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Cultural Adaptation Strategies for English Translation of Intangible Heritage in Folk Culture Tourism

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SUMMARY: *The study integrates the use of information alignment algorithm and DR-Reformer network to construct the DR-Reformer English translation model based on optimal transportation. The information alignment algorithm realizes the modeling of correspondence between source and extended vocabularies and can output high-quality aligned utterances, while the DR-Reformer network can complete the tasks of vocabulary long-distance encoding and memory allocation, which improves the computational efficiency and scalability of the model. Under the constructed experimental environment, the cultural adaptability of the model in English translation of intangible heritage in folk culture tourism is evaluated according to BLEU and TER indicators. The G-mean value of the model is 0.912 when the feature dimension of the test dataset is 100 and the positive: negative ratio is 1:2, at which time the recognition of intangible heritage information sentences is the best. The model in this paper has a stable BLEU value of 37.5 and a stable TER value of 57.49 for the translation of sentences containing intangible heritage information, which has a better translation effect compared with the comparison model. The accuracy, fluency and logic of the intangible heritage texts translated by the model meet the reading requirements of tourists, with an average score between 7.77 and 8.34, and have better cultural adaptability.*

KEYWORDS: *information alignment algorithm; DR-Reformer; English translation model; folk culture tourism; intangible heritage*

1 Introduction

China has a glorious history of thousands of years of civilization, which has condensed a variety of cultural forms that play an important role in the development of tourism economy. The deep cultural heritage and rich tourism resources have created different viewing experiences for tourists, while the government has introduced various relevant policies to create a favorable investment environment, laying the foundation for creating and enhancing tourism culture [1-3]. Many conditions drive China's tourism industry to attract many foreign tourists. As an important part of tourism culture, the significance of folk culture to the development of tourism industry cannot be underestimated [4, 5]. Intangible cultural heritage as a key item of national culture tourism, its translation accuracy is extremely important for international tourism services.

Translation is a bridge between many different cultures, in order to let foreign tourists get a good tourism experience, translators need to ensure the quality of folklore tourism materials translation. High-quality translations in travel agencies or official tourism websites can not only

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give foreign tourists a good impression of the tourist destination, but also further promote the development of folk culture tourism [6, 7]. Since Chinese and Western cultures differ in various aspects, translators will encounter different difficulties in English translation of intangible heritage of folk culture tourism. Literature [8] found that the problems of English translation of intangible cultural heritage in Shaanxi mainly lie in the inaccurate translation of place and culture loaded words, missing information and semantic ambiguity. Literature [9] focuses on the subtitled English translation of the Chinese paper sculpture documentary “Paper Cutting Life” to explore the problem of cultural transmission in audiovisual translation of intangible cultural heritage; the study finds that translation faces multiple challenges on the technical, cultural and linguistic levels, and that omission, direct translation, equivalence and adaptation are effective strategies to deal with such cultural elements, which provides a reference to similar translation practices.

Literature [10] focuses on the English translation of Guangdong and Qiong intangible cultural heritage texts, and proposes to follow the principle of “two closenesses” and the five “C” criteria. On the basis of the alienation and adaptation strategies, titles, cultural sentences and short texts are dealt with by the comprehensive use of transliteration, annotation and compensation, which not only retain the cultural characteristics of the original text, but also make the translated text close to the thinking of the target readers. Literature [11] suggests that when translating the cultural elements of Guangzhou's intangible cultural heritage, the strategies of naturalization and alienation should be integrated, and seven methods such as direct translation, direct translation with transliteration, and direct translation with notes should be flexibly applied to take into account the preservation of cultural characteristics and the acceptability of the target readers. Literature [12] points out that different levels need to adopt differentiated NRM translation strategies, in which 80.2% of the translations focus on the methods of direct translation, paraphrase and combination of alienation and naturalization. However, literature [13] takes the Xixia Tombs as an example, constructs a dynamic framework of “cultural translation”, integrates site protection, digital technology and value reconstruction, emphasizes the necessity of technology, scene and value creation for translation, and establishes a dynamic and balanced digital tourism ecosystem. Literature [14] proposes a solution combining corpus and computer-assisted translation (CAT) technology to address the challenges of cultural connotation and regional characteristics in the English translation of non-heritage texts, which is to build a parallel corpus and use three modes, namely, machine translation, human-computer interaction, and human translation, in order to improve the translation efficiency and quality, as well as to promote the standardization of terminology and cultural dissemination. Literature [15] applies integrated multimodal translation methods such as hypertext and augmented reality to translate NRLs, which not only enhances the tourism experience, but also effectively promotes the international dissemination and understanding of this unique cultural heritage. However, the analysis of literature [16] shows that although it is convenient to explore neural machine translation of English translation of Chinese non-heritage texts, human editors are still required to remedy its deficiencies in lexical connotation and syntactic structure through strategic adjustments. In addition, there are semantic ambiguities in the cultural connotation of NRT, and some NRT items containing dialectal connotations need to be translated in context, and the cultural adaptability under direct translation is insufficient.

In this paper, we constructed an English translation corpus of folk culture tourism intangible cultural heritage, realized the sentence alignment processing of folk culture tourism corpus based on the sentence alignment method of English-Chinese dictionary, and at the same time established an English translation model based on optimal transportation with DR-Reformer. The model takes Reformer as the core network, and combines position-sensitive hashing and reversible Transformer technology to realize the mapping of high-dimensional vectors to lowdimensional space, and reduce the model parameters and computational complexity. In addition, the model transforms the vocabulary alignment problem into an optimal transmission problem, obtains alignment information based on word frequency and similarity of vocabulary, and then generates a high-quality parallel corpus. Experimental comparisons on relevant datasets prove that the proposed model has higher translation quality and faster efficiency.

2 Research on Adaptive Strategies for Cultural English Translation Based on Translation Modeling

The study aims to explore the culturally adaptive strategies for English translation of intangible heritage in folk culture tourism, for which relevant research is conducted. Firstly, an English translation corpus of intangible heritage of folk culture tourism was constructed, secondly, the DR-Reformer English translation model based on optimal transportation was developed, and then the effectiveness of the proposed strategy was verified through the experimental setup and relevant evaluation methods.

2.1 English Translation Corpus Construction for Folk Culture and Tourism Intangible Heritage

2.1.1 English-Chinese/Chinese-English Bilingual Tourism Corpus Collection

Aiming at the needs of English translation of intangible heritage in folk culture tourism, the study constructed an English-Chinese/Chinese-English bilingual sentence alignment parallel corpus of intangible heritage in the field of folk culture tourism. The corpus sources of the English-Chinese/Chinese-English bilingual tourism corpus of intangible heritage include:

a. English-Chinese corpus of intangible heritage in folk culture tourism of a region with English as the source language and Chinese as the translation.

b. Chinese-English corpus of intangible heritage in folk culture tourism of a certain region with Chinese as the source language and English as the translation.

Tourism corpus is not only limited by domain, but also seriously restricted by region. The tourism corpus of one region is usually very different from that of another region. The English-Chinese/Chinese-English bilingual tourism corpus of a region that has been collected in this study mainly includes:

a. Publicly published English-Chinese/Chinese-English bilingual literature about intangible heritage in folk culture tourism in a certain region.

b. English-Chinese/Chinese-English bilingual electronic texts on the Internet about intangible heritage in folk culture tourism in a certain region.

At present, this study has collected the English-Chinese/Chinese-English bilingual tourism corpus of intangible heritage of folk culture tourism in a certain region with a capacity of more than 500,000 words/phrases.

2.1.2 Sentence Alignment Processing for Intangible Heritage Corpus

The study realizes sentence alignment processing of English-Chinese bilingual corpus using sentence alignment method based on English-Chinese dictionary. Sentence alignment processing is carried out on the already collected English-Chinese/Chinese-English parallel corpus with the help of the publicly available English-Chinese/Chinese-English parallel corpus sentence alignment processing platform. The process is as follows:

a. Call the parallel corpus of English-Chinese/Chinese-English translations that need to be processed into the working window. If there is a mixed-typed English-Chinese/ Chinese-

Chinese parallel corpus, it can be automatically split by utilizing the relevant functions provided by the processing platform.

b. Using the function of checking paragraph alignment provided by the English-Chinese/Chinese-English parallel corpus sentence alignment processing platform, check whether paragraph alignment can be realized first before parallel corpus sentence alignment processing.

c. After checking the paragraph alignment, select English-Chinese sentence alignment, and then you can get the results of English-Chinese/Chinese-English parallel corpus sentence alignment processing.

d. Manually proofread the sentence alignment results. The sentence alignment results after proofreading can be used by the fully automatic machine translation system. By converting the alignment results into TM or TMX, the translation memory that can be directly called up by the computer-assisted translation system can be obtained and used directly by the computer-assisted translation.

2.2 DR-Reformer English Translation Model Based on Optimal Transportation

In order to realize the cultural adaptability of intangible heritage after English translation in folk culture tourism, the study designed a novel machine translation strategy, i.e., DR-Reformer English translation model based on optimal transportation, to realize the machine translation task by using the intangible heritage corpus constructed above.

2.2.1 Information Alignment Algorithm

Information Alignment Algorithm studies how to solve the lexical alignment problem between source and target languages, and then generate a high-quality information-aligned intangible heritage corpus to facilitate the realization of machine translation tasks. The study of optimal transportation-based information alignment algorithms establishes correspondence between source and extended vocabularies, which facilitates the learning of more diverse vocabularies in the translation process. Therefore, the alignment problem is transformed into an optimal transportation problem that transports high frequency and high similarity vocabularies to generate high-quality aligned utterances suitable for specific domains. The vectors of the source vocabulary and the vectors of the extended vocabulary are denoted as:

$$\begin{aligned} s_i &= w_{i1}, w_{i2}, \cdots, w_{it} \\ e_j &= w_{j1}, w_{j2}, \cdots, w_{jt} \end{aligned} \tag{1}$$

where the dimension of the vector is denoted as t. Therefore, the matrix containing the alignment information will be defined as:

$$P(s_i) = \frac{Token(s_i)}{\sum_{i \in V_s} Token(s_i)}, \quad \sum_{i=1}^{n} P(s_i) = 1 \tag{2}$$

$$P(e_j) = \frac{Token(e_j)}{\sum_{j \in V_e} Token(e_j)}, \sum_{j=1}^{m} P(e_j) = 1 \tag{3}$$

$$U(S,E)=\left\{P\in R_{\geq 0}^{n\times m}\,\middle|\,S=s_i,\,E=e_j\right\} \tag{4}$$

where S denotes the source vocabulary with n total number of words and E denotes the extended vocabulary with m total number of words. $P(s_i)$ and $P(e_j)$ denote the marginal probability distribution. The source vocabulary and extended vocabulary have different transportation distances and their preference matrices are calculated as:

$$M_{i\in V_s,\,j\in V_e}(s_i,e_j)=\frac{\sum_{a=1}^{t}W_{i_a}\cdot W_{j_a}}{\sqrt{\sum_{a=1}^{t}(W_{i_a})^2}\sqrt{\sum_{a=1}^{t}(W_{j_a})^2}} \tag{5}$$

where $M(s_i,e_j)$ is a preference matrix with n rows and m columns. In addition, the study introduces information entropy to align the source and extended vocabularies more equally. The information entropy is defined as:

$$\begin{aligned} H(P) &= -\sum_{i,j}P(s_i,e_j)\log P(s_i,e_j)P(s_i,e_j) \\ &= P(s_i)\times P(e_j) \end{aligned} \tag{6}$$

Finally, the problem of aligning the information of the source and extended vocabularies is reconstructed as the following objective function as:

$$d_M^2=\min_{P\in U(s_i,e_j)}\sum_{s_i,e_j}P(s_i,e_j)M(s_i,e_j)-\frac{1}{\lambda}H(P) \tag{7}$$

where d_M^2 is the distance between two probability distributions, and λ is the entropy regularization coefficient for balancing similarity and word frequency.

The optimal transportation-based information alignment algorithm utilizes the word frequency and similarity of the vocabulary to obtain the alignment information, and Figure 1 shows an example of optimal transportation-based information alignment. The black box is the source vocabulary, the red box is the extended vocabulary, M is the preference matrix (the preference information of the vocabulary), C is the number of vocabulary lists, and the black dashed line is the transportation distance. First, the intangible heritage corpus is supplemented or augmented by reverse translation to increase the size and diversity of the corpus. Second, the number of words in the corpus and the expanded vocabulary are counted, while the preference matrix is calculated. Finally, input to the optimal transportation-based information alignment algorithm to generate a high-quality multilingual aligned information parallel corpus.

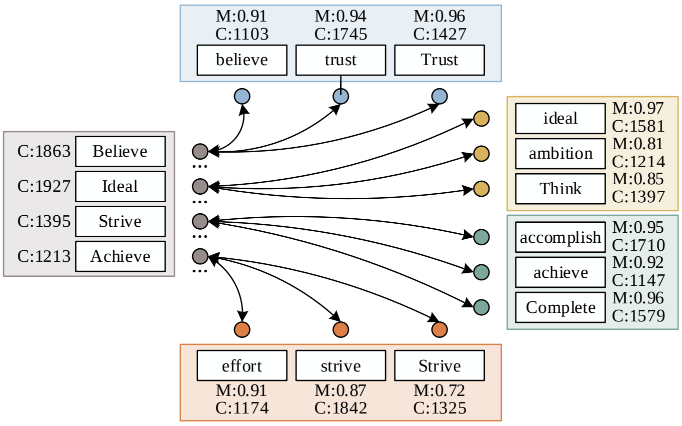

Figure 1: Examples of information alignment based on optimal transport

2.2.2 DR-Reformer network

(1) Reformer

The study adopts Reformer as the backbone network, which is a variant model based on Transformer that not only inherits the advantages, but also combines location-sensitive hashing and reversible Transformer techniques to solve the problem of long distance coding and memory allocation.

a. Local Sensitive Hashing

Local Sensitive Hashing (LSH) is a technique for approximate nearest neighbor search for high dimensional data.LSH maps high dimensional vectors to low dimensional space, so that vectors that are similar in the original space are still similar in the new space. Where the hash function is a set of random mappings that convert the original data into hash values, thus enabling the projection of data points into buckets, and the hash values of data points in the same bucket have similar characteristics, which facilitates fast approximate search.DR-Reformer uses locally-sensitive hashing instead of dot-product attention, and maps the high-dimensional features into the lowdimensional feature space through the hash function, keeping the distance of spatial distribution unchanged , defined as:

$$\begin{gathered} Attention(Q,K,V)=\sum \exp(Q\cdot K-M-Z)V \\ where\ M=\begin{cases} +\infty, & if\ first\ word \\ 0, & otherwise \end{cases} \end{gathered} \tag{8}$$

where M is the set of masks, Z is the normalization function, and locally sensitive hashing avoids Q paying attention to other locations and reduces the overall computational complexity to $O(L*\log(L))$.

b. Reversible Transformer

Reformer employs the Reversible Transformer to achieve reversibility by splitting the input into two sub-tensors, i.e., channel and position sub-tensor. The channel sub-tensor contains information about all channels, while the position sub-tensor contains information about the position of each channel. The Reversible Transformer then performs multi-head self-attention computation and feed-forward neural network computation on the channel sub-tensor and splices the results with the position sub-tensor to get the final output. In this way, the computation and memory consumption is reduced by half, which improves the computational efficiency and scalability.

(2) Dropout and Reduction

Dropout is a technique that removes some neurons randomly during the training process, forcing the model to learn more robust and generalized features. As Dropout removes some neurons, it prevents the Reformer model from being too sensitive to some specific inputs, thus avoiding overfitting.

Reduction introduces a learnable dimensionality reduction matrix into the model, which is obtained by training to compress the information in the high-dimensional input vectors into a low-dimensional space, thus preserving the most important features in the input vectors. At the same time, Reduction projects the input from linear to $soft\max$ before the output, which produces a one-to-one prediction, reducing the number of parameters and computational complexity of the model, while improving the accuracy of the model, defined as:

$$\mathrm{Re}\,duction(x) = Concat\left[soft\max\left(W_1 x^T\right)x_1, \cdots, soft\max\left(W_n x^T\right)x_n\right] \tag{9}$$

where W is the learnable parameter.Reduction not only reduces the model parameters and computational complexity, but also avoids the overfitting problem and improves the generalization ability of the model.

(3) DR-Reformer

In order to further reduce the model parameters and improve the translation quality of the intangible heritage corpus, a Dropout1/2D layer is added to the Reformer model, which reduces the parameters of the model by repeatedly dropping useless features. At the same time, the Reduction layer is added to reduce the model parameters and computational complexity.The DR-Reformer model further improves the model training speed and accuracy without affecting the model accuracy.The overall framework of the DR-Reformer model is shown in Figure 2.

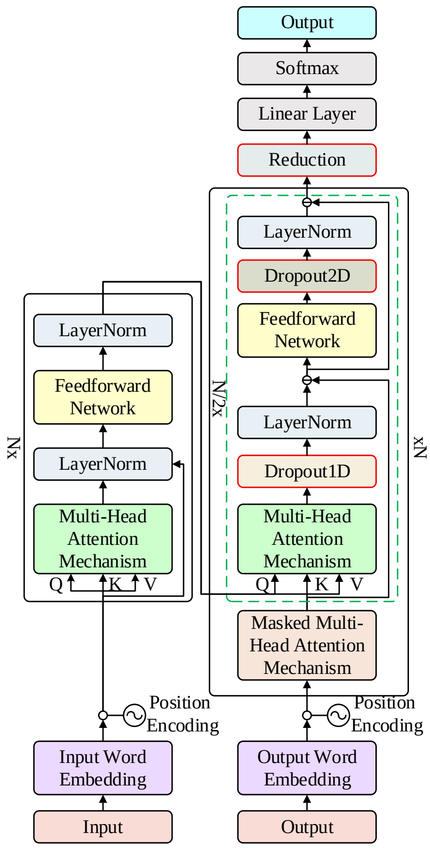

Figure 2: DR-Reformer structure

2.2.3 Translation modeling framework

The framework of the multilingual alignment information translation model based on optimal transportation is shown in Fig. 3. The steps to realize the translation are as follows:

a. Use the optimal transportation-based alignment information algorithm for data enhancement. If the target language is a low-resource language, the bilingual parallel corpus is first obtained by back translation. If the target language is a high-resource language, the word lists are directly extracted from the source vocabulary and extended vocabulary, which are fed into the algorithm of this paper to screen the best replacement words and generate high-quality alignment data, so as to narrow the representation gap between multilinguals.

b. Input the intangible heritage corpus alignment data into DR-Reformer for pre-training to learn richer semantic information.

c. Input the required target language data into DR-Reformer for fine-tuning to eliminate the noise interference caused by the language training and complete the translation model training.

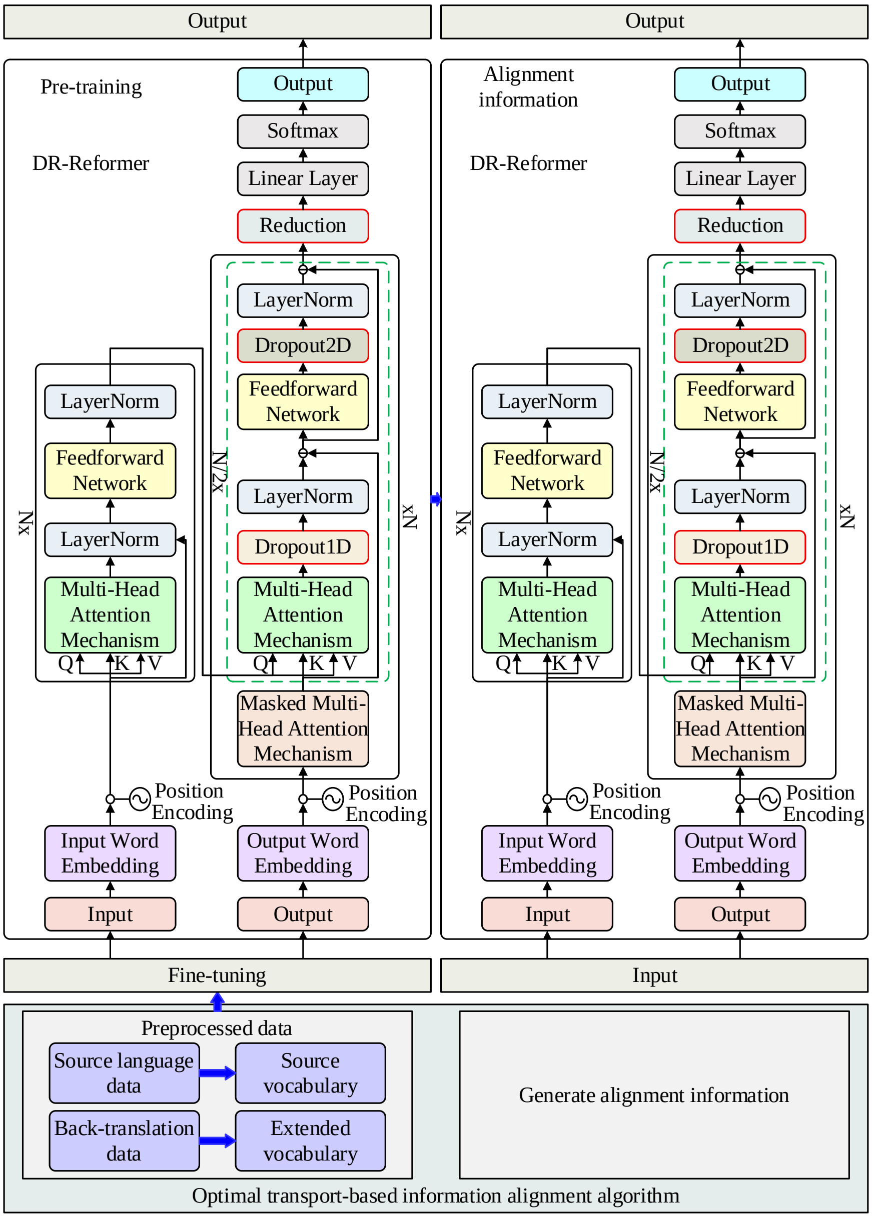

Figure 3: DR-Reformer English translation model framework

2.3 Experimental setup

(1) Experimental environment

All model training is based on the open-source framework Fairseq, which relies on the base environment Pytorch-1.0+, the programming language python3.7, and the GPUs used are 8 NAVIDIA TESLA V100 (32GB), where the size of the batch on each GPU is set to 4096 words.

(2) Dataset and Preprocessing

Based on the English corpus of intangible heritage constructed above, the study made its own dataset needed for the experiment, which contains more than 500,000 sentences containing intangible heritage in folk culture tourism in a certain region, and the study divides it into training set and testing set in the ratio of 8:2.

After obtaining the dataset, the data need to be preprocessed first to adapt to the input form of the model. Firstly, the Chinese data were segmented using the jieba3 segmentation tool, and the English was segmented using mosesdecoder4. In order to alleviate the problem of unregistered words and the problem of oversized vocabularies, the standard subword excision method (BPE) was used to sub-subscribe the text after word-splitting. For Chinese-English parallel data, the Chinese and English data were subword-sliced separately using separate BPE, and then a 30k merge operation was applied. Finally, the corpus is cleaned up to keep the sentences whose parallel text length is greater than 1 and less than 150.

(3) Model Setting

In order to evaluate the translation reliability of the DR-Reformer English translation model based on optimal transportation in this paper, the study introduces a machine translation model with the base Transformer framework and a machine translation model with the BERT+Transformer framework. The setup model has 8 layers of encoders and 8 layers of coders, the size of the hidden layer state is 512, the size of the transpose dimension of the fully connected layer is 4096, and the number of heads of the multi-head attention mechanism is 10. All parameters are randomly initialized. The peak learning rate of the translation model is 0.0001, and the number of training steps is 50k. The AdamW optimizer is employed and the learning rate warmup (warmup) strategy is used to train the model with an initial learning rate of 1e-6 for the first 1,000 steps. As the number of training steps increases, the learning rate slowly rises until it reaches the pre-determined maximum learning rate, after which the learning rate will be in the form of a negative root sign function for decay.

2.4 Evaluation methodology

(1) BLEU Translation Quality Evaluation

BLEU (Bilingual Evaluation Understudy) translation quality evaluation method is one of the world's recognized methods for automatic evaluation of machine translation models, which considers that the closer the model's translated translation is to the result of human translation, the higher the model's translation quality is.

The steps of the BLEU evaluation method are to first calculate the maximum number of possible occurrences $Max\,\mathrm{Re}\,fCount(n\text{-}gram)$ of a certain n meta-word $(n\text{-}gram)$ in a subsequence of that human-translated sentence, and then compare it with the number of occurrences of this n meta-word in the translated text translated by the model, and take the smallest value of the comparison as the final number of matches for that n meta-word, which is calculated as follows:

$$\begin{aligned} &Count_{clip}(n\text{-}gram) = \\ &\min\left\{Max\,\mathrm{Re}\,fCount(n\text{-}gram), Count(n\text{-}gram)\right\} \end{aligned} \tag{10}$$

where $Count(n-gram)$ denotes the number of times the n meta-word appears in the translated text translated by the model.

And then the comparison results of all the n-gram words in the sentence are summed up and divided by the sum of the number of times all the n meta-words appear in the translated text translated by the model, which is calculated as follows:

$$p_n = \frac{\sum_{c\in candidates}\sum_{n\text{-}gram\in c} Count_{clip}(n\text{-}gram)}{\sum_{c'\in candidates}\sum_{n\text{-}gram'\in c'} Count_{clip}(n\text{-}gram')} \tag{11}$$

where $candidates$ denotes multiple sequences of sentences translated by the model.

If the translated text translated by the model is much shorter than the translated text translated by human, then p_n will end up with a very high score, which is actually unreasonable. For this reason, BLEU introduces a penalty mechanism, whose formula is as follows:

$$BP = \begin{cases} 1 & c > r \\ e^{1-\frac{r}{c}} & c \le r \end{cases} \tag{12}$$

where c denotes the number of translated words translated by the model and r denotes the number of translated words translated by the human.

Therefore the final formula of BLEU is as follows:

$$BLEU = BP \times \exp\left(\sum_{n=1}^{N} w_n \times \log p_n\right) \times 100\% \tag{13}$$

where N denotes the maximum order of the set n elemental words, and w_n denotes the weight coefficient of n elemental words.

(2) TER Translation Quality Evaluation

TER (Translation Edit Rate) translation quality evaluation method is also one of the world's recognized methods for automatic evaluation of machine translation models, and the overall idea of TER is the error rate, so the lower the value of TER, the lower the error rate of the model translation, and the better the translation performance.

The conversion operation used by TER contains add, delete, shift and replace, and its calculation formula:

$$TER = \frac{Ins + Del + Shf + Sub}{r} \times 100\% \tag{14}$$

where Ins, Del, Sub, and Shf denote the number of addition, deletion, shifting, and substitution operations, respectively, and r denotes the number of translated words translated manually.

3 Cultural adaptation analysis of English translations of intangible heritage

3.1 Feature dimensions and positive and negative class ratio effects

In order to evaluate the superiority of DR-Reformer network used in this paper, the study introduces the basic Transformer framework and BERT+Transformer framework, and conducts experiments on the influence of feature dimensions and the ratio of positive and negative classes. From the labeling results of the test set, the ratio of positive and negative classes in the intangible heritage dataset of folk culture tourism is about 1:10, and the positive classes are labeled from the unlabeled training data by the rule method, and then the negative classes are randomly under-sampled according to the ratio different from that of the positive classes. The training set is constructed according to the ratios of 1, 2, 5, and 10, and comparative experiments are conducted on different numbers of feature dimensions, using the G-mean value as the evaluation index. Considering the randomness of the training set constructed by random under-sampling, each experiment is conducted 10 times, and then the average value is taken as the result of the experiment.The G-mean value is calculated as follows:

$$G-mean=\sqrt{\frac{TP}{TP+FN}*\frac{TN}{TN+FP}} \tag{15}$$

where TP is the number of sentences that the model correctly judged as positive categories, and TN is the number of sentences that the model correctly judged as negative categories. FP is the number of sentences in which the model misjudged the negative category as positive, and FN is the number of sentences in which the model misjudged the positive category as negative.

The experimental results with different feature dimensions and different positive and negative class ratios are shown in Fig. 4. In the problem of recognizing intangible heritage information sentences in folk culture tourism, the recognition effect of this paper's model is better than that of Transformer and BERT+Transformer model. In the same training set with the same positive and negative ratios, the recognition effect reaches the best when the feature dimension is 100 dimensions, and the recognition effect shows a decreasing trend with the increase of dimension. This indicates that as the feature dimension increases, after a certain dimension, features that do not contain distinguishing information and are quite sparse in the dataset are introduced, leading to a decrease in the recognition effect of the model. From the experimental results of different sample ratios with the same feature dimensions, the model in this paper achieves the best classification effect with a positive:negative ratio of 1:2, and the G-mean value reaches 0.912 when the feature dimension is 100, while the same positive:negative ratio of 1:2 in the Transformer and BERT+Transformer models is the best for the recognition of the intangible heritage information sentence, and the G-mean value is 0.912 when the feature dimension is 100. The G-mean values are 0.842 and 0.873 when the feature dimension is 100.When the positive-negative ratio is larger than 1:2, there is a significant decrease in the recognition effect of all the three models in terms of the overall effect. It indicates that in unbalanced data, the models are easy to overfit to multi-class samples, which reduces the recognition ability of fewer class samples, leading to a decrease in the recognition effect of intangible heritage information sentences. Through the results of the experiments in this section, the recognition effect of intangible heritage information sentences is better when the feature dimension is 100 dimensions and the positive-to-negative ratio is 1:2, and the following experiments are carried out under such a setting.

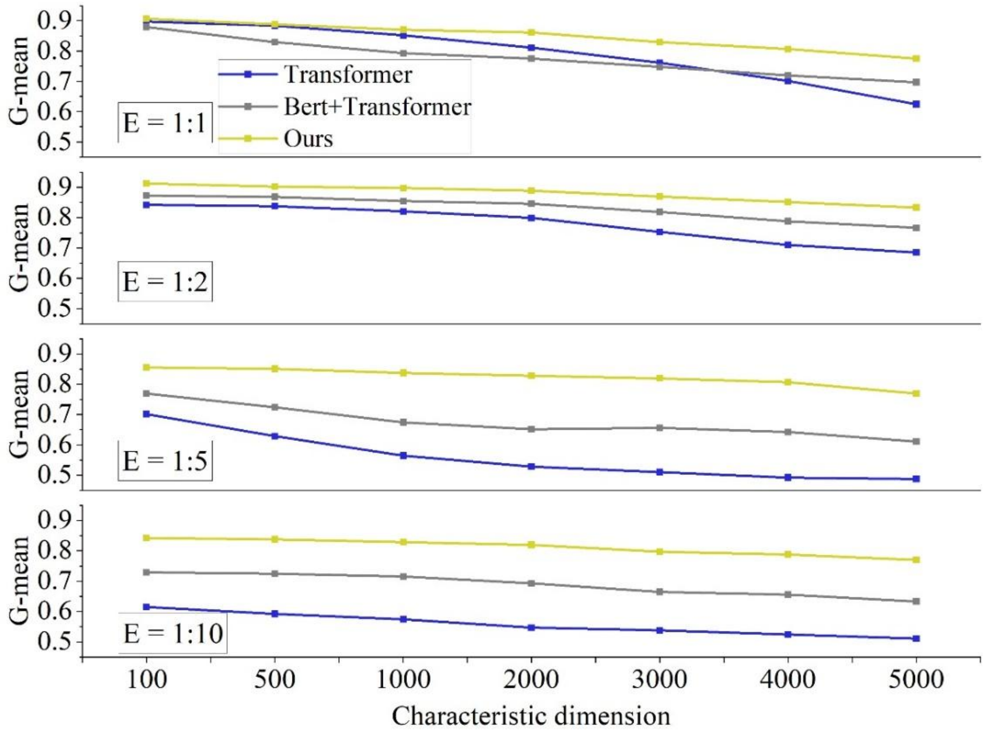

Figure 4: The characteristics and the positive and negative analogies are affected

3.2 Comparative Analysis of Multi-Perspective Translation Effects

In this section, the machine translation model of the basic Transformer framework and the machine translation model of the BERT+Transformer framework are used to compare the translation performance in the intangible cultural heritage dataset of folklore culture tourism with the positive-to-negative ratio of 1:2 and the feature dimension of 100. The experiment uses BLEU and TER introduced in section 2.4 as the translation quality evaluation indexes, where the higher the BLEU the better, and the lower the TER the better.

The BLEU and TER test results of each machine translation model are shown in Figs. 5 and 6, respectively. Each machine translation model has conducted a total of 40 test experiments on the dataset, and the average measurements of BLEU and TER indexes are recorded every 5 experiments. Analyzed in combination with the two figures, with the increasing number of experiments, the translation effect of the three groups of machine translation models is gradually enhanced. For the BLEU index, the measured value change of each model gradually improves and stabilizes after 25-30 experiments. Among them, the BLEU stabilization value of this paper's model reaches 37.5, which is about 8.7 higher than that of the basic Transformer framework, and about 4.3 higher than that of the BERT+Transformer framework as well.As for the TER index, the trend of changes in the measured value of each model is opposite to that of the BLEU index, i.e., it decreases first and then stabilizes. Similarly, the final stabilized value (57.49) of the model in this paper performs the best, which is 5.7 and 3.4 TER units lower than the base Transformer framework and the BERT+Transformer framework, respectively. After comparative experiments, it is concluded that the DR-Reformer English translation model based on optimal transportation proposed in this paper has better performance and better English translation effect in the folk culture tourism intangible heritage dataset.

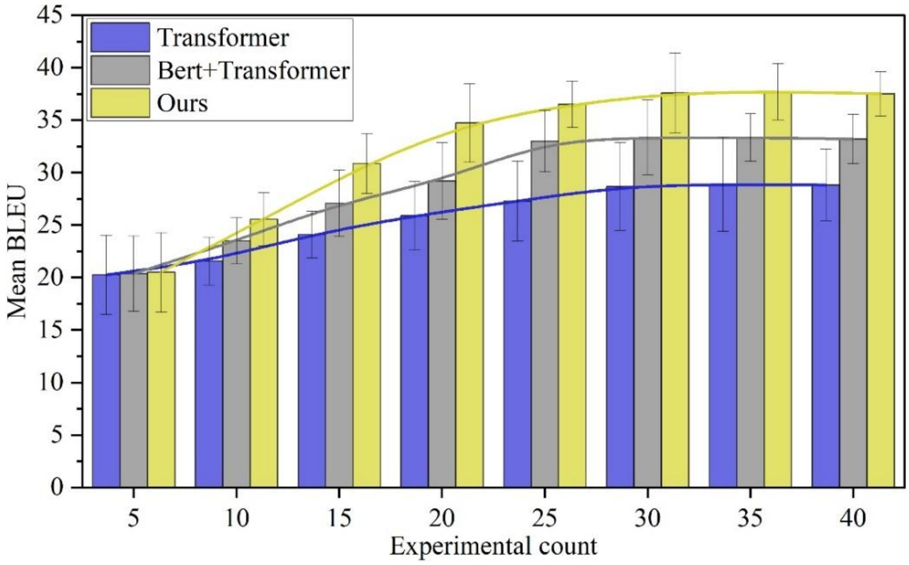

Figure 5: The BLEU test results of each machine translation model

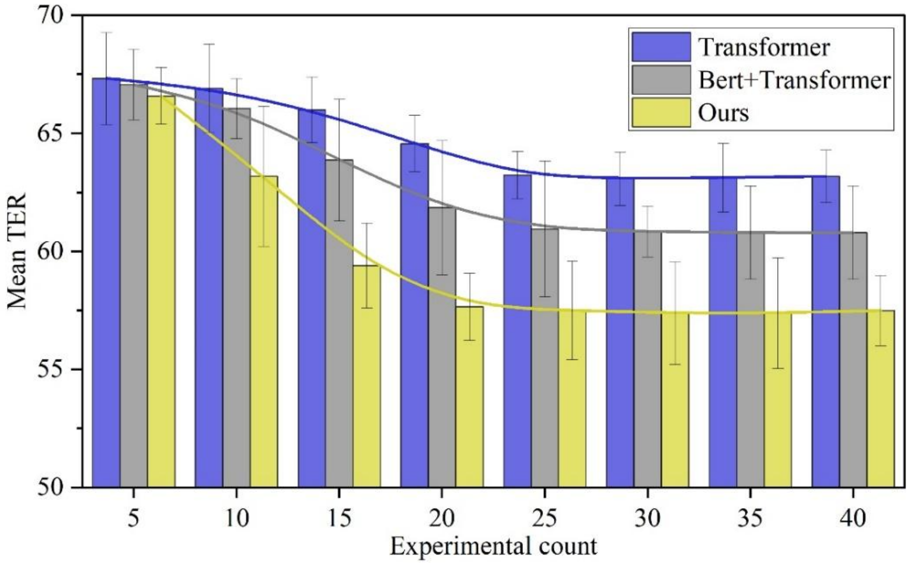

Figure 6: The TER test results of each machine translation model

In order to further verify the better translation effect of DR-Reformer English translation model based on optimal transportation, this subsection adopts three different machine translation models to translate long sentences and short sentences in the dataset respectively, and compares the translation accuracy of the three. The results of translation accuracy test for long sentences and short sentences are shown in Figure 7. The average accuracy of the translation effect of the basic Transformer framework on long sentences is 70.91%, and the average accuracy of the translation of short sentences is 76.66%, which is a better translation effect. The average accuracy of translation effect of BERT+Transformer framework for long sentences is 80.80%, and the average accuracy of short sentence translation is 88.20%, which is 9.89% and 11.54% higher than the base Transformer framework respectively. And the DR-Reformer English translation model based on optimal transportation in this paper has an average accuracy of 92.18% for the translation effect of long sentences and 97.05% for the translation of short sentences, which is 11.38% and 8.85% higher than the BERT+Transformer framework, respectively. It shows that the model in this paper substantially improves the machine translation effect and verifies the feasibility and effectiveness of the DR-Reformer English translation model based on optimal transportation.

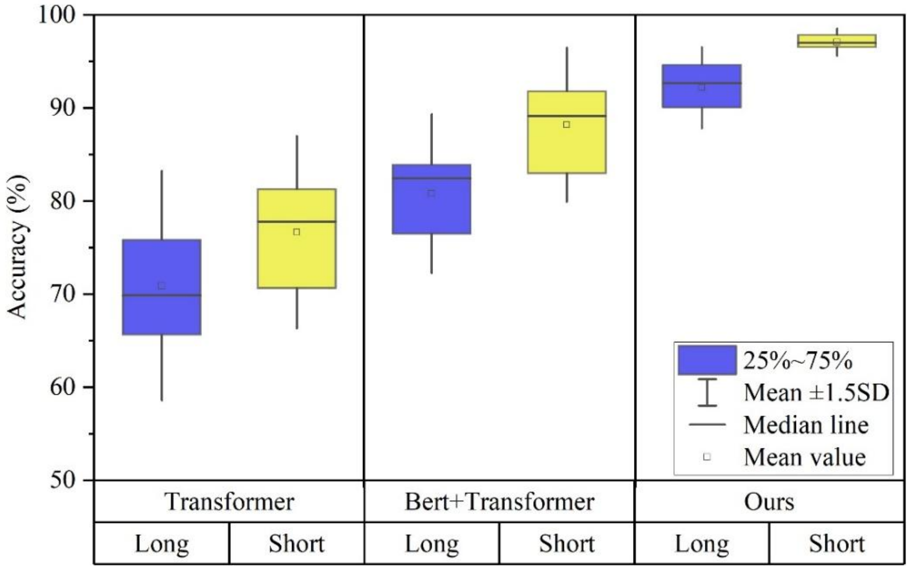

Figure 7: Test results of long sentence and short sentence translation accuracy

3.3 Evaluation of Intangible Heritage Translation Measures

The quality assessment of translations in previous studies mainly focuses on the lexical and syntactic levels, and less on the discourse level. For this reason, this section intends to examine the errors at the lexical, syntactic and discourse levels at the same time, and refine the indexes in combination with the existing studies, so as to construct an evaluation system applicable to the English translation of intangible heritage in folk culture tourism.

a. Accuracy: Translation accuracy refers to the degree of precision in converting the source language into the target language. Errors in accuracy include mistranslation, non-translation, omission of translation, multiple translation and so on.

b. Fluency: problems in fluency are mostly related to sentence form or information expression, thus affecting the readability of sentences, mainly including text style errors, language style errors and information expression errors.

c. Logic: machine translation often fails to clarify the logical relationships involved, thus leading to confusion between sentences and relationships within sentences. The study subdivided the problems under the logic dimension into: unclear references and confusing relationships.

The study scores the above errors according to the number of occurrences, and the fewer the occurrences, the higher the score, i.e., the stronger the model's accuracy, fluency and logic of English translation of intangible heritage in folk culture tourism. Thirty sentences containing information about intangible heritage are selected from the dataset and translated using the machine translation model of the basic Transformer framework, the machine translation model of the BERT+Transformer framework, and the translation model constructed in this paper, and 10 experts related to the field of intangible heritage and English are invited to score the 30 sentences, and the full score of each index is set at 10 points. Figure 8 shows the results of the model's evaluation of the translation of 30 sentences containing intangible heritage information.

In terms of accuracy dimension, the machine translation model of the basic Transformer framework, the machine translation model of the BERT+Transformer framework, and the translation model constructed in this paper, the average rating values of the translation accuracy of the 30 sentences containing information about intangible heritage are 6.55, 7.34, and 8.34, respectively, and the model in this paper has the best performance but still has some accuracy errors. For example, mistranslation, general word mistranslation is mainly reflected in the multiple meanings of words, which may be related to the fact that machine translation often cannot accurately recognize the multiple meanings of words and often makes mistakes. The transformation of lexical properties is mostly reflected in the words ending with “ed” and “ly” in English, which cannot be recognized by machine translation, resulting in the accuracy of English to Chinese translation due to the lack of timely conversion of lexical properties.

In terms of fluency dimension, the model in this paper obtains an average score value of 7.91, which is improved by 1.69 compared with the machine translation model of the basic Transformer framework, and there is also an improvement of 0.48 points compared with the machine translation model of the BERT+Transformer framework. Among them, the problems at the syntactic level greatly affect the fluency, and the model optimization needs to pay further attention to the problems of syntactic transformation, missing components and order adjustment. However, the translation results of this paper's model for sentences containing intangible heritage information are sufficient to convey the syntactic meaning of the sentences and meet the reading fluency needs of tourists.

In terms of the logic dimension, the average logic score of the three groups of translation models scores the lowest compared to the other two indicators, and the average score values of the machine translation model of the basic Transformer framework, the machine translation model of the BERT+Transformer framework and the translation model of this paper are 6.04, 7.18, and 7.77, respectively, and the model of this paper has the the best translation logic performance. Analyzing the translation results, it is found that the current machine translation cannot accurately translate the content referred to by pronouns (e.g., it) in the chapter. In addition, when English sentences unfold in a tree-like manner, it is often difficult for machine translation to clarify the logical relationships, which may disrupt the logical relationships of the sentences or chapters.

By evaluating the translation of 30 sentences containing intangible heritage information, the DR-Reformer English translation model based on optimal transportation in this paper has the best overall performance, which is much better than the comparison model in terms of folk culture embodiment and adaptation, and can better realize the dissemination of intangible heritage in folk culture tourism.

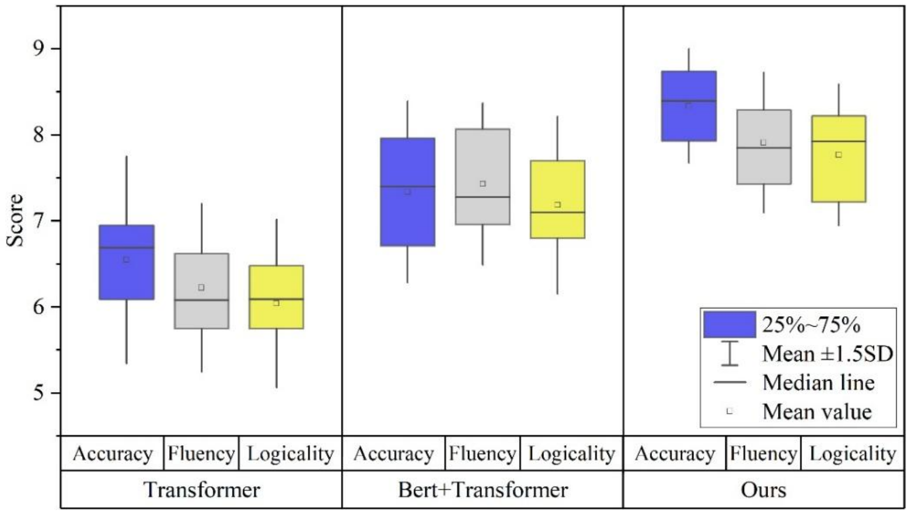

Figure 8: The model of the translation evaluation of 30 sentences

4 Conclusion

The article introduces the DR-Reformer English translation model based on optimal transportation in detail from the aspects of algorithmic principle and model framework, and solves the problems of long-distance coding and memory allocation while lightweighting the English translation model through the information alignment algorithm and DR-Reformer framework. Based on the folk culture tourism corpus data, several experiments are conducted to verify the feasibility of the model as a culturally adaptive strategy for English translation of intangible heritage.

The feature dimensions and the positive and negative class ratios will affect the model's recognition effect on the informative sentences of intangible heritage, and the recognition G-mean value when the feature dimension is 100 and the positive and negative ratios are 1:2 is 0.912.The accuracy of the proposed model for translating long and short sentences on the intangible heritage dataset is 92.18% and 97.05%, respectively, and the BLEU value and the TER value are stabilized at 37.5 and 57.49. The average score values of accuracy, fluency and logic of the translation results of this model are 8.34, 7.91 and 7.77 respectively, which are improved to different degrees compared with the comparison model.

Although the model in this paper has a better adaptive performance for the English translation expression and cultural embodiment of intangible heritage in folk culture tourism, there are also limitations, including mistranslation, syntax and other problems, future research can be improved in terms of syntactic conversion, structural adjustment, etc., to further enhance the translation performance of the model.

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