International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 8445-8453

https://doi.org/10.70517/ijhsa463722

Exploration of Digital Transformation Paths and Technological Applications of Cultural Relics Museums Driven by the Reconstruction of Visual Charms and Renewal of Dynamic Environments

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Abstract Cultural relics are the valuable wealth left behind by ancestors in the process of historical development, and they are an important carrier connecting the past and the present. The development of digital technology provides more development paths for the display of cultural relics. In this paper, we use BERT-BiLSTM-CRF modeling technology to extract the cultural relic entities, construct the knowledge graph ontology and RDF triad, and propose the cultural relics knowledge graph expression model. Combined with the reasoning engine based on the TBCRM model, the determination of cultural relic entities and relationships in the knowledge graph is realized. By adopting the cultural relics knowledge mapping expression model to integrate cultural relics resources and digitally display them, a digital cultural relics museum system construction method is proposed with the back-end data service layer, intermediate application layer and front-end Web browsing layer as the main framework. The application of this method assists in the establishment of a digital display system for the cultural relics museum in Province B. The overall function obtains an average user rating between 70-90, showing a high practical effect.
Index Terms knowledge graph expression model, digital cultural relics museum, inference engine, cultural relics resources

I. Introduction

The rapid development of digital technology and the arrival of the fourth industrial revolution have brought mankind into the era of digitalization. More and more countries recognize the strategic significance of digitization, and more than 170 countries have released national digitization strategies in an attempt to catch the fast train of the fast-developing era [1]. Facing the surging wave of digitization, China has also accelerated its strategic deployment of digital technology. In today's era, digital technology is being integrated into all fields of human economic, political and cultural construction in a new mode, and cultural digitization is an indispensable part of it [2]. The integration and development of culture and digital technology has pointed out the development direction for traditional Chinese culture, expanded the scope of cultural dissemination and enhanced the influence of culture [3], [4].

Cultural relics museum is a carrier for preserving human history and culture, a guardian of the memory of human civilization, and an important place for passing down human civilization [5]. In the 5G information age, technology is developing at a high speed, and museums have also started a digital journey, introducing many technologies such as VR panorama and 3D modeling, which have a new luster in the new era [6], [7]. In recent years, heritage museums have made significant breakthroughs with the help of digital technology, constantly strengthening the collection, storage, education, service and other value enhancement [8]. The traditional display of cultural relics museums mainly rely on the text, as well as the introduction of cultural relics by the lecturer, and such a form is difficult to ensure that tourists get a good experience every time they visit [9]. With the development of digital technology, heritage museums have gradually shifted from physical display to digital display, enhancing the diversity, experience and interactivity of cultural relics display, and cloud curation, cloud viewing, cloud evaluation, etc. have enriched the immersive experience of heritage museums [10]-[12]. More and more cultural relics museums choose to use VR, AR, MR and other digital technology to innovate the form of cultural relics exhibition to provide more new experiences for visitors [13].

With the continuous optimization and upgrading of the consumption structure, people care more about the spiritual resonance in tourism and hope to enhance the sense of cultural acquisition [14]. Digital technology, as a catalyst, can not only integrate cultural elements into consumption behavior in various ways, but also satisfy consumers' new consumption preferences and further enhance the overall quality of consumption [15]. On the other hand, under the premise of realizing the unity of cultural value and commercial value, it helps to transform consumption from "material" to "spiritual" [16], [17]. In the face of the booming digital technology and people's growing spiritual and cultural needs, heritage museums are actively embracing digitization, and under this development trend, how to use digital technology to digitally transform heritage museums and promote the high-quality development of digital technology in museums is an issue that cannot be ignored.

In this paper, we first sort out the idea of constructing the cultural relics knowledge graph expression model under the support of BERT-BiLSTM-CRF model. Then it describes in detail the basic construction of BERT module, BiLSTM module and CRF module as well as their operation principles. Secondly, on the constructed cultural relics knowledge graph expression model, Jena rule engine is introduced to assist in defining and executing knowledge rules. And the inference engine based on the TBCRM model is proposed to establish the inference rule base to realize the knowledge inference of the cultural relics museum exhibits. Again using the cultural relics knowledge graph expression model for the digital display of cultural relics resources, explaining the architecture of the digital cultural relics museum system, so as to complete the digital transformation of the digital cultural relics museum. Finally, we compare the performance of the knowledge graph expression model algorithm with the traditional baseline model algorithm in terms of the relationship types of cultural relic entities and the public dataset to test the overall performance of the proposed model. The proposed model is used to construct the knowledge graph of the cultural relics museum in Province B, and user experience evaluation is carried out.

II. Digital Heritage Museum Based on Knowledge Graph Representation Modeling

II. A. Constructing the expression model of cultural relics knowledge map

This paper adopts the bottom-up knowledge graph construction method. Under the premise of following the extraction rules formulated by experts, after years of accumulation, a large number of entities such as cultural relics proper names have been identified in actual business scenarios, as well as the relationships in the cultural relics knowledge graph model from the fields in the existing cultural relics basic information table. On this basis, through the BERT-BiLSTM-CRF model, we realize the automated extraction of entities and make supplementary improvement to the existing cultural relics knowledge base. The recognized entities are disambiguated to construct the knowledge graph ontology and RDF triples, thus completing the construction of the cultural relics knowledge graph expression model.

(1) BERT module

BERT is placed at the bottom layer for extracting contextual text information, and BERT is a pre-trained language representation model. It abandons the traditional method of pre-training through a one-way language model, or the way of shallow splicing two one-way language models, but adopts the way of the new masked language model MLM to generate a deep two-way language representation. The model has the following advantages:

a) The deep bi-directional Transformers are pre-trained using the Masked Language Model MLM, and the whole model is constructed to generate deep bi-directional language representations that incorporate contextual information.

b) After pre-training, only an additional output layer is added for fine-tuning to achieve state-of-the-art performance in multiple downstream tasks. No task-specific structural modifications to BERT are required in this process.

BERT interfaces with BILSTM-CRF by simply calling getsequenceoutput of BERT to obtain the sequence output of the BERT model, and input this sequence output to the subsequent BILSTM-CRF.

(2) BiLSTM module

The purpose of the second layer BiLSTM is to extract bi-directional text information, the development of BiLSTM bi-directional long and short-term memory network goes back to the RNN recurrent neural network, a special type of RNN is the LSTM long and short-term memory, and the combination of forward LSTM and backward LSTM constitutes the BiLSTM.

RNN is a type of neural network used to process sequential data. It contains a recurrent network, i.e., the same neural network will be replicated multiple times, and each neural network module will not only process the current message, but will also receive a message from the previous module as input, constituting a chained sequence that ensures persistence of information. Understanding the current module speculatively through the message of the previous module increases the accuracy of recognizing the information of the current module, but when the module that can provide valid information is far away from the current module, the RNN loses the ability to learn and receive information, and the emergence of the LSTM solves this problem. Figure 1 shows the RNN loop unfolding form.

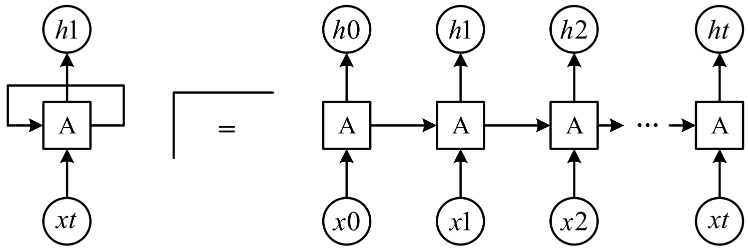

Figure 1: RNN loop expansion

RNN in the long sequence training process of the existence of gradient disappearance and gradient explosion problem, and LSTM can be a good solution to this problem, the reason is that the LSTM in the basis of RNN, the introduction of the concept of gating, to remove the invalid information or increase the effective information to the next moment, to realize the long term memory, each neural network module in the LSTM including forgetting the gate, input gates, output gates, and the memory cells, and the LSTM is the most effective way to achieve the long-term memory. Each gating contains sigmoid neural network layer and pointwise multiplication operation.

The gating in the LSTM network is shown in Fig. 2, which has three gates to control the cell state.

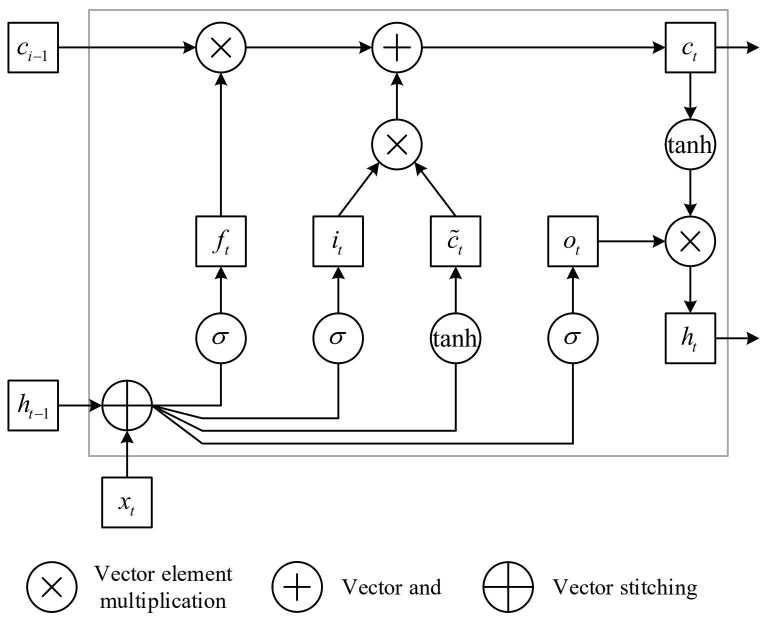

Figure 2: Gating in the LSTM network

A neural network module in LSTM is taken for the study, from left to right it can be seen as three parts the leftmost is the forgetting gate, which is used to decide the information to be discarded as in equation (1):

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f) \tag{1}$$

The middle to determine the updated information consists of two parts, the input gate and the tanh layer, the input gate is used to determine the updated information and the tanh layer creates a new vector of candidate values $\tilde{C}_t$ and adds it to the state, replacing the old one with the new subject with the formulas in equations (2) and (3):

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = \tanh(W_C * [h_{t-1}, x_t] + b_C) \tag{3}$$

Update the cell state by discarding the information of the old pronouns and adding new information as in Equation (4):

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{4}$$

The output information, the rightmost output gate, contains two parts, the part that runs the sigmoid layer to determine the output of the cell state, and the part that undergoes tanh processing to determine the final output as in Eq. (5) and Eq. (6):

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t * \tanh(C_t) \tag{6}$$

After the above operation completes the input to the output of a neuron, and then multiple neurons form a complete LSTM network.BiLSTM uses forward LSTM and reverse LSTM for each word sequence respectively, and the outputs at the same moment t are merged for processing, for each moment, it corresponds to the forward and backward information, so BiLSTM can better capture the bidirectional semantic dependency. As in equations (7)-(9):

$$\overrightarrow{h_t} = RNN_{FW}(\overrightarrow{h_{t+1}}, x_t) \tag{7}$$

$$\overleftarrow{h_t} = RNN_{BW}(\overleftarrow{h_{t-1}}, x_t) \tag{8}$$

$$h_t = \left[\overrightarrow{h_t}, \overleftarrow{h_t}\right] \tag{9}$$

(3) CRF module

The extracted bi-directional text information will be transferred to the next layer CRF module for sequence prediction.

The third layer CRF conditional random field is a basic model in natural language processing, which is widely used in the scenarios of word segmentation, entity recognition, and lexical annotation, in which it is used to predict the optimal sequence. Sequence labeling model has gone through the iteration from HMM to MEMM to CRF, CRF retains the advantages of MEMM discriminative model, Markov state transfer, and the fact that each state relies on the complete context, and CRF directly regularizes globally to solve the labelbias problem. In contrast to MEMM, where probabilities are obtained by regularization at each step, CRF is directly regularized by computing global probabilities for all N^T possible state paths of T steps.

CRF defines a set of feature functions, each feature function in the set scores the same labeled sequence, and the weighted sum of the scores of all feature functions in the set is the final score of the labeled sequence.

The feature function of CRF consists of four parameters:

S: the sentence that needs to be labeled lexically.

i: the ith word or words in the sentence.

l_i: the lexicality of the ith word or words, the output value 1 means the labeled sequence meets this feature, 0 is not.

l_{i-l}: lexicality of the i-1st (previous) word or words, output values 0 and 1 are judged as above.

After defining a set with m feature functions, assign a weight f_j to each feature function λ_j, define the sentence that needs to be labeled with lexical properties as s, and the labeled sequence as l. Take each feature function in the set of feature functions to score 1 respectively as in equation (10):

$$score(l \mid s) = \sum_{j=1}^{m} \sum_{i=1}^{n} \lambda_j f_j(s, i, l_i, l_{i-1}) \tag{10}$$

Two summation formulas are used in Eq. (10), the inner one sums the eigenvalues of the words at each position in the sentence, and the outer one sums each eigenfunction f_j. A log-linear representation of this score yields the probability value of the labeled sequence $p(l \mid s)$ as in equation (11):

$$p(l \mid s) = \frac{\exp\left[score(l \mid s)\right]}{\sum_{l'} \exp\left[score(l' \mid s)\right]} \tag{11}$$

II. B.Intellectual reasoning

Knowledge graph reasoning is a process of determining new information and relationships through relationships and rules of sentences. By analyzing the existing nodes and relationships in the knowledge graph, it is possible to draw some new conclusions or discover some new conclusions added associative relationships. Reasoners are important techniques in the field of artificial intelligence for inferring and reasoning about potential relationships and information in the knowledge graph.Jena is a popular semantic web and RDF graph data processing framework that provides a range of powerful reasoners.The Jena rule engine allows the user to define and enforce rules that are used to infer new information in the knowledge graph. It infers new triples based on the facts of the RDF graph and user-defined rules. Users can define rules using the RDF Rule Language (Rul) and then execute them using Jena's Rule Engine.Jena's Rule Engine supports both forward and backward reasoning, and can infer new triples based on existing triples, as well as determining whether or not a triple to be verified satisfies certain rules based on the triple to be verified.Jena also provides built-in reasoners, of which the most commonly used ones are RDF and OWL language based reasoners. These reasoners are capable of executing inference rules defined in the RDF and OWL languages to infer potential relationships and information in the knowledge graph. For example, OWL language-based reasoners can infer new instance relationships and attributes based on the semantics defined by the OWL ontology.

The advantages of the Jena reasoner include flexibility, high customizability and extensibility. Different types of inference rules can be defined and executed according to one's needs, thus enabling rich inference and reasoning about the data in the knowledge graph. This is the main reason why Jena is chosen as the inference module in this study, because the built-in OWL inference engine of Jena is not suitable for the TBCRM model of the Artifact Knowledge Graph, so a set of inference rule base is redefined based on the TBCRM model. Figure 3 shows the working of the inference engine with customized rule base based on this set of TBCRM model.

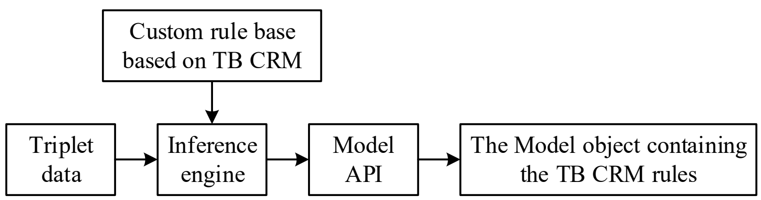

Figure 3: The working principle of the reasoning engine for customizing the rule base

Based on the TBCRM model, a set of customized inference rules were constructed. These rules were then imported into the inference engine of the Jena framework to allow reasoning on the specified ontology, thus generating an ontology model that follows the TBCRM rules. Queries using this newly generated model implement the retrieval and reasoning functionality of the custom rules. The key to the inference engine is the inference rule base, which plays a central role in the search system. The system recommends artifacts with high similarity to the target entity searched by the user. The similarity of artifacts can be based on a variety of factors, such as usage, shape, period, material, excavation location, and collection. Therefore, there is a need to customize the criteria for artifact similarity, i.e., to develop rules for recommending artifacts with a high degree of similarity.

II. C.Realization of the overall structure of the digital heritage museum system

II. C. 1) Concept of digital heritage museum system

The establishment of digital heritage museum system focuses on the establishment of an integrated central database for users to query and use, using the above constructed cultural relics knowledge map expression model to carry out the digital processing of cultural relics information, digital display and storage management. Figure 4 is the conceptual structure of the digital heritage museum system.

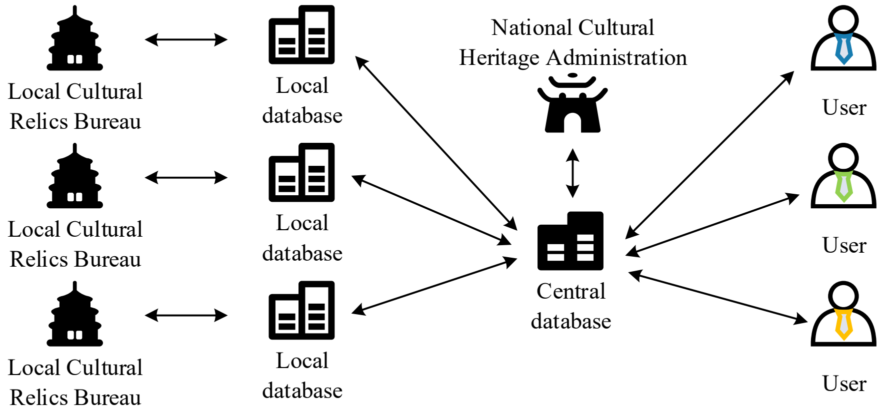

Figure 4: Conceptual Map of the Digital Cultural Relics Museum System

II. C. 2) Digital Heritage Museum System Architecture

The three-layer architecture of the digital cultural relics museum system is as follows: the back-end data service layer, the middle application layer, and the front-end Web browsing layer, and its architecture is shown in Figure 5.

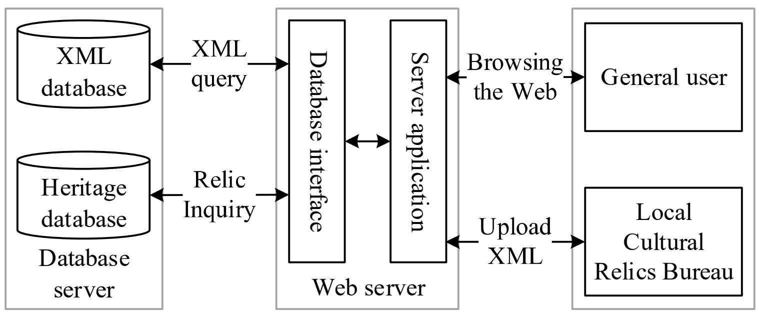

Figure 5: System Architecture Diagram of Digital Cultural Relics Museum

There are three main types of users of the system: general users, local cultural heritage bureaus, and the State Administration of Cultural Heritage.

General Users: Users are inquirers of cultural relics information, and their main purpose is to inquire about the information stored in the central database. It is the ultimate beneficiary of this system.

Local Cultural Relics Bureau: the main task of the Local Cultural Relics Bureau is to digitize the cultural relics. It is the main data inputter of the system.

State Administration of Cultural Heritage: The State Administration of Cultural Heritage is mainly responsible for the management and maintenance of the digital heritage museum system, which provides a good interface for the local cultural heritage bureaus and users, so that the local cultural heritage bureaus can better input the information into the central database, and at the same time, the users can quickly and easily find the information they need.

III. Performance test of the model and application evaluation of the system

III. A. Performance Analysis of Artifact Knowledge Graph Representation Models

III. A. 1) Performance comparison of entity relationship types

After analyzing the data characteristics of the artifacts in detail and referring to the existing literature research and expert opinions, this paper classifies the potential entity relationships existing in the artifact data into the following eight categories: (CT) time of collection, (CC) collection in, (PT) time of exhumation, (PC) time of excavation, (PN) author of the artifacts, (RT) time/date of manufacture, (PP) production/publication in, and (DT) time of publication. In order to analyze the performance of this paper's method on the artifact dataset, comparing the performance of the BERT-Globalpointer model with this paper's method on different entity relationship types in the artifact dataset is shown in Fig. 6, and on all the relationship types, this paper's method improves compared to the baseline model, with the highest gap of 2.036 on the (CT) curation time relationship type.

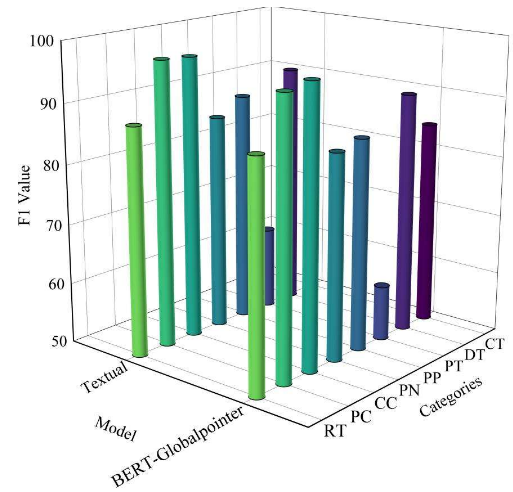

Figure 6: Comparison of F1 values of different relationship types

III. A. 2) Comparative experiments on public datasets

To validate the generalization of this paper's method, the results of comparing the precision, recall, and F1 values of this paper's method with nine baseline modeling methods: CasRel, TPlinker, EmRel, PRGC, SPN4RE, OneRel, PMEI, PARE, and ERGM on the NYT dataset as well as the WebNLG dataset are shown in Table 1.

Table 1: Comparative experiments on public datasets

Data set	ERGM (%)			WebNLG (%)		
Model	Precision	Recall rate	F1 value	Precision	Recall rate	F1 value
CasRel	92.3	92.1	88.4	92.2	92	93.7
TPlinker	93.9	95.1	90.7	90.6	93.9	93.8
EmRel	94.3	95.1	90.9	91.5	94.9	94.8
PRGC	96	92.3	89.6	92.8	94	94.9
SPN4RE	95.9	94.3	91.3	91.9	95.5	95.3
OneRel	95.4	94.1	91.6	92.9	95.5	96.2
PMEI	93.1	92.4	88.9	89.8	94.8	93.9
PARE	95.5	94	90.9	92.6	92.9	94.3
ERGM	95.9	94.1	91.2	91.5	94.9	94.8
Textual	97.6	95.5	92.5	93.7	96.3	95.9

On the ERGM dataset, this paper's modeling approach performs best among the 10 modeling approaches in the precision rate, recall rate, and F1 value metrics, with 97.6%, 95.5%, and 92.5%, respectively. On the WebNLG dataset, this paper's modeling approach far outperforms the nine comparative baseline modeling approaches in terms of precision and recall, reaching 93.7% and 96.3% in that order. However, it slightly underperforms the OneRel model in terms of F1 value performance by 0.3%.

III. B. Application of Digital Heritage Museum System

In this paper, taking the cultural relics museum of Province B as an experimental object, the proposed cultural relics knowledge graph expression model is used to extract cultural relics features, establish knowledge reasoning relationships, so as to construct a knowledge graph, and establish a digitization system for the cultural relics museum of Province B. The overall effect of this digitization system is evaluated from the perspective of user experience.

III. B. 1) Construction of Knowledge Maps

Construct a comprehensive and rich knowledge map, whose local structure is shown in Fig. 7.This map lays a solid data foundation for the functional experiment of digital cultural relics system in Province B, which can provide users with smarter and comprehensive cultural relics knowledge services.

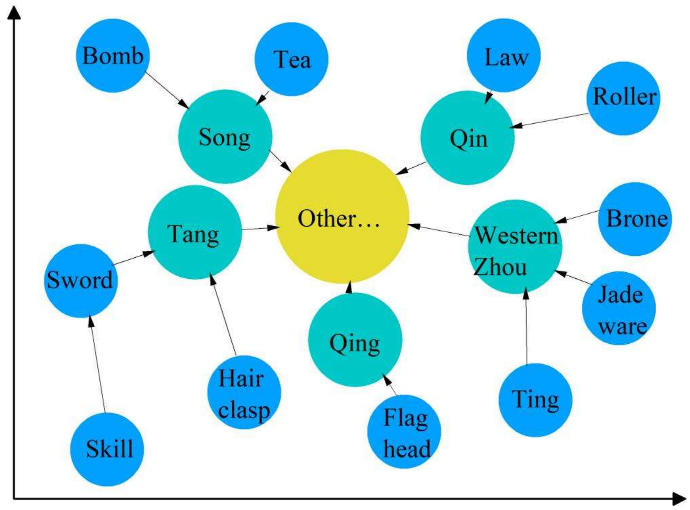

Figure 7: Knowledge graph local structure diagram

Table 2: Evaluation results of teachers' visit and experience

Evaluation Index	Evaluation grade score					Total points
	L1	L2	L3	L4	L5	
I1	1	4	0	0	0	87
I2	2	2	1	0	0	87
I3	0	2	2	1	0	77
I4	1	2	2	0	0	83
I5	2	0	1	2	0	79
I6	1	1	3	0	0	81
I7	0	1	1	3	0	71
I8	2	0	1	2	0	79
I9	0	4	1	0	0	83
I10	0	2	3	0	0	79

Table 3: Evaluation results of students' visit and experience

Evaluation Index	Evaluation grade score					Total points
	L1	L2	L3	L4	L5	
I1	2	1	3	4	0	76
I2	1	2	7	0	0	79
I3	2	3	3	2	0	80
I4	3	3	4	0	0	84
I5	3	4	2	1	0	84
I6	5	3	2	0	0	88
I7	0	0	3	6	1	64
I8	2	3	3	2	0	80
I9	6	2	1	1	0	88
I10	0	6	3	1	0	80

III. B. 2) Experience evaluation

Fifteen users were invited to participate in the digital museum experience program, including a total of 10 students of different ages and 5 teachers of different majors. After the experience, a questionnaire was designed to evaluate the satisfaction of the digital museum experience. The evaluation indexes of the questionnaire are: (I1) overall style of the museum, (I2) model display effect, (I3) UI interface design, (I4) colorful sculpture DIY design, (I5) video image playback, (I6) colorful sculpture cultural and creative products, (I7) interactive experience, (I8) richness of cultural relics resources display, (I9) smoothness of the system use, and (I10) humanistic connotation, and the full score of each index is set to 100 points. The full score is set to 100 points, divided into the following five levels: (L1) excellent (90-100), (L2) good (80-89), (L3) medium (70-79), (L4) pass (60-69), (L5) unqualified (0-59). When calculating the total score for each indicator, the median of the evaluation level score range is taken. Among them, the evaluation results of teachers' visiting experience are shown in Table 2, and the evaluation results of students' visiting experience are shown in Table 3.

Observation of Tables 2 and 3 reveals that the overall ratings of teachers and students for this digital heritage museum system are concentrated between 70-90, indicating that the overall user experience of the digital system is good and feasible to a certain extent. However, in (I7) interactive experience, the digital system received an average rating of 71 from teachers and only 64 from students, which suggests that the digital system should improve and optimize the design of the interaction function with users, improve the user experience and enhance the attractiveness of the system.

IV. Conclusion

In this paper, the knowledge graph is constructed by establishing the expression model of cultural relics knowledge graph, determining the entities and relationships of the knowledge graph. Combined with the digital cultural relics museum system composed of the back-end data service layer, the middle application layer, and the front-end Web browsing layer, it realizes the dynamic updating of cultural relics as well as the reconstruction of visual charm. The modeling method in this paper not only outperforms the baseline modeling method in different cultural relic entity relationship types, but also has a difference of 2.036 in the collection time relationship types. on the ERGM dataset, the modeling method in this paper has a performance far exceeding the nine baseline modeling methods, with the precision rate, the recall rate, and the F1 value of 97.6%, 95.5%, and 92.5% in that order. The proposed method is used to assist in the construction of the digital display system of the Cultural Relics Museum of Province B, which receives a high rating in the 70-79 range in the overall user-oriented functional performance evaluation.

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