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Research of natural language processing based on dynamic search corpus in cultural translation and emotional analysis

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Abstract

In order to enable students to directly face empirical data, summarize translation rules and learn translation skills, this paper studies the basis, motivation and methods of applying research dynamics in translation and teaching. Presenting data in class is the main method of dynamically searching corpora, which enables learners to face enough bilingual data that are easy to choose, and makes translation skills and teaching of translation of selected language items relatively focused. In recent years, the emotional analysis text has attracted academic scientists, and the professionals involved in the research, the use of research methods, and the cultural background related to language have become more and more extensive. In this paper, natural language processing is used to analyze emotions contained in translated texts. Natural language processing not only helps to manage the huge ability of data to efficiently translate text, but also helps to extract the hidden emotions in text translation. It only takes half the effort to achieve the multiplier effect. The multi label classification in natural language processing can reflect the information contained in emotion. The translated text is more detailed, which is helpful for further research.

Keywords Corpus · Natural language processing · Cultural translation · Emotional analysis

1 Introduction

Although the research on corpus based translation teaching has achieved preliminary results, there are still many problems about its value in translation teaching and possible resources and means (Odacıoglu and Kokturk 2015). Corpus based translation research has not solved the problem. From the macro and micro perspectives, translation teaching research is an unsolved translation teaching model; From a micro perspective, "the consistency between parallel corpora, translation and teaching has not been solved," and the establishment of a parallel corpus directly serving English and Chinese translation and teaching has not been effectively carried out (Odacıoglu and Kokturk 2015). In this paper, a learner centered cultural translation model based on dynamic search corpus is established. In addition, by guiding students to use programs to research and retrieve practical data, we can build a modern learning environment and cultivate students' self-learning ability, so as to improve their ability to practice translation in real situations (Ferraz and Mizan 2019).

Natural language processing technology is one of the most important cross research fields in computer and artificial intelligence research. Its goal is to enable computers not only to understand human language, but also to perform specific tasks (Crowston et al. 2012). Natural language is a language that develops with the development of human beings, such as Chinese, English, Japanese, Spanish, etc. Natural language processing technology makes electronic equipment have the ability to understand and process human language, which greatly improves the efficiency of human work (Yue et al. 2012). In fact, important emotion analysis texts have been extended to many different fields, such as psychology and sociology. Therefore, the importance of extracting, analyzing and computing emotional text is self-evident in the field of natural language processing. Emotional analysis in text translation has become a hot research direction in the research (Ghanem et al.

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2020). This research focuses on the translated text, including the analysis of text features and the relationship between content and emotional information. The purpose of this study is to explore the emotional expression in the translated text, understand and recognize the emotional information in the translated text (Saule and Aisulu 2014). The main direction of this research is to understand and analyze the emotional information contained in the translated text. The emotion analysis of translated text can help devices understand human emotions more accurately and intelligently through natural language, and provide technical support for the future development of human–computer interaction (Prieto-Ramos 2017).

2 Related work

The literature studies the construction and application of learner translation, and attempts to build a method based on translation teaching and translation model evaluation (Wurm 2020). The literature points out that with the progress of deep learning technology and the continuous improvement of various aspects of graphic computing, especially the storage and computing capabilities, people began to use computers to simulate artificial neural networks on a large scale (Yang and Wang 2020; Sangaiah et al. 2023; Zhang et al. 2023; Satpathy et al. 2023). At the same time, with more research, natural language processing has made more outstanding achievements in important fields. The literature proposed that text emotion analysis is a special classification of problem text (Rout et al. 2018). The purpose of text analysis is to extract a summary of emotional information from the text, which is usually difficult to obtain and process from the information. More emotion analysis tasks are divided into three parts: emotional information extraction, classification, retrieval and inference. The literature focuses on corpus tagging to broaden the application of corpus in translation teaching, and discusses how to build a corpus, as well as a self-created corpus dual mode tagging system and tagging extraction tools (Fonseca et al. 2015). By comparing the translation quality between the two teams, the literature finds that a group of students who use the research dynamic group to teach translation are better than those who use traditional teaching methods in terms of terms and expressions in understanding topics and choosing translation. Since the middle of 1990, great progress has been made in natural language processing (Goldberg 2016). With the development of Internet technology, the significant increase in computing power and hard disk storage space provides basic equipment for natural language processing research. Information extraction and retrieval based on natural language processing become more and more important (Otter et al. 2020). During this period, natural language processing entered a relatively mature stage, and a set of methods based on technical rules began to be applied to machine translation in this field. A neural network algorithm for web page classification is proposed in the literature (Kishore and Kaur 2012). The experimental results show that the neural network is more accurate than the traditional learning machine based on the classification algorithm. In traditional classification, the classification based on supervised algorithm will lead to cumulative errors in the classification process.

3 Dynamic search corpus and natural language processing

3.1 Dynamic search corpus

At present, “discovery based learning and data based learning and training methods can be used to master translation skills, improve translation skills and become familiar with the characteristics of translation.” Many scholars in the field of translation generally believe that traditional translation teaching methods should be reformed by managing and operating the total number. With the participation of corpus approach, translation studies have made significant progress in translation theory and application, including general terminology and model translation. Researchers and teachers have become more and more concerned about the resources and means of corpus in translation teaching. The research shows that the corresponding corpus language can not only provide various bilingual examples directly for specific projects or common structures, but also provide many translations from the same source. Bilingual groups can improve students’ ability to understand translators, improve language and cultural awareness, and cultivate foreign language learners’ ability.

This study combines dynamic research with corpus. In the preprocessing stage, it is mainly composed of corpus cleaning, word segmentation, part of speech tagging, and word removal. In the characterization part of the next stage, the processed text must be quantitative, and the words processed in the carrier form can be calculated by the computer. This process can help find similar relationships between words through expression vectors. Calculating the probability of data based on language model is one of the common methods to judge whether a language model is good or bad. A high-quality language model can provide a higher probability value for test data. Puzzlement is a measure of a language model. The language model for studying test data and data distribution possibility is LM, and the formula for calculating the degree of confusion is:

$$\text{Perplexity} = 2^{-\frac{1}{n}\sum_{i=1}^{n}\log_2 \text{LM}(w_I:w_1:i-1)} \tag{1}$$

The degree of confusion is related to the corpus. The same evaluation corpus can compare the degree of confusion in two different language models.

3.2 Natural language processing

As an important part of natural language processing, text classification has become one of the hot spots in academic research. Products created based on text classification are also ubiquitous in our lives, such as spam filtering, text sentiment analysis and social platform topic detection. Faced with a large amount of data on the world's Internet, manual collection, processing and classification of data cannot meet the needs of users. Text classification technology can help people effectively manage big data, but it can also help people extract information hidden in the database. It only takes half the effort to achieve the multiplier effect.

In the training model link, including traditional supervised training methods, unsupervised and semi supervised learning models, specific models need to be selected according to various applications. In order to evaluate the impact after modeling, the indicator impact assessment is usually used, including accuracy rate, recall rate, etc. The following is the statistical model of natural language processing:

$$P(a,b,c) = P(a|b,c)P(b,c) \tag{2}$$

$$P(b,c) = P(b|c)P(c) \tag{3}$$

$$P(a,b,c) = P(a|b,c)P(b|c)P(c) \tag{4}$$

Naive Bayes classifier is a kind of classifier widely used in text classification. The classifier is mainly based on the independent hypothesis of feature conditions and Bayesian law. NBC originated from classical mathematical theory, which has been widely recognized by experts and scientists in theory and practice. In text classification, NBC requires less parameter estimation and is not too sensitive to missing data, so the algorithm principle is relatively simple. The essence of NBC is to compare the probability of text classification in different text categories. When text is most likely to appear in a particular category, it is likely to belong to that text category. The principle of text classification is to calculate the common probability distribution of different words in different categories of text, and finally determine the category of text. Now, calculate the probability of distinguishing words in different categories and determine their categories. The specific formula is as follows:

$$c_k = \text{argmax}(P(c_k|w_i)) \tag{5}$$

The calculation formula of the above equation $P\ (c_k|w_i)$ is as follows:

$$P(c_k|w_i) = \frac{P(c_k)P(w_i|c_k)}{P(w_i)} \tag{6}$$

When classifying texts, we need to calculate the joint probability distribution of all the feature words contained in a text in different categories, that is, the joint probability distribution of multiple feature words. The above formula can be summarized as:

$$P(c_i|W) = \frac{p(c_i)}{P(W)}\prod_{j=1}^{d}P(w_j|c_i) \tag{7}$$

The advantage of classifier SVM is that the low latitude nonlinear advantage in space uses the kernel function to convert the low size into the spatial function with high linear size. Among the highest linear dimensions of space, the best surface linearity rating can be obtained. In addition, the hyperplane maximization processing of the segmentation category requires the SVM classifier to process, and will not actively have doubts about singular values. The distance from any point in the sample space to the hyperplane can be expressed as:

$$d_i = \frac{|W^T x_i + b|}{||w||} \tag{8}$$

The operation of transforming neuron input into neuron is called convolution. The convolution operation is as follows:

$$s(t) = (x * w)(t) \tag{9}$$

In the traditional neural network model, each convolution layer contains only one convolution kernel. With the application of convolution network, text classification usually calculates convolution cores in different dimensions to improve the accuracy of feature extraction because vocabulary is involved more in a single text and the context information of the text has some degree of relevance. The convolution formula is:

$$y_{\text{out}}^h = f_a\Big(\sum_{r=1}^{F}(y_r^{h-1} * w_r^h) + b^h \tag{10}$$

Set the encoding process to En and the decoding process to De. The input data X becomes the intermediate semantic Mid after encoding. The coding process can be expressed as:

$$\text{Mid} = \text{En}(x_1, \ldots, x_n) \tag{11}$$

The decoding process actually decodes the intermediate semantic Mid, which can be expressed as:

$$y_n = \text{De}(y_1, \ldots, y_{n-1}, \text{Mid}) \tag{12}$$

4 Cultural translation and emotional analysis based on algorithm improvement

4.1 Cultural translation

This study attempts to modify the traditional model by constructing new translation and teaching models. In the new situation of translation teaching, teachers are no longer the leading role of teaching, but the assisting role. They create a discovery based learning environment for students, so that students can make full use of their initiative and self-learning ability, use dynamic research and software retrieval to translate typical, real, rich observation, analysis and thinking examples, and then the interaction between teachers and students to discuss language features, Translate translation methods and techniques into two ways. In order to evaluate translation quality, teachers can guide students to use relevant statistical data retrieval procedures to judge translation quality and style more comprehensively and objectively.

The traditional method of translating teaching content according to the top-down hierarchical structure starts with translating words, and then expands to the level of phrases, sentences and texts. This arrangement conforms to learners' psychological expectations and the public's views on translation teaching. However, in translation teaching at all levels, the translation methods and techniques that are first described and emphasized should be separated, and the translation methods and techniques that are later described and briefly described should also be separated. In short, teachers rely entirely on self-consciousness and do not have enough theoretical or empirical basis.

According to the latest catalog issued by CSSCI in January 2022, 378 translation research papers were obtained from 15 foreign journals (including the expanded version), which were selected as the source of CSSCI database. The topics are "Corpus" and "Corpus Translation." The two topics were searched in the journal. After manual differentiation, the meeting notice and the documents not related to corpus translation research were deleted, and 378 papers related to corpus translation research were obtained. Taking time as the horizontal axis, the research trend of corpus translatology is shown in Fig. 1, based on the name and real nature of all documents.

Classics Chinese textbooks are taken as the main collection objects of dynamic corpora, including the new HSK test text corpus released by the National Hanban, as well as ordinary natural corpora and classic Chinese textbooks for primary and secondary schools. The current scale is close to 200,000 sentences. See Table 1 for composition ratio. Chinese textbook corpus is an important part of dynamic corpus. This set takes into account such attribute characteristics as textbook type, application level, publishing age and influencing factors.

It can be seen from Table 1 that in terms of the types of textbooks, general and comprehensive textbooks are mainly used. Most of these textbooks are written spoken, reflecting the language form of the Chinese translation teaching model. In addition, textbooks aimed at developing listening, speaking, reading and writing skills, a few textbooks for special purposes and other cultural textbooks have been supplemented to reflect the language characteristics of textbooks in specific fields.

The two translations of the same article are compared by means of dynamic search corpus. In the analysis of the results, it is found that translation 1 and translation 2 differ greatly in the use of keywords, as shown in Table 2.

Table 2 shows that there are significant differences in the use of pronouns (I, we, this) in the translated versions, which shows that the effect of using dynamic search material library in cultural translation is significant.

4.2 Emotional analysis

Natural language processing is a sub problem in the research of artificial intelligence. Its purpose is to enable computers to effectively understand human language and complete specific tasks instead of humans. Although natural language will continue to evolve with the development of human society, the language used in human communication is ambiguous. At present, there are two popular processing methods, rule based method and statistics based method. The former is based on rules expressed in language use, while the latter discovers potential rules through statistical analysis of a wide range of data. Therefore, the universality and quality of data are very important in natural language processing. With the development of the translation industry, the classification of emotions in translated texts has become increasingly rich, which provides more research for natural language processing. With the increasing demand for emotion analysis in translated texts, the development of translated texts has become faster and faster, which also promotes the expansion of emotion analysis skills in translated texts.

The analysis of emotional text is an important trend in the field of natural language processing. Text is classified based on emotion details, and important emotion analysis can be divided into two categories according to rough particles and fine particles. In the field of emotional text analysis, researchers usually use it to analyze coarse granular emotions, which is called emotional analysis, that is, to classify texts according to emotional polarity, which is usually divided into two types: positive and negative emotions; Or it can be divided into three categories according to positive emotion, negative emotion and

Fig. 1 Research names and published articles of translatology in corpus of 15 journals from 2004 to 2022

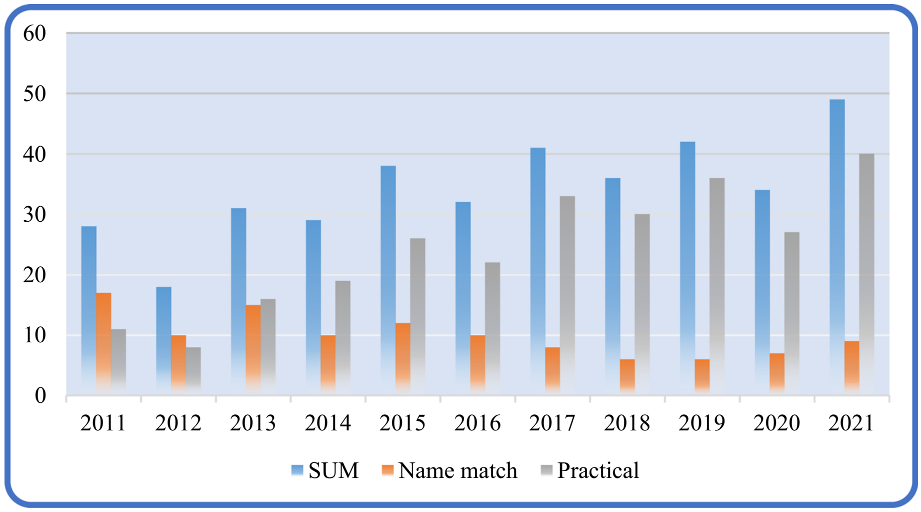

Table 1 Composition of corpus

Serial no.	Corpus content	Number of statements	Proportion
1	Textbook Corpus of Classical Chinese	140,000 sentences	65.7%
2	Text Corpus of HSK True Title	21,000 sentences	9.9%
3	Language materials of natural literature	40,000 sentences	18.8%
4	Corpus of Contemporary Chinese Textbooks	12,000 sentences	5.6%

Table 2 Comparison of key values of translation 1 and translation 2

	Function word	Translation 1	Translation 2	Key value	Significance
1	However	79	15	47.10	0.000
2	But	7	58	− 46.37	0.000
3	From then on	63	16	29.38	0.000
4	From	19	57	− 20.38	0.000
5	I	140	34	68.27	0.000
6	We	67	26	18.25	0.000
7	This	60	107	− 14.03	0.000
8	Of	1345	1112	20.45	0.004

ruthlessness. The construction of emotion dictionary, multi category emotion classification, text preprocessing, multi label emotion analysis, and the construction of emotion resource library are common research contents of fine-grained emotion analysis.

In the previous experiment, the comparative analysis of “anger” and “hate” emotions in the classified emotion corpus found that these emotions had some similarities, although some controversy would often occur in the case of manual classification. For this phenomenon, this paper takes “anger” as the unified label of the two kinds of emotional data. On the basis of the original emotion classification, the criteria for manual classification are summarized and analyzed, as shown in Table 3.

Compared with traditional text classification, affective learning is more difficult. The research on natural language processing and emotion analysis based on natural language processing has also attracted much attention in affective learning research. In terms of experience in emotion analysis, this paper uses the Naver sensory movie corpus 1.0 data set as the experimental data set, and the results are shown in Fig. 2.

From the chart, we can see that most of the translated texts are within 60 words in length, even in an LSTM design with a sentence length of 60 words, fill in the blank with a 0 vector, and then eliminate the parts with more than 60 words.

Next, the algorithm is introduced. A common classification method is Boosting. The basic idea of this algorithm is to judge and analyze the results of multiple learners. This result is better than that of each individual learner. There is a certain dependency relationship between each classifier,

Table 3 Definition of emotion classification

Emotional classification	Classification criteria
Anger	There are obvious mood swings, a large number of mood particles, and even curses or very harsh words
Fear	There are mood fluctuations, which are reflected in the gloomy and horrible context, and the subjective expression of fear semantics
Disappointment	There is no obvious emotional fluctuation, and the context is negative
Emotionless	Objective opinions, advertisements, explanations, reports, etc.
Joy	Subjective expression of emotional fluctuation, happiness and satisfaction
Praise	Positive context, expressing appreciation and praise for an object

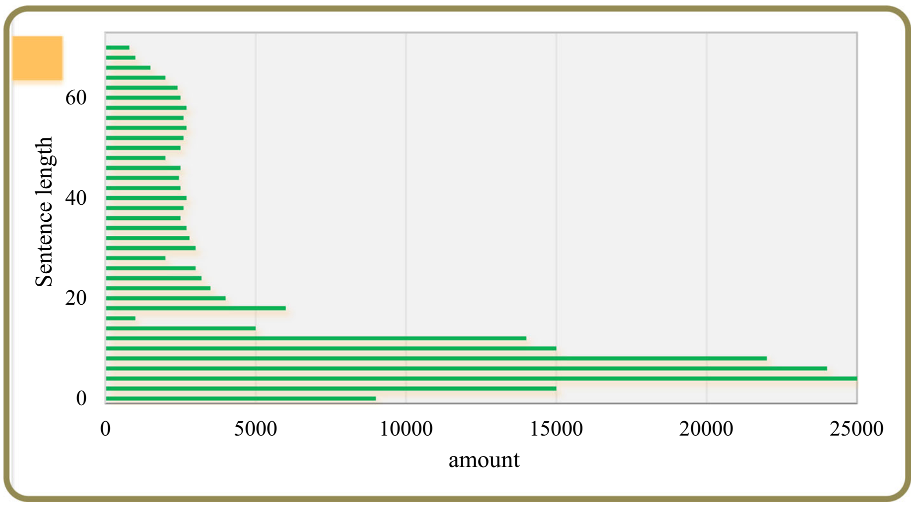

Fig. 2 Recognition of sentence length and number of emotional words

which is considered as a relationship by Boosting method. Under the influence of this relationship, multiple classifiers are trained by changing the distribution of training samples. Finally, each classifier is combined to get a more powerful learner. AdaBoost algorithm is one of the Boosting algorithms. Without changing the training data, it redistributes the weight of the training data, making the direction of the learner's focus on the data set different. The final classifier is the result of linear combination of these learners.

$$H(x) = \mathrm{sign}\left(\sum_{t=1}^{M} \alpha_t h_t(x)\right) \tag{13}$$

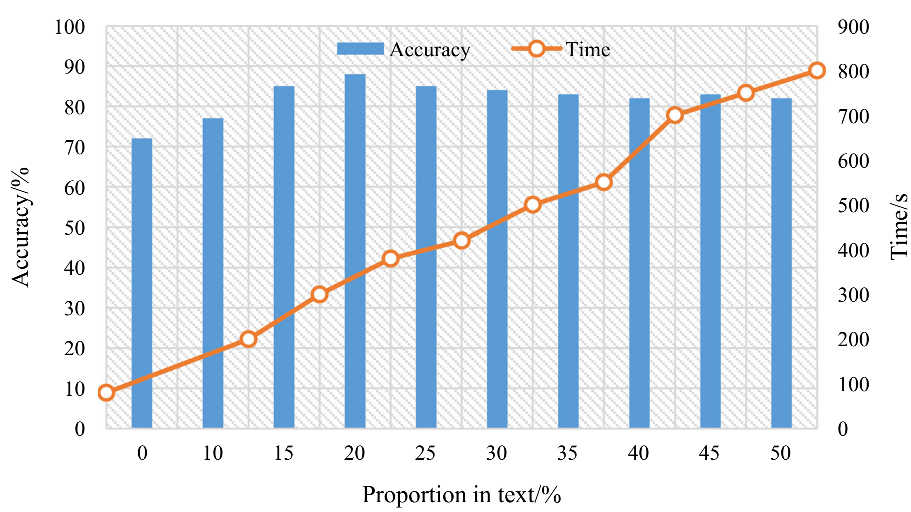

Fig. 3 Proportion of feature vector in text

Table 4 Distribution of emotional tendency of large-scale corpus marked by natural language processing

Option	Anger	Nausea	Fear	Sadness	Expect	Joy	Pleasantly surprised	Trust	Neutral
Group 1									
Quantity	3551	1977	6694	7579	15,744	5946	1187	6779	19,962
Proportion (%)	5.07	2.82	9.54	10.81	22.45	8.48	1.69	9.66	28.47
Group 2									
Quantity	3571	2009	6733	7679	15,866	5987	1197	6885	19,808
Proportion (%)	5.07	2.85	9.56	10.90	22.52	8.50	1.70	9.77	28.13

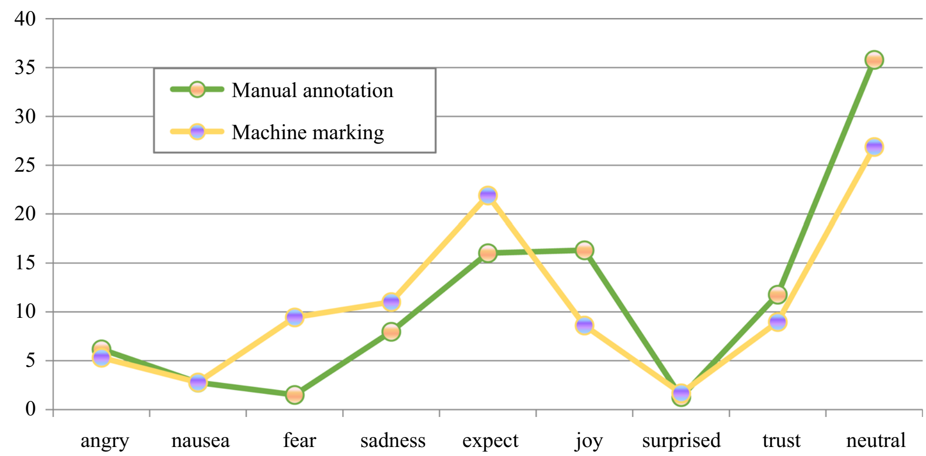

Fig. 4 Comparison of emotion distribution between manual annotation and machine annotation

Table 5 Comparison of experimental results

	Accuracy	Recall	F_1 value
Bert-CNN	80.9	80.7	80.3
Bert-LSTM	80.0	80.9	80.9
CNN	78.0	78.5	78.2
NB	74.9	77.0	76.0
Bert	81.9	81.2	81.4
Bert_BiLSTM_CNN	82.9	83.8	83.5

Linear combination construction of multiple classifiers:

$$f(x) = \sum_{t=1}^{M} \alpha_t h_t(x) \tag{14}$$

The final AdaBoost classifier can be expressed as:

$$H(x) = \mathrm{sign}(f(x)) \tag{15}$$

The self-service sampling method is the core content of Bagging algorithm. The self-service sampling method samples the original data set using random data samples that have been put back. Repeat N times to get a data set containing N samples. According to the formula:

$$\lim\left(1-\frac{1}{N}\right)^N = 0.368 \tag{16}$$

With M_1 and M_2 as inputs, the CAN network outputs the vector M_3 with the same dimension as M_1 and M_2 to learn the dependency between words and local text vectors. The specific formula for the dependency between local text vectors and learning words is as follows:

$$Q_m = \mathrm{elu}(Q_3 \otimes M_1) \tag{17}$$

$$K_m = \mathrm{elu}(K_3 \otimes M_2) \tag{18}$$

$$M_1' = \mathrm{elu}(V_1 \otimes M_1) \tag{19}$$

$$M_2' = \mathrm{elu}(V_2 \otimes M_2) \tag{20}$$

The sentence (string) similarity fuzzy matching method based on N-Gram model measures the difference between two similar sentences to measure the similarity. N-gram similarity is calculated by dividing the parts of the original sentence according to the length of n. The Jaccard similarity is a relatively simple calculation. The ratio operation of the intersection and union of word sets between two sentences is the calculation of the Jaccard similarity principle. Therefore, the principle is relatively simple and easy to understand. The higher the above ratio, the greater the similarity between the two sentences. If it is a large-scale parallel operation, the advantages of this method will be reflected in efficiency.

After the algorithm is set, text emotion analysis based on natural language processing is started. In the experiment, the number of selected feature words has a certain impact on the accuracy and efficiency of PRE-TF-IDF algorithm. Through the experiment, the proportion of feature words that give consideration to both accuracy and operation efficiency is calculated. In the experiment, the number of training sets and test sets is set to 8800. Under the same conditions, by adjusting the proportion of feature words, observe the changes of operation efficiency and accuracy, and select the best proportion of feature words.

According to the statement in Fig. 3, when the word function represents more than a certain value of the text, it will reduce the efficiency of the classification algorithm, which will have a negative impact on the accuracy of the classification. With the increase in the proportion of featured words in the text, it will take longer to classify the text. Finally, the average peak resolution value is 17.57% of the text. In this case, PRE-TF-IDF algorithm can consider the accuracy and efficiency of classification.

In the result analysis of emotional orientation tagging, the analysis of the tagged text is ignored, and only the text that successfully judges emotional orientation is analyzed and counted. Table 4 shows the statistics of specific annotation results. The total number of texts in the following table is the result of calculating the proportion of each item based on successful annotation.

According to the annotation results in Table 4, it is compared with the manual annotation results of 6500 small-scale translated texts, focusing on the proportion of each emotion. The comparison results are shown in Fig. 4. It can be seen from the comparison that the proportion of texts marked neutral in natural language processing is far less than that of manual annotation. One of the reasons is that texts that cannot be judged by natural language processing are not included in the statistical results. A large part of texts may not be judged by the machine, but the actual emotion is neutral. In addition, the proportion of fear, expectation and joy represented by natural language is quite different from the actual situation.

In order to test the actual performance of the model, Bert-CNN, Bert RNN and Naive Bayes (NB) are used as experiments to compare with the modified model. The evaluation criteria of the experiment are accuracy, recall and $F1$ value. The comparison results of the accuracy of various models in different translated text datasets are shown in Table 5.

It can be seen from the analysis in Table 5 that compared with naive Bayes (NB), Bert-CNN, Bert-LSTM model, Bert_ BiLSTM_ CNN model has better effect.

According to the comprehensive experiments, Bert pretraining language model based on natural language processing has obvious advantages over the word vector model built by World2Vec. In order to significantly improve the effect of text emotion analysis, we can make full use of the text features that Bert language model can obtain.

5 Conclusion

With the continuous development of natural language processing, researchers are no longer satisfied with simply analyzing the emotional polarity in the text. Emotional analysis is gradually moving toward the research direction. More accurate emotional analysis is carried out when translating text. From the perspective of research direction, there are two types, one is emotional expression, the other is emotional state classification, both of which are hot topics studied by researchers. With the emergence of artificial intelligence, the emergence of emotion research methods in the analysis of translated text has also changed, the most obvious change is that more and more researchers tend to study methods based on natural language processing, rather than dictionary and grammar methods based on emotion. In fact, in recent years, some researchers have combined emotional text compounds by analyzing them. In this study, we discussed the cultural translation model based on dynamic search corpus, and the construction of cultural translation based on dynamic search corpus. We focused on corpus tagging, mainly involving part of speech tagging, language feature information tagging, and translation methods and skills tagging.

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Data availability Data will be made available on request.

Declarations

Conflict of interest The authors declare that they have no conflict of interests.

Ethical approval This article does not contain any studies with human participants performed by any of the authors.

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