integrated the translation memory bank [J]. Application of electronic technology, 2023, 49 (09): 39-45.

[6] Hu Jian and Fan Zirui. The nature of translation from a machine-translation perspective [J]. Contemporary Foreign Language Studies, 2023, (02): 90-96.

[7] Li Xiang, Liu Yang, Chen Wei, Liu Qun. Improving the translation quality of neural machine translation

compression models using monolingual data [J]. Chinese InformJournal, 2019, (07): 46-55.
[8] Han Dong, Li Junhui, Zhou Guodong. Neural machine translation of fused word translation [J]. Chinese InformJournal, 2019, (07): 40-45.
[9] Zhang Falien. Discussion on machine translation technology in legal translation [J]. Foreign Language audio-visual Teaching, 2020, (01): 53-58.
[10] Shen Fang. Machine translation quality estimation algorithm study of fused translation knowledge study [J]. Digital Communications World, 2021, (04): 243-244.