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Intelligent Semantic Annotation and Knowledge Graph Construction Methods for Design Historical Materials

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SUMMARY: *With the continuous development of digital technology, the digitalisation and intelligent processing of design history materials have gradually become research topics. In light of the deficiencies in the treatment of large-scale, complex and diverse historical materials for design by traditional methods, this paper puts forward an intelligent semantic annotation and knowledge graph construction method based on natural language processing (NLP). Compare the processing speed of the proposed way and that of the traditional Transformer algorithm through experiments. Based on the emotional information in the historical materials of design, an experiment has been conducted on text emotional analysis to verify the accuracy of the method. Based on the above experiments, this way of operation is much more efficient in terms of runtime and can process the text data for design more promptly. This way is also relatively precise in terms of area for text emotion analysis, and rich emotional information can be obtained from historical materials. The approach of intelligent semantic annotation and knowledge graph construction for design historical materials proposed in this paper enhances processing efficiency, improves the accuracy of emotional analysis, and promotes the digitalisation and intelligence of design historical materials.*

KEYWORDS: *Digital humanities perspective; Historical materials; Design; Intelligent semantic annotation; Knowledge graph construction; Text data*

1 Introduction

All the departments in society have changed dramatically recently. Digital humanities is now an interdisciplinary research model that has gradually attracted the attention of scholars [1]. Use high-end digital technology to add new life to traditional humanities research and expand the scope of research [2]. Therefore, the field of art design is also facing new problems. Art design is a way to convey human culture and aesthetic ideas; it has a rich history and deep cultural connotations [3]. Ancient pottery patterns and modern industrial product designs are all different.

Architectural styles and contemporary digital media art and other works of art are products of society at different times [4]. Historical materials of art design are valuable resources for recording and observing the development of art design, and are indispensable for an in-depth study of the historical context, cultural inheritance, style evolution and innovative development of art design [5].

The old way of sorting out and studying historical materials of art design has many problems. A large number of historical materials on art design have been collected, including written

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documents, images, physical files and other forms [6]. As it is dispersed among libraries, museums, archives and private collectors, it is very difficult to collect and organise. Traditional research methods mainly rely on the researchers' manual reading, sorting and analysis, are easily influenced by the researchers' subjective perspectives, and thus fail to explore all the contents of historical materials [7]. At present, given the rapid development of information technology, new ways and methods are being proposed to organise, process and apply digital technology to traditional Chinese-style materials [8]. NLP is a general-purpose type of artificial intelligence. It is good at handling text information [9]. It can automatically analyse and understand a large amount of text data, such as text classification, sentiment analysis, named entity recognition, topic mining, etc. [10] Introducing NLP algorithms for the collation and analysis of art design history materials is expected to overcome the deficiencies of the old way and achieve intelligent processing of these materials.

With the help of NLP algorithms, we can extract information from the written materials in the history of art design more deeply. For example, a large number of art and design documents can be automatically classified into different themes, periods and regions by text classification algorithms [11]; Named Entity Recognition technology is employed to identify key entities in the literature, such as designers, design works, materials and processes, etc., and construct a knowledge map of the field of art and design [12]; Emotional analysis algorithms can be used to uncover the evaluation of art and design works in historical documents and understand the value orientation of art and design at different times [13]. NLP algorithms can be combined with other digital technologies to digitise the image data and physical files of historical materials in art design, and thus achieve the integration of multi-modal data [14].

This paper studies methods for intelligent semantic annotation and knowledge graph construction of design history materials in the field of digital humanities using natural language processing (NLP) algorithms. Based on research of related technologies and analysis of actual cases, this paper proposes a system for intelligent methods in an organised and efficient way. This study will help to improve the efficiency of organising and analysing the historical materials of design, deepen the exploration of information in these materials, and promote the cross-disciplinary integration of design. At the same time, the results of this study will also offer a reference for the design education, cultural heritage protection and creative industries, etc.

Summary:

(1) This study breaks through the limitations of traditional research methods of design historical materials, and applies NLP algorithms to intelligent semantic annotation and knowledge graph construction, which is helpful to dig deeper information in historical materials.

(2) This article introduces how to use NLP technology to perform intelligent semantic annotation and construct a knowledge graph for design historical materials, covering text preprocessing, entity recognition, relationship extraction and other key steps, with the aim of building a scientific method system.

(3) In this study, representative historical cases of design are selected, and the proposed intelligent method is used for empirical research, which shows the application effect of NLP algorithms in the research of actual design historical materials. The empirical results verify the feasibility of the proposed method, and reveal the hidden patterns in the historical materials of design, which provides a new empirical basis for design research.

(4) The research results are helpful to improve the efficiency of organizing and analyzing design historical materials, provide more abundant resources for design education, provide a scientific decision-making basis for the protection of cultural heritage, and offer inspiration for the development of creative industries.

2 Historical materials of digital humanities and art design

2.1 Digital humanities

Digital humanism first emerged in the academic community at the end of the 20th century. With the development of computer technology in recent years, many humanities scholars have started to use it. The first digital humanities focused only on text modification, arrangement and search functions. With the development of technology, many areas have been continually expanded, and now a variety of fields have been covered, including text mining, data visualisation, GIS applications, VR/AR technology, digital archives and museum construction, etc., forming a new research paradigm [15]. At the same time, more advanced research methods have emerged; now, combined qualitative and quantitative analysis are being employed [16]. By collecting and organising a large amount of data, such as texts, images, audio and video, we can learn about the features of literary creation through text mining of literary works. GIS technology can be used to present the distribution of past events and to explore the effect of location on these events.

The other is the cooperation among all regions in computer science, information science and so on. All areas of study have new technologies and ideas, which promote the convergence and synergy of various fields to expand the scope of research. Many universities and research institutions have established research centres or laboratories to carry out related projects and activities for academic achievements [17]. Libraries and museums have digitised rare books and cultural relics of ancient books to allow more people to access and study them online. Some teams have created historical and cultural VR scenes to improve the effect of cultural communication.

Digital humanities are also facing problems. The quality of the data is uneven, and it is difficult to ensure the accuracy, integrity and reliability of data from all over the place [18]. Copyright problems have arisen due to the large amount of digital materials; now we need to know how to use and share them legally. With the development of artificial intelligence and other technologies, despite the existing problems, digital humanities have been gaining popularity and are expected to solve many problems.

2.2 Historical materials of art design

It has various forms due to the above reasons. There are many kinds of written works, such as theoretical works on art design and manuscripts by designers. Image materials are such as paintings and design drawings, and they can show the appearance and style of the work in a visual way [19]. Important treasures of physical archives include ancient ceramics and modern industrial products. It can also serve as a type of display for materials and technology.

The other is also its history. Historical materials of art design contain a large amount of information about society and culture, the economy, science and technology, and aesthetics at that time [20]. For example, in the industrial period, the production of art and design gradually shifted from manual labour to industrial production. The modern design movement in the 20th century has broken away from traditional ideals and spread throughout various areas as a result.

It has been used for many purposes to date. As a foundation for the research of art design, historical research provides the background context of art design, helps establish the style law, explores concept innovation and communication effects in art design, etc. In the area of art design education, it is a valuable resource that can provide materials and ideas for students, help them develop a sense of beauty and history, and motivate new ideas [22]. It can also be done to protect the cultural heritage and promote the development of the culture and creativity industry. On the one hand, it can protect against or prevent losses by means of digitalisation; at the same time, it can provide material and inspiration for the creation of works of art.

The development of digital humanities can offer new ways to protect, research and disseminate historical materials of artistic design. The two have been developed and advanced in tandem, providing strong support for the development of humanities, social sciences and the arts.

3 The basis of NLP in the arrangement of historical materials of art design

3.1 Overview of NLP algorithm

Natural Language Processing is a type of interdisciplinary study involving computation, AI and language. The Goal of NLP is to help computers understand and handle human language normally [23]. With the rapid development of artificial intelligence technology, the scope of application for natural language processing (NLP) has also expanded significantly over time, and it now includes areas such as machine translation and information retrieval, text classification, sentiment analysis, named entity recognition, text generation, etc.

Written documents in the historical materials of art design are rich in natural language information, such as design theory, creative experience, work description and historical evaluation [24]. The above text data provide a large-scale basis for applying NLP technology. Natural Language Processing (NLP) technology can be applied to process and analyze the text data automatically, extract relevant information, and thus provide strong support for the collection and study of materials on the history of art design.

3.2 Application of NLP in the arrangement of historical materials of art design

3.2.1 Text classification

Text classification aims to organise the divided text data into some categories automatically. Text classification technology can be used to organise a large number of historical materials in the collection of art and design texts [25]. Some typical text classification algorithms are Naive Bayes classifier, Support Vector Machine classifier, Convolutional Neural Network (CNN) and Long Short-Term Memory Network (LSTM). Naive Bayes Classifier is based on Bayes' theorem, assumes that the features are independent of each other, and calculates the feature words and their corresponding category probabilities for classification of text. A support vector machine classifier finds the optimal hyperplane to separate different data points. CNN and LSTM are also good deep-learning algorithms for text classification.

3.2.2 Named entity recognition

Named entity recognition technology seeks to identify entities in text that have specific meanings. Named Entity Recognition technology can be employed in the collation of historical materials on art design to extract key information, such as designers, work names, materials and techniques mentioned in the literature [26]. This information will help us create a knowledge map of art design to show how various parts are related. A set of rules and patterns is used to identify entities in the rule-based method. A statistical method that learns from labeled data to identify entities by combining statistical features. The method based on deep learning builds a neural network model to learn the features of the text automatically and recognize it.

3.2.3 Sentiment analysis

The objective of sentiment analysis technology is to discover the emotional disposition of an author in a piece of writing [27]. Emotion analysis technology can be used to study the emotions people feel about art design works in historical materials for research [28]. A dictionary method is used to build an emotional dictionary, and the emotional tendency in the text is determined based on the emotional vocabulary of the dictionary. The machine learning method is used to train a model with labelled data and then extracts features of the text for prediction of emotional tendency. A method that builds a neural network model based on deep learning to automatically learn text features and conduct emotional analysis.

4 Methodology

4.1 Data processing and word vector learning

The Basis of intelligent arrangement and analysis of historical materials for art design is data processing. A large number of text data on art design were collected in this study, including historical documents, artist biographies and work descriptions. The above data are the foundation for this study. To make better use of the above data, it needs to be in a format that computers can understand and process.

Word-Vector Technology will be used to process the data and represent words in text. Word vectors are a way to map words into a high-dimensional vector space and can show the semantic relationships among them. Learn word vectors using continuous bag model (CBOW) in Word2Vec technology. Based on the context of a word, predict the next word and learn its vector representation through this process. Word vectors contain semantic information about words and also show how and in what contexts words are used and appear together. Learned word vectors are fed into a CNN for feature extraction. As the input layer of CNN, word vectors can learn to capture language features from the text.

4.2 Feature extraction and model construction

CNN is used in this paper to extract features from text and, in turn, to build a semantic annotation and knowledge graph. CNN is a deep feedforward neural network that has the properties of local connection and weight sharing. The Design of the CNN structure in our research is shown in Figure 1. First, a sequence of convolution layers is applied to process the input word vector. The convolution layers in this way can extract various levels of linguistic features from the text, such as the contextual clues near entities, semantic relationships and descriptive phrases; all of which are needed for the subsequent annotation and graph-filling tasks. The design of the convolution layer will automatically learn important semantic information in the text without the need for manual feature engineering.

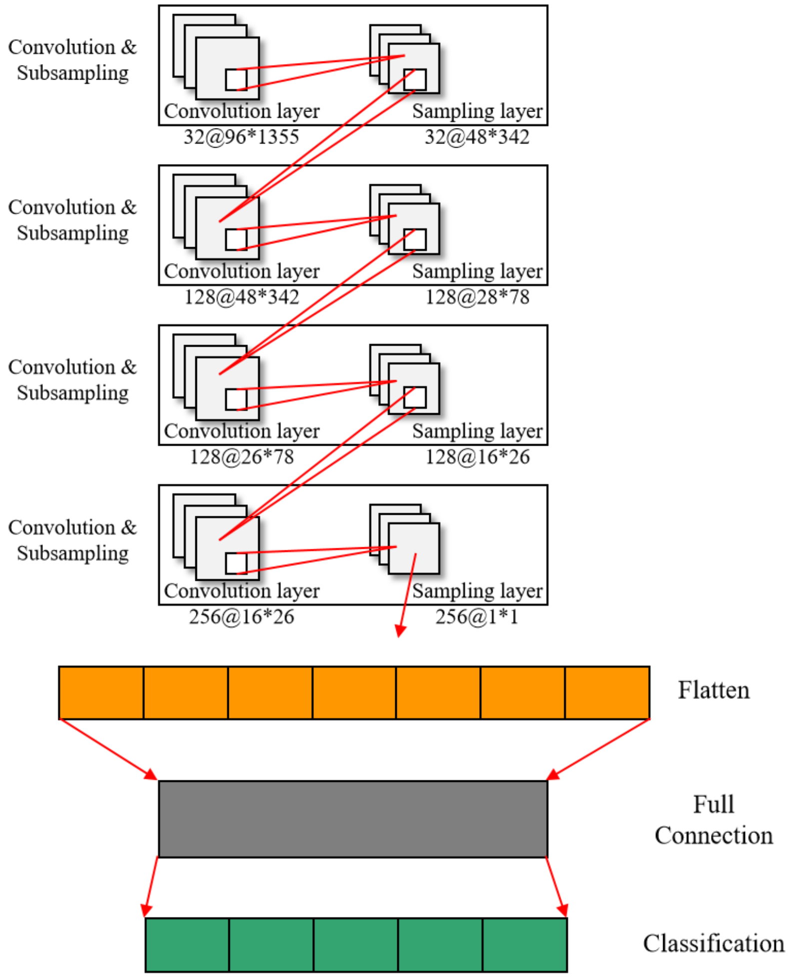

Figure 1: CNN Structure

The mean pooling layer is applied to the output of the convolution layer to obtain a sentence vector. This vector contains the semantic information of all the words in the sentence and serves as a feature representation for that sentence. Global average pooling can reduce the number of parameters in the model and improve the generalisation performance of the model.

Next, the sentence vectors are fed into a two-hidden-layer Multilayer Perceptron (MLP) for additional processing. MLP is a nonlinear transformation that maps sentence vectors to the category space of art design historical materials and generates a softmax activation score for each category of historical material. Finally, these features are mapped to a probability distribution to obtain the probability value of each category and thus perform classification of art design historical materials.

In CNN architectures, global average pooling is employed to generate feature representation vectors for classification. This technique effectively extracts relevant features from the text, offering precise and thorough input for the classifier. Consider a CNN with an L-layer structure operating on a dependency graph $g=(v,\varepsilon)$, where v and ε represent the node and edge sets, respectively. The output of node i in the k-th layer, denoted as $h_i^{(k)}$, is computed as follows:

$$h_i^{(k)} = \rho\left(\sum_{j=1}^{q} A_{ij} W^{(k)} h_j^{(k-1)} + b^{(k)}\right) \tag{1}$$

In this context, $h_j^{(k-1)}$ denotes the output representation of node j within the $k-1$-layer CNN, $W^{(k)}$ corresponds to the weight matrix, $b^{(k)}$ signifies the bias vector, $\rho(\cdot)$ refers to the ReLU activation function, and A represents the adjacency matrix of the dependency tree. The probability distribution for emotion analysis can be expressed using the following formula:

$$P(i_j|k,\theta)=\frac{\exp(x_j(k,\theta))}{\sum_{1\le i\le|X|}\exp(x_j(k,\theta))} \tag{2}$$

Here, $x_j(k,\theta)$ represents the average pooling result; the parameter set θ is associated with class j, while the class space is represented by X. To minimize the negative log probability, the stochastic gradient descent method is applied, utilizing the cross-entropy function as the loss function:

$$loss=-\sum_i\sum_j y_i^j \log \hat{y}_i^j+\lambda\|\theta\|^2 \tag{3}$$

Here, y denotes the expected value, $\hat{y}$ represents the predicted value, λ stands for L2 regularization, and θ corresponds to the neural network's parameter set.

4.3 Entity link and knowledge map construction

Entity linking maps text-based entities (e.g., artists, artwork titles) to their respective nodes in a knowledge graph. This paper proposes a simple neural network model to identify whether the two entities are the same. The form of the model is:

$$P(e_1=e_2)=\sigma(W_1\cdot(e_1+e_2)+b_1) \tag{4}$$

Here, e_1 and e_2 denote the vectors of two entities, while W_1 and b_1 are parameters of the model. The function σ serves as an activation function, such as ReLU or sigmoid.

Entity disambiguation is required to construct knowledge graphs of art and design history data. A similarity-based method will be used in this paper to determine how similar the two items are and whether they are the same. Among the above, the most commonly used is cosine similarity.

$$\text{CosineSimi larity}(e_1,e_2)=\frac{e_1\cdot e_2}{\|e_1\|\|e_2\|} \tag{5}$$

Here, e_1 and e_2 denote the vectors of two entities, $e_1\cdot e_2$ signifies their dot product, while $\|e_1\|$ and $\|e_2\|$ represent the magnitudes (norms) of these vectors.

To achieve intelligent semantic annotation and knowledge graph construction for design historical materials in this paper, a new model that directly integrates the source syntax tree into the encoder-decoder framework is proposed. The structure of the encoder in the design will be a recurrent neural network (RNN) consisting of bidirectional gated recurrent units (GRU). The two RNN modules of the encoder are as follows: The first is a forward RNN module that captures the semantic information of left-to-right history in the design documents; the second is a reverse RNN module that extracts contextual hints from right-to-left during reversal (as shown in Figure 2). The two-way code design is able to help the model better understand the full context of the historical texts on design.

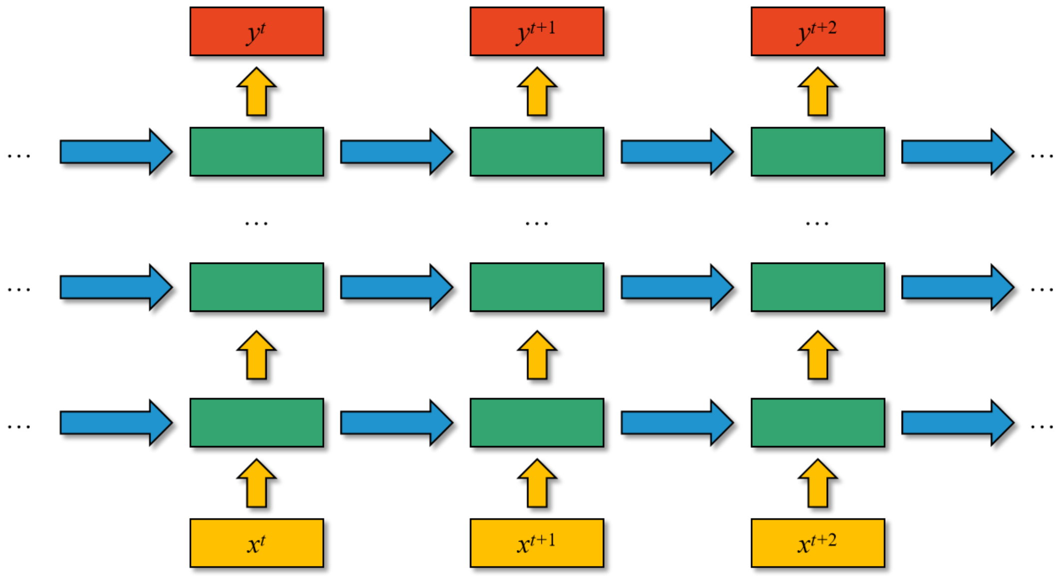

Figure 2: Example of bidirectional serialization encoder

A simple neural network model is introduced in this paper to determine if two entities are the same. The model can be expressed as follows: take the vector representations of the two entities as input, apply a non-linear function of a neural network, and then output a score that reflects how similar the two entities are. Based on this score, it has been determined whether the two entities are the same entity in this study.

Word vectors are used to comprehensively analyze and process textual data in the materials of art and design history. The above vectors are produced by the Continuous Bag of Words (CBOW) model in Word2Vec:

$$p(w_i \mid w_c) = \frac{\exp(v_{w_i} \cdot h)}{\sum_{\hat{i} \in \overline{V}} \exp(v_{w_i} \cdot h)} \tag{6}$$

Here, w_i represents the target word to be predicted, w_c denotes the context set of word w_i in the current training instance, $p(w_i \mid w_c)$ signifies the probability of generating word w_i given the context w_c of word w_i, and h is defined as follows:

$$h = \frac{1}{n}\sum_{i=1}^{n} v_{w_{c_i}} \tag{7}$$

Here, v_{w_i} represents the word vector being trained for word w_i, $i \in (1, \overline{V})$ is set to 2, $\overline{V}$ denotes the dictionary size of the required data, and n indicates the quantity of context words for word w_i in this training instance. The CBOW model predicts the target word based on its surrounding context, enabling the learning of word vector representations. These vectors serve as input for the subsequent CNN model, facilitating the intelligent organization and analysis of art and design historical materials.

For sentence-level text processing, a sentence is treated as a matrix of word vectors, with each row representing a word vector. Convolutional kernels are applied to extract features. If the sentence length is n and the word vector dimension is d, the i-th word vector in the sentence can be denoted as $x_i \in R^{n \times d}$. The entire text can be represented as a matrix $x \in R^{n \times d}$, consisting of n d-dimensional vectors, as illustrated in the following formula:

$$x_{1:n} = x_1 \oplus x_2 \oplus \cdots \oplus x_n \tag{8}$$

Here, $\oplus$ represents the concatenation operator. The convolutional kernel $w \in R^{h \times d}$ is applied to perform the convolution operation, where the filter's height is h and its width matches the word vector dimension, denoted as d. This operation can be expressed as:

$$c_i = f\left(W \cdot x_{i:i+h-1} + b\right) \tag{9}$$

Here, b denotes the bias term, and f refers to the activation function. To enhance training efficiency, the ReLU function is chosen as the activation function. $x_{i:i+h-1} \in R^{h \times d}$ represents a filter window containing h consecutive words. Following the convolution operation, a feature sequence C is generated, comprising $n-h+1$ feature vectors:

$$C = \left[c_1, c_2, \cdots, c_{n-h+1}\right] \tag{10}$$

With the help of entity linking and entity disambiguation, the entities in the historical materials of art design can be linked to those in the knowledge map, and a rich knowledge map of art design will be built. This knowledge map can provide support for research on art design and offer ideas for the creation and application of art design.

5 Result analysis and discussion

5.1 Experimental results

Design historical materials are rich in cultural background and emotional colours; therefore, intelligent semantic annotation and knowledge graph construction methods need to be able to process large volumes of text data efficiently and have accurate emotional analysis capabilities to explore the emotions and values contained in historical materials more deeply. Based on the above demand, this study puts forward a new framework for intelligent semantic annotation and knowledge graph construction of design historical materials, and tests its performance in experiments.

To show how much better this framework is for improving the efficiency of operation in a clear and concrete way, it will be directly compared with the traditional Transformer algorithm based on computing and processing time. The design of the experiment should be scientifically sound and fair; the test environment should be stable, and no other factors should affect the experimental results. A design historical text dataset of the same scale has been selected for this study as the test object, and both methods will be evaluated under the condition of processing the same volume of data to confirm their actual speed difference.

As shown in Figure 3, the experimental results indicate that this algorithm is relatively simple in terms of speed. Under the same hardware conditions and data-processing tasks, the processing speed of this algorithm is significantly slower than that of the original Transformer. The above differences can also be seen in the processing of small-scale data sets, and when dealing with large-scale, complex, and diverse artistic design text data, the algorithm can still function normally and stably.

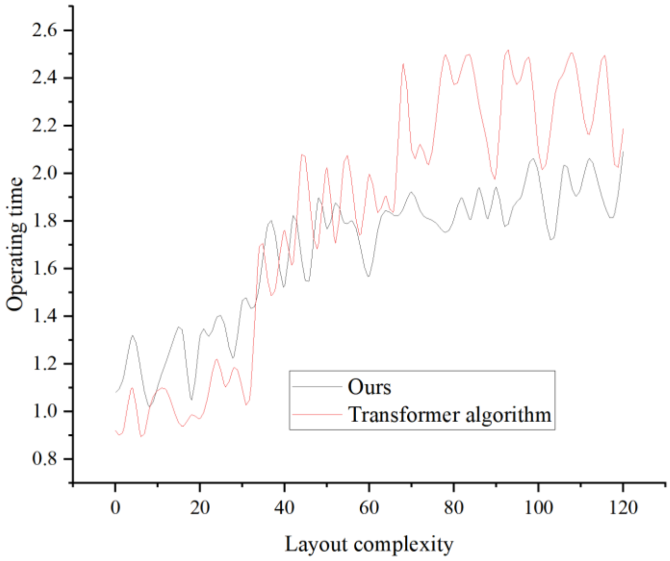

Figure 3: Calculation Time of Algorithm

The Intelligent arrangement and analysis of historical materials of art design require text emotion analysis as one of the tasks. Identify the reasons for the design based on culture, society and psychology. To explore more cases of application for the algorithm, we will now examine some text sentiment analysis examples. Therefore, a set of training samples containing emotional information from historical materials of art design is prepared. These samples include descriptions of design works from different times and in various styles, as well as related text information such as comments and evaluations. The above samples are respectively fed into this algorithm and the traditional Transformer text sentiment analysis model for learning, and the two models will be compared under the same training conditions.

After training for a long time, both models have been used on separate test sets. The test results are as follows: Figure 4 and Figure 5. Figure 4 is the accuracy of this algorithm for emotional analysis in art and design history materials. As shown in the figure, the algorithm can distinguish among positive, negative and neutral emotions accurately. It is more sensitive to the subtle emotions in complex emotional text and closer to what people feel.

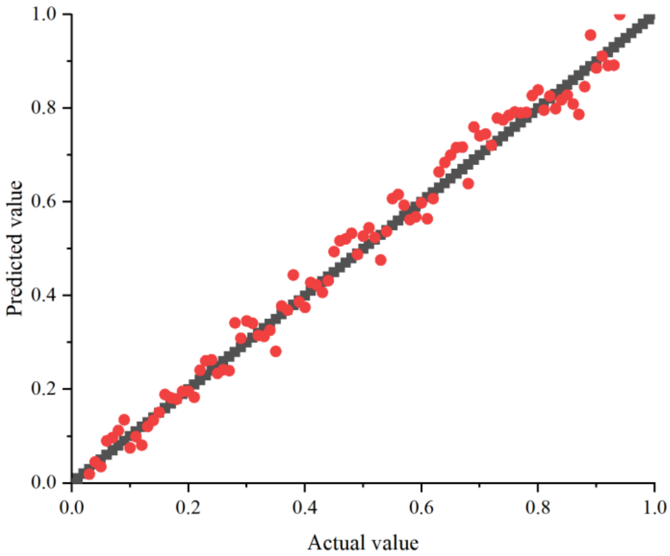

Figure 4: Sentiment Analysis Accuracy of the Proposed Algorithm

Figure 5 is the accuracy test result of the Transformer algorithm on the same task. Although the Transformer algorithm is an excellent, high-performing deep learning model, it has not outperformed this algorithm in terms of the specific task of emotional analysis for art design historical materials in this experiment. Text that is culturally rich and emotionally complex has shown an even greater reduction in the Transformer algorithm's accuracy.

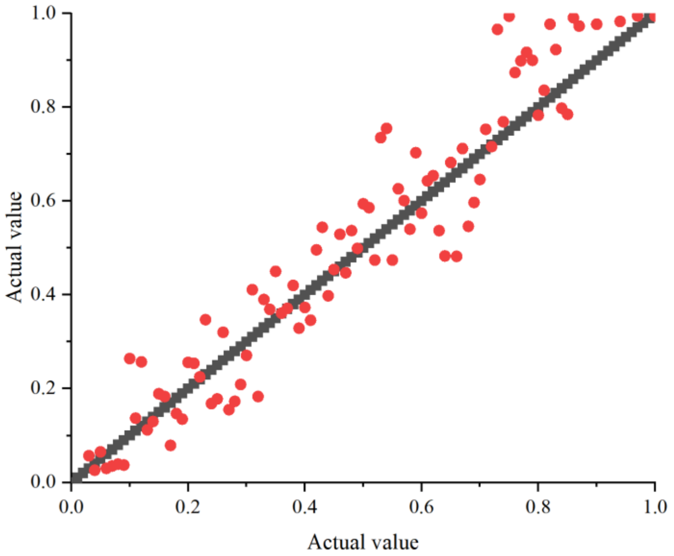

Figure 5: Sentiment Analysis Accuracy of the Transformer Algorithm

Compared with the traditional Transformer algorithm, this algorithm is more accurate and reliable for text emotion analysis of art design historical materials. Therefore, it is suitable for the particular kind of text data in that area.

As shown in Table 1, it is not difficult to see that with an increase in the size of the data, the advantages of this algorithm in terms of memory consumption are gradually becoming more prominent. The memory requirements for dealing with small-scale, medium-scale, large-scale and super-large-scale data are relatively low in this algorithm compared with those of the Transformer algorithm.

Table 1: Comparison of Memory Usage

Algorithm	Memory Usage for Small-scale Data (MB)	Memory Usage for Medium-scale Data (MB)	Memory Usage for Large-scale Data (MB)	Memory Usage for Extra-large-scale Data (MB)
Our Algorithm	512	768	1024	1536
Transformer	768	1280	2048	3072

Table 2 shows that the model training time of this algorithm is relatively short. When employing small-scale, medium-scale, large-scale and ultra-large-scale data sets for training, the time taken by this algorithm is lower than that for the Transformer algorithm.

Table 2: Comparison of Model Training Times

Algorithm	Training Time for Small-scale Dataset (hours)	Training Time for Medium-scale Dataset (hours)	Training Time for Large-scale Dataset (hours)	Training Time for Extra-large-scale Dataset (hours)
Our Algorithm	2	4	8	12
Transformer	4	8	16	24

As shown in Table 3, the model is relatively stable. When using data sets of different sizes, the error of this algorithm is still in the same range. Based on the above results, the algorithm is relatively stable and not overly sensitive to fluctuations in the size of the data.

Table 3: Model Stability Comparison (Shown as Accuracy Fluctuation Range)

Algorithm	Accuracy Fluctuation Range for Small-scale Dataset (%)	Accuracy Fluctuation Range for Medium-scale Dataset (%)	Accuracy Fluctuation Range for Large-scale Dataset (%)	Accuracy Fluctuation Range for Extra-large-scale Dataset (%)
Our Algorithm	±1.5	±1.8	±2.0	±2.2
Transformer	±2.5	±3.0	±3.5	±4.0

Table 4 is a general list of the strengths of this algorithm for interpretability. The algorithm has good basic visualisation of feature importance, as well as more detailed visualisation and visualisation of feature interactions. Based on the overall interpretability score, this algorithm is relatively more transparent than the Transformer model.

Table 4: Interpretability Comparison (Rated by the Degree of Feature Importance Visualization, Full Score 10)

Algorithm	Basic Visualization Score of Feature Importance	Detailed Visualization Score of Feature Importance	Visualization Score of Feature Interaction	Overall Interpretability Score
Our Algorithm	7.5	8.5	8.0	8.2
Transformer	5.0	6.0	5.5	5.8

The above reasons indicate that the algorithm will be more practical in terms of applications and meet the demands of intelligent sorting and analysis of historical artistic design materials better.

5.2 Discussion

According to the experimental results and analysis, the method of semantic annotation and knowledge graph construction proposed in this paper has superior operating efficiency and accuracy for the design of historical materials in text emotional analysis. The quantity of historical design materials in the digital age has increased rapidly. Given its relatively high efficiency, it can now deal with the growing quantity of old records in a short period of time. It can help us obtain rich materials for studies on history and boost the development of integrated design courses.

Historical materials for design contain rich emotional content; they are not only the designer's feelings at the time of creation but also a way to communicate these emotions to the audience through the work. Accurately determine the emotional tendencies of historical materials to gain a deeper understanding of the designer's creative intent and expose the cultural, social and psychological reasons for the works.

This way also has some shortcomings. Although the accuracy of text sentiment analysis is relatively high, there will still be problems of judgment or omission for some kinds of historical materials. It may be that there are particularities in the historical materials, a complex form of emotion, or intrinsic limitations of the algorithm. In the future, further optimize the model and enhance its generality for many different kinds of historical materials.

At present, this way has focused mainly on the processing and analysis of text data, and its application to multimedia historical materials such as images and audio is relatively limited. Multimedia historical materials are also rich in content and use in design. Extend this way to support intelligent semantic annotation and knowledge graph construction of multimodal design historical materials in the future.

The Application of this method is also affected by the quality of the data and labelling. To ensure the accuracy and completeness of the input data in practice, otherwise, the method will not perform well. Improve Data quality control and annotation accuracy in future research.

6 Conclusions

In this paper, a method for intelligent semantic annotation and knowledge graph construction of design historical materials is proposed and verified experimentally. The Transformer algorithm for computing processing time is no longer as slow as the old one; now it is quite fast. Process a large volume of text data on design more quickly and efficiently. The method has good stability in the application experiment of text sentiment analysis and is relatively superior to the old Transformer algorithm. It can explore the emotional content of historical materials in design in greater depth and provide more rich information for researchers on the cultural, social and psychological factors of these historical materials.

In short, the intelligent semantic annotation and knowledge graph construction method for design historical materials proposed in this paper can help to improve the efficiency of processing historical materials and enhance the accuracy of emotional analysis. This has provided strong technical support for the research on design from the perspective of digital humanities. Future work will extend research further, improve the efficiency of the algorithm, expand the application range, and contribute more to intelligent design.

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