Cultural Perspectives on the Translation System of Political Text Metaphors Using Artificial Intelligence Research

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Abstract. To improve the translation effect of political text metaphors, this paper combines artificial intelligence algorithms to study the translation system of political text metaphors and enhance the algorithm according to the actual translation needs. Moreover, this paper completes the exploration of dimensional space from the perspective of attributes and data objects of high-dimensional multi-features of data. After adopting feature selection, this paper uses subspace clustering and subspace exploration techniques to complete the projection of the correlation between attributes and assist users in finding subspaces of interest. In addition, this paper discusses the method of building a hierarchy of attributes and a model of dimensional space exploration. For the visualization task, this paper designs the visualization process and visualization system scheme and designs and implements the visual analysis system for political text data. The experimental results show that the research on the translation system of political text metaphors based on artificial intelligence proposed in this paper can play an essential role in translating political text metaphors.

Keywords: artificial intelligence; political text; metaphor; translation; Cultural Perspectives
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1 INTRODUCTION

In metaphorical translation, firstly, the translator communicates with the source language author as a reader, fully understands the communicative intention that the source language author wants to achieve, and finds the best relationship preset by the source language author, that is, to reach the ideal reader level of the original author. Then, the translator, as the author, communicates with the target readers. Moreover, according to the prediction of the readers' prior knowledge and experience, different translation strategies are adopted when translating metaphors so that the readers of the translated text can achieve the best association preset by the source language author and successfully achieve the purpose of communication [14].

Literature [6] divides the translation methods of metaphors into four types: literal translation, living translation, free translation, and transliteration. The translations of metaphors summarized are highly operational, generalized, and refined. The first three categories are identical to Newmark's translations, but the expressions differ. The traditional metaphor translation theory is generally rhetorical.

With the establishment of the symbolic cognition view, scholars completely understand the causes of metaphors. Comparing Chinese and English metaphors in terms of pragmatics and culture, it is proposed that a combination of literal translation and free translation should be adopted in the mutual translation of English and Chinese metaphors to make up for the inadequacy of literal translation being challenging to convey and free translation being difficult to get [8]. Literature [3] believes translating metaphors is compulsory for cultivating translation ability and conducting translation research. This paper proposes three principles for the Chinese-English translation of metaphors: maintaining the metaphorical characteristics, connecting the cultural connotation of Chinese-English metaphors, and making up for the lack of cultural metaphors according to the context. The principles of extended translation aim to guide the translation of Chinese metaphors into English, while the method of translating English metaphors into Chinese is not touched. Literature [17] believes that conceptual metaphor is based on the cognitive experience of national culture. Metaphor translation activities are potentially affected by factors such as the society, national culture, and literary traditions on which the metaphor occurs. The translation must be a cultural context, academic language, etc. The product under the conditions of context, context, etc. She proposed experience-based metaphor translation strategies: literal translation (foreignization), free translation (domesticization), and compensation strategies. The literature [5] supplements the third strategy. The compensation strategy is implemented simultaneously with literal translation and free translation. A compensation strategy is a remedial measure taken due to language barriers and cultural differences. However, the compensation strategy is similar to the annotation method proposed by the previous ones.

Traditional metaphor research is limited to the rhetorical level, and metaphor is regarded as a variant expression of language and a rhetorical means. With the rise of cognitive science and cognitive linguistics, scholars' research on metaphor has deepened, and the understanding of metaphor has risen to the mental level [7]. The conceptual metaphor theory of cognitive linguistics emphasizes that metaphor is not only a rhetorical means but also a mental means and way of thinking that people rely on for survival. "Metaphors are ubiquitous in everyday life, not only in language but also in thought and behavior. The everyday conceptual systems in which we think and act are fundamentally metaphorical. [15] The cognitive process is a universal thinking method for understanding unknown things with the help of known things[20]. It is usually composed of "ontology" and "metaphor" and includes two cognitive domains belonging to different categories: "target domain." In the "source j domain," the former is the object of knowledge, usually unfamiliar, unknown, and abstract concepts; the latter is the object of borrowing, often familiar, known, and concrete concepts. In this way, metaphors connect ideas in different categories, transfer semantic features through mapping across categories, and realize the re-understanding, classification, and conceptualization of the characteristics of the target domain, that is, the metaphor ontology. As a way and means for human beings to understand the objective world and express their thoughts and emotions, metaphors are ubiquitous in human language [19]. The specific metaphor in English and Chinese says its meaning is profound, vivid, euphemistic, humorous, and concise. It condenses the essence of the language and reflects the commonality of the two cultures and the distinctive national cultural characteristics. The conceptual metaphor theory of cognitive linguistics emphasizes that the meaning expressed by a stable metaphor has a cognitive basis arising from a psychological mechanism, such as the structural mapping of one cognitive domain and another cognitive domain. Metaphor translation is a complex process. The mental process should be cognition-oriented. Therefore, when translating metaphors, the translator must deeply understand their psychological basis and their psychological operating mechanisms from the perspective of cognition. Based on this, specific translation strategies are determined to reproduce the cultural connotation of the original language and, simultaneously, to be accepted by the target language readers [10].

Metaphor is the way and means of human cognition. It arises from the life experiences of various ethnic groups and is closely related to culture. Culture is the total of behaviors, arts, beliefs, institutions, and other products of human labor and thought conveyed in society. It has distinct national characteristics and results from different nationalities having a specific history. Unique creations in geography, religion, customs, etc. [16]. Language is an integral part of culture and the carrier of culture, with rich cultural connotations. Metaphoric expression embodies human cognition of the objective world in language. It is not only a language or a thinking phenomenon but also a cultural phenomenon. It reflects different nations' cognitive methods and cultural differences [12]. The metaphorical expressions such as idioms, allusions, and proverbs that widely exist in English and Chinese are rooted in different cultural soils with distinctive national characteristics, reflecting the unique national cultural psychology and containing the different philosophical thoughts of the two nationalities. , cognitive styles, religious beliefs, values and customs, and other cultural information [4]. Translation is a form of language communication. It is also a cross-cultural exchange of ideas. It is the conversion of meaning between two languages and the communication and integration between two cultures [18].

Metaphor translation is the epitome of all language translation because it presents the translator with a variety of choices: either to convey its meaning, to reshape its image, to modify it, or to combine its meaning and image perfectly. All kinds of things are inseparable from contextual and cultural factors, not to mention the connection with the importance of metaphor in the text [11]. It can be seen that metaphoric translation is complex and changeable. It condenses the translation laws of the whole language, is closely related to cultural factors such as philosophy, history, religion, values, and living customs, and is restricted by relevant national cultures. The translator is both the first reader of the source text and the creator of the target text, whose primary role in translation is constrained by the culture of the source text's author and the target text's reader. Therefore, translators must be proficient in both English and Chinese, familiar with the social and cultural information in metaphorical expressions, and aware of cultural differences between English and Chinese. Search for figurative expressions equivalent to their meaning and emotional color. Use appropriate translation strategies to translate them into the target language to convey the national cultural characteristics and cultural information carried by the source language metaphors to readers to realize the integration of the two languages. Real exchanges between the two countries promote the dissemination and fusion of national culture [13].

A complete metaphor is usually composed of "noumenon" and "metaphor," and sometimes also has "metaphor," which is the similarity between the two different things in the noumenon and the metaphor. Translators should interact with authors and readers in multiple ways, understand their diverse cultural backgrounds, grasp the psychological mechanisms behind different metaphorical expressions, and choose reasonable translation strategies for domestication and foreignization [19]. Regarding how to deal with cultural differences in translation, there are two opposing viewpoints in the translation field, namely, domestication and foreignization of translation. Domestication translation takes the target language, or the reader, as the destination. It adopts the authentic and smooth expression of the target language to translate so that the translated text conforms to the target language's language norms and cultural values [1]. The strangeness of the original text is weakened, making it easier for readers to understand the content of the translation with their cultural concepts. In contrast, foreignization translation takes the source language or the original author as its destination, breaking the target language's expression habits and wording and preserving the original language. Exotic culture. Thus enriching the target language culture and the language expression of the target language. In metaphor translation, the translator can appropriately choose domestication and foreignization strategies to transmit the source text information and be accepted by the target language readers [2].

This paper uses artificial intelligence algorithms to study the political text metaphor translation system. It improves the algorithm based on the translation needed to enhance the quality of political text metaphor translation.

2 POLITICAL TEXT CLUSTERING ALGORITHMS

2.1 Spatial Clustering

The basic process of high-dimensional multivariate data visualization based on subspace clustering is as follows:

1. The algorithm preprocesses high-dimensional multivariate data.

2. The algorithm selects one of the methods in Table 2-3 to combine with the visual analysis method.

3. The algorithm utilizes human-computer interaction technology to enable users to analyze data more deeply. The visualization process of high-dimensional multivariate data based on subspace clustering is shown in Figure 1:

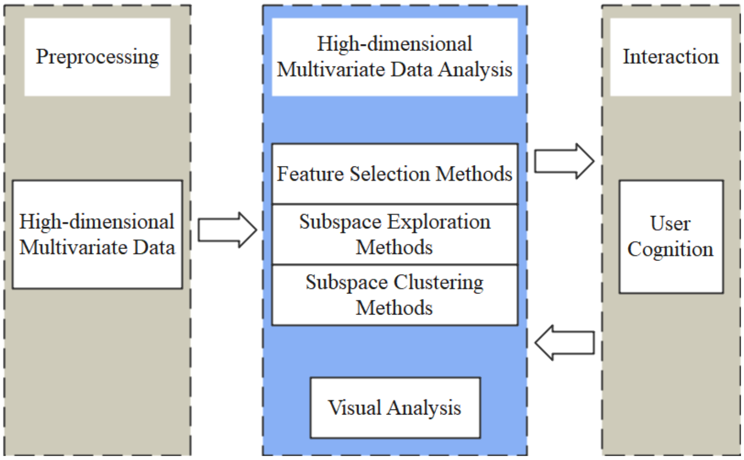


Figure 1: Visualization process of high-dimensional multivariate data based on subspace clustering.

Clustering by fast search and finding density peaks opens a new way of thinking in clustering algorithm research. The idea is novel, simple, and intuitive. The algorithm defines two parameters: the sample point density p and the distance eight from the nearest higher density point. When the data points are discrete, the density ρ_i of the sample point i is calculated using the cut-off kernel, and the formula is:

$$\rho_i = \sum_{j \neq i,(i,j \in S)} \chi\left(d_{ij} - d_c\right) \tag{1}$$

The function x(x) is defined as:

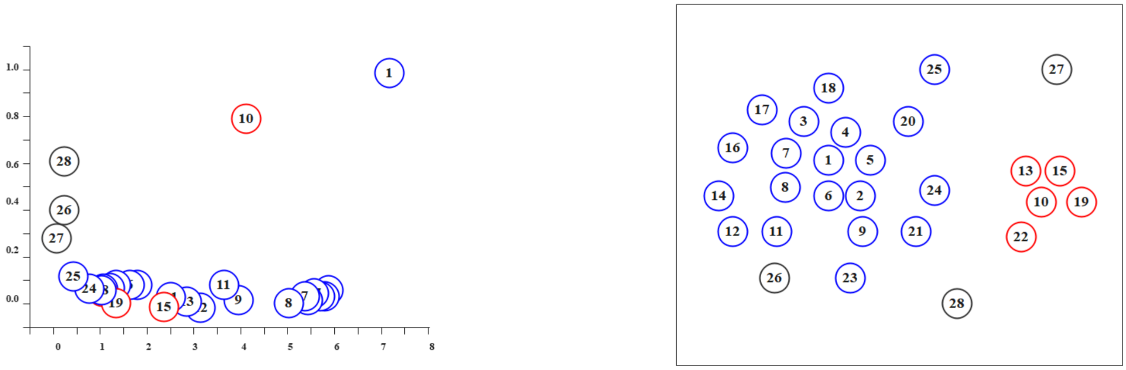
$$\chi(x) = \begin{cases} 1 & x \leq 0 \\ 0 & x > 0 \end{cases} \quad (2)$$

When the data points are continuous, the density p of the sample point i is calculated using the Gaussian kernel function, and the formula is:

$$available\rho_i = \sum_{j\neq i} e^{-\left(\frac{d_{ij}}{d_c}\right)^2} \quad (3)$$

$$\delta_i = \min_{j:\rho_j>\rho_i}(d_j) \quad (4)$$

After calculating the sample point density p and the distance δ from the nearest higher density point, we draw the decision diagram with the sample point density ρ as the y-axis and the distance δ as the x-axis, as shown in Figure 2 (a). In this algorithm, the sample points with the more prominent local density$\rho_i$and the highest local density distance $\delta_i$are the cluster centers. In decision diagram 2(a), two sample points, 1 and 10, are cluster centers. The high local density distance δ_i is more extensive, but the local density p; minor sample points are considered discrete points, and the discrete points in Figure 2(a) are 28, 26, and 27 three sample points. The distribution characteristics of the data in the two-dimensional space are shown in Figure 2(b). The discrete points are also three sample points, 28, 26, and 27, and the other sample points are classified according to the distance closest to the cluster center. Figure 2(b) shows that the original data are distributed around two known cluster centers, 1 and 10, divided into two categories.



(a) (b)

Figure 2: Decision diagram and data distribution in two-dimensional space.

2.2 Attribute Hierarchy

This paper uses the TextRank method to calculate the weight of each word. In the graph-structured model, each word is represented as a node in the word-structured network. If two words appear simultaneously, there is an association between the two words, and an edge should be constructed to link the nodes. Finally, the weight of each word is obtained by iterative calculation and sorted, and the formula is:

$$WS(v_i) = (1-d) + d * \sum_{v_j \in In(v_j)} \frac{w_{ji}}{\sum_{v_k \in Out(v_j)} w_{jk}} WS(v_j) \quad (5)$$

In the formula, $WS(v_i)$ represents the weight of each word, d represents the damping coefficient value of 0.85, $In(v_i)$ represents the set of all words before word i, and $Out(v_j)$ represents the set of all words after word i.

Finally, keywords and words whose word frequency is greater than the threshold are selected as the core words of the classification, that is, the class core words, which are expressed as:

$$CoreWord(C_j) = \{w_1, w_2, \ldots, w_n\} \tag{6}$$

In natural language processing, the vector space model (VSM) is a classic theoretical method for text representation. Each text in VSM can be represented by conceptual words expressing its content. Each attribute's name, introduction, and source are extracted and merged into an attribute document. According to the second step, each attribute is subjected to keyword extraction and feature vector weight calculation to establish a text vector space model, which is expressed as:

$$d = \{(t_1, w_1), (t_2, w_2), \ldots, (t_m, w_m)\} \tag{7}$$

The formula represents the feature vector, and wi is the feature weight corresponding to the feature vector.

For text categories, each category is a specific domain set by people, and the text representing the category is an overview of that domain. Moreover, each domain consists of a core set of concept words that recur in texts belonging to that category. In this paper, the rule-based classification method is used to determine the category to which the classified text belongs by using the extracted class core words; that is, the similarity between the established vector space model and the selected class core words is used for classification. The formula is:

$$Score(T_i, C_j) = \alpha \times V(T_i, C_j) + b\omega \cos(T_i, C_j) \tag{8}$$

similarity between the class core word and the text vector space of a single attribute. Cj represents the set of class core words CoreWord, a and b represent the weight, where a+b = 1, and $V(T_i, C_j)$ represents the influence value of the attribute Ti belonging to essentialtegory. If there are a total of m categories, the important categories are expressed as:

$$Max\left(Score(T_i, C_j)\right), i, j \in [1,2, \ldots, m] \tag{9}$$

This paper uses network data. After the hierarchical construction of attributes introduced in 3, the data attributes are divided into seven categories: agriculture, environment, development, population, economy, education, and resources. These seven categories also contain two-level classifications, so the attributes of the data are finally converted into a three-level hierarchical structure.

The accuracy of text classification results is evaluated by three fundamental indicators: recall, precision, and F1-measure. The formula for the recall is:

$$R = \frac{TP}{TP+FN} \tag{10}$$

In the formula, R represents the recall rate, and TP represents the true positive (TP) of the classification result; that is, a document belongs to a specific classification in the prediction set, and it also belongs to the same classification in the actual annotation set. FN represents the false negative (False Negative, FN) of the classification result; a document does not belong to a particular classification in the prediction set but belongs to this classification in the actual annotation set.

Precision refers to the ratio of correctly classified samples to the total number of samples in the classification results, which is used to measure the accuracy of the retrieval system. The formula is:

$$P = \frac{TP}{TP+FP} \tag{11}$$

In the formula, P represents the precision, and FP means the false positive (FP) of the classification result; that is, a document belongs to a specific classification in the prediction set but does not belong to this classification in the actual annotation set.

The F value is a commonly used comprehensive evaluation standard, and the formula is as follows:

$$F = \frac{2PR}{P+R} \tag{12}$$

The number of attributes to be processed is reduced after using the feature extraction method to extract essential features from the data. However, the distribution patterns that reflect the feature information are still distributed in the full-dimensional space after the dimension reduction, and the traditional clustering algorithm can no longer meet the needs. The subspace clustering technology divides the entire feature space into different feature subsets, thereby reducing the interference of irrelevant features. Therefore, the subspace clustering technology is used to process it.

This paper uses KNN-Pearson to enable researchers to intuitively observe the distribution of correlations between attributes of high-dimensional multivariate data. This method provides a macro view of the correlation between essential attributes. Also, it gives evidence for researchers to explore interesting subspaces in the future to assist researchers in discovering them. The steps are as follows:

1. Calculate the distance between attributes:

1. The n countries in the dataset can be represented as $X = (x_1, x_2, \ldots, x_n \quad)$, the m attributes contained in each country are represented as $Y = (y_1, y_2, \ldots, y_m)$, and the dataset is represented as a matrix of n*m. Then, the K-Nearest Neighbor classification algorithm calculates the distance d(n,d) of the country's closest point xn on a particular attribute ya. The formula is:

$$d_{(n,d)} = \sum_{i=0}^{m} |x_i - y_i| \tag{13}$$

2. The algorithm uses formula 14 to calculate the density of country xn on a specific dimension yd, and the formula is:

$$\rho(x_n, y_m) = k - \frac{1}{max\left[max\left(d_{(n,m)}\right) - min\left(d_{(n,m)}\right), \frac{1}{n}\right]} \tag{14}$$

3. The algorithm calculates the distance between any two attributes, yj, and yh; the formula is:

$$L\left(y_j, y_h\right) = 1 - \frac{\sum_{i=1}^{n}\left(\rho\left(x_i, y_j\right) - \overline{\rho y_j}\right)\left(\rho\left(x_i, y_h\right) - \overline{\rho y_h}\right)}{\sqrt{\sum_{i=1}^{n}\left(\rho\left(x_i, y_j\right) - \overline{\rho y_j}\right)^2 \sum_{i=1}^{n}\left(\rho\left(x_i, y_h\right) - \overline{\rho y_h}\right)^2}} \tag{15}$$

4. Project the attributes

Multidimensional scaling is a visualization method to display the main features of high-dimensional space in low-dimensional space. It is a method used to visualize data similarity and dimensionality reduction. This paper uses the distance matrix constructed above to perform dimension reduction projection on attributes using multidimensional scale transformation.

3. Discover the subspace of interest

Using the projection of attributes, they can directly observe the similarity between attributes and find attractive clusters in the two-dimensional projection of characteristics according to the analysis task requirements. The related elements that make up this cluster are called interest subspaces. In this way, the user can focus on further exploration of the subspace of interest in the future, avoiding the interference of the irrelevant feature space.

According to the introduced method of discovering subspaces of interest, users can complete data exploration from the perspective of data objects in the reconstructed subspaces. This paper uses clustering by fast search and finding density peaks (CFSFDP) to observe each country's two-dimensional spatial distribution characteristics in the subspace. In CFSFDP, the cluster center has two factors: the density is higher than its neighboring points, and the other density peak points are farther away. According to the sample point density p calculated by CFSFDP and the closest distance δ_i to the high-density point, a decision diagram is generated, and the data's cluster center and discrete points can be visually observed. Each country in the dataset is a sample point, and the corresponding density p and the nearest distance δ_i are calculated for each country. Since the national data set is discrete, the formula used to calculate the density pi of sample point i is:

$$\rho_i = \sum_{j \neq i,(i,j \in S)} \chi\left(d_{ij} - d_c\right) \tag{16}$$

In the formula, S represents the national data set after reconstructing the subspace, d_{ij} represents the distance between two countries; dc represents the cut-off distance, which is the first 2% of the distance between countries in ascending order, and the function $\chi(x)$ is defined as:

$$\chi(x) = \begin{cases} 1 & x \leq 0 \\ 0 & x > 0 \end{cases} \tag{17}$$

$$\delta_i = \min_{j:\rho_j > \rho_i} \left(d_j\right) \tag{18}$$

The attitude system is integrated into the cross-domain mapping mechanism of translation, and an attitude-based political metaphor translation model is built (see Figure 3).

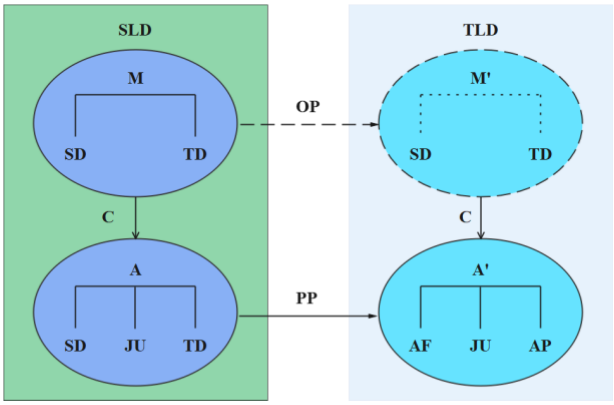


Figure 3: Political metaphor translation model based on attitude.

The concept of metaphor (M, Metaphor) is rooted in the source language domain (SLD, Source Language Domain), which is composed of the source domain (SD, Source Domain) and the target domain (TD, Target Domain).

This paper designs and develops a national data visualization system using cleaned national data and a model of hierarchical construction and dimensional space exploration using attributes. Furthermore, it completes the visual analysis of high-dimensional multivariate data from the perspective of data objects and attributes, helping researchers achieve data analysis and understanding of the data at a deeper level. The visualization task and analysis process are shown in Figure 4.

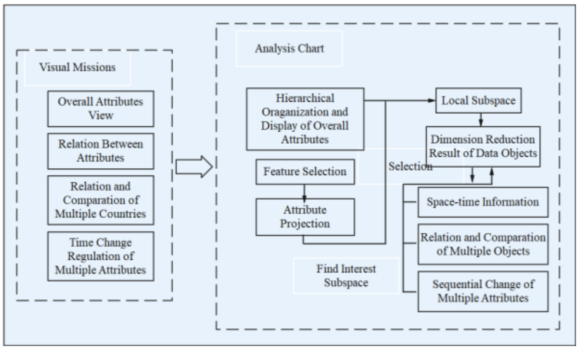


Figure 4: Visualization tasks and analysis flow.

The overall framework of the system is shown in Figure 5. The system consists of data preprocessing, an algorithm model, and visual design. Data preprocessing uses Python to clean, organize, and filter the original data. The process of the algorithm model has been introduced in detail in the third and fourth chapters. The system belongs to the B/S architecture, consisting of the back and front end. The backend uses the Python-based Flask framework. Flask is a web micro-framework implemented by Python that can add corresponding functions according to development needs, so it is more flexible and lightweight than other frameworks of the same type.

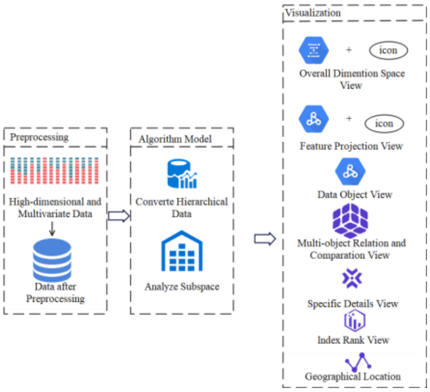


Figure 5: System block diagram.

3 EXPERIMENTAL RESEARCH

This paper calculates the sample point density ρ and the distance δ from each country's nearest higher density point and draws a decision diagram as shown in Figure 3(a). The x-axis is the sample point density ρ, the y-axis is the distance δ to the nearest higher density point, and the sample point with a larger local density ρ_i and a high local density distance δ_i is the cluster center. The cluster center in Figure 6(a) is "Paraguay," the points with a significant, high local density distance ρ_i but a small local density δ_i are regarded as discrete points. In Fig. 6(a), "Uruguay," "Argentina," "Suriname," "Venezuela, RB," and "Guatemala" are discrete points. Figure 6(b) shows the distribution trend of countries in two-dimensional space under the reconstructed subspace of interest. Since there is only one cluster center in the decision diagram, countries are divided into one class and discrete points. The cluster centers and discrete points in Figure 6(b) are consistent with those in Figure 6(a).

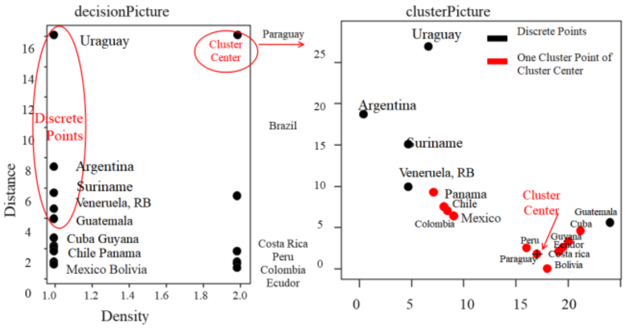


Figure 6: Distribution of countries under decision graph and interest subspace.

Figure 7 shows the distribution status of each country in the three-dimensional space in the full-dimensional space of the country data set. It can be seen that even in the 3D view, due to the interference of many irrelevant factors, it is not easy to ensure the structural information of the data, and the dimensionality reduction results will produce a lot of overlap, which cannot be effectively analyzed. Therefore, the result of the dimensionality reduction of data objects in the reconstructed subspace is better.

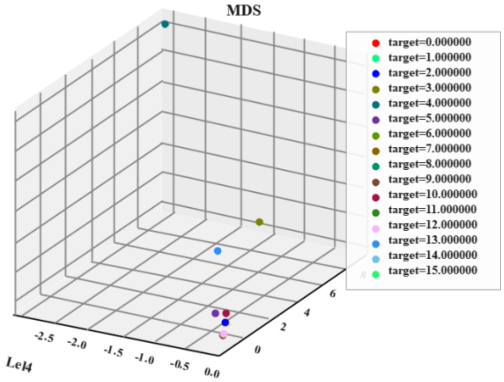


Figure 7: Dimensionality reduction results of countries in the full-dimensional space.

Based on the above, the model proposed in this paper is verified, and the translation effect of the model's political text metaphors is counted. The experimental results obtained are shown in Table 1.

Number	*Translation effect*	*Number*	*Translation effect*
1	*86.07*	*17*	*86.10*
2	*84.67*	*18*	*87.63*
3	*80.19*	*19*	*86.68*
4	*84.47*	*20*	*87.46*
5	*87.74*	*21*	*85.83*

6	*85.22*	*22*	*81.40*
7	*85.64*	*23*	*88.73*
8	*88.68*	*24*	*84.51*
9	*84.10*	*25*	*81.27*
10	*86.99*	*26*	*85.54*
11	*80.42*	*27*	*84.46*
12	*81.33*	*28*	*81.18*
13	*86.23*	*29*	*83.63*
14	*85.74*	*30*	*85.54*
15	*84.26*	*31*	*86.09*
16	*80.04*	*32*	*82.16*

Table 1: The effect of the translation system of political text metaphors based on artificial intelligence.

From the experimental research, the translation system of political text metaphors based on artificial intelligence proposed in this paper can play an essential role in the symbolic translation of political texts.

4 CONCLUSION

Translation is a dual communicative activity. On the one hand, the translator should communicate with the original author as a reader. The success of this communication process depends on whether the translator's knowledge and experience of the target culture can reach the level of the original author's ideal reader to the greatest extent. On the other hand, the translator has to act as the author to communicate with the target readers. The success of this communication process depends on the accuracy of the translator's prediction of his target readers' prior knowledge and experience, and this prediction directly affects the choice of strategies in translation communication. This paper studies the translation system of political text metaphors based on artificial intelligence algorithms and improves the algorithm based on actual translation needs. From the experimental research, the research on the translation system of political text metaphors based on artificial intelligence proposed in this paper can play an essential role in the translation of political text metaphors. The advent of AI in translation systems, mainly through machine translation and advanced NLP techniques, offers a scalable solution for handling the complexity of political text. However, to truly capture the nuances of political metaphors, it is imperative to consider cultural perspectives deeply. The cultural sensitivity required for accurate translation involves understanding historical context, ideological nuances, and the symbolic weight of language in different cultural settings.

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