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Computer-supported analysis of the Tang Dynasty clothing symbol system and the cross-media dynamic evolution mechanism of cultural symbols

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Abstract Most existing records of Tang Dynasty clothing are scattered and largely unstructured, with a massive volume of data. To conduct an in-depth analysis of the symbolic system of Tang Dynasty clothing, this paper introduces knowledge graphs and proposes a knowledge graph construction method based on BiLSTM-CRF named entity recognition. The BiLSTM-CRF model is used for entity extraction, and BiLSTM is combined with a two-layer attention mechanism for relation extraction. The extracted knowledge is stored in the Neo4j graph database to construct a knowledge graph of Tang Dynasty clothing symbols. Based on the knowledge graph, this study analyzes the evolution and characteristic changes of Tang Dynasty clothing cultural symbols from multiple aspects, including clothing style, color, and openness. The overall style of Tang Dynasty clothing was characterized by splendor, elegance, and grandeur, with clothing colors deeply influenced by the "Five Colors Theory." The evolution of clothing openness is closely related to the prosperity of the Tang Dynasty. During the prosperous Tang period, clothing openness reached its peak, while it significantly decreased during the late Tang period, gradually becoming more restrained.

Index Terms knowledge graph, BiLSTM-CRF, named entity recognition, relation extraction

I. Introduction

Tang Dynasty clothing holds a pivotal position in the history of Chinese clothing, renowned for its rich diversity and distinctive characteristics [1], [2]. During the early Tang Dynasty, clothing styles were relatively simple and elegant [3]. Men typically wore round-collared robes, which were generally narrow-sleeved, with decorative borders at the collar, cuffs, and hem [4], [5]. The colors of round-collared robes were primarily solid hues such as black and white in the early period, but gradually became more varied in later periods [6]. For women's clothing, the early Tang Dynasty saw the popularity of narrow-sleeved short blouses paired with long skirts, with the skirts often featuring high waists and cinched waists to highlight the curves of the female figure [7], [8].

By the mid-Tang Dynasty, with the prosperity of the economy, clothing styles became more elaborate [9]. Men's attire, based on the round-neck robe, began to incorporate more decorative elements, such as intricate patterns embroidered on the collar and cuffs, with the robe's colors becoming more vibrant and eye-catching [10]-[12]. Women's attire placed greater emphasis on the texture of fabrics and the elegance of patterns. Skirt lengths gradually increased, with floor-length skirts becoming fashionable [13], [14]. At this time, it was also popular to tie elaborate belts around the skirts, often adorned with various exquisite accessories such as jade pendants and perfume pouches [15], [16]. In the later Tang Dynasty, clothing styles built upon the opulence of the mid-period while incorporating new elements [17]. Men's clothing featured designs with ethnic minority characteristics, reflecting the trend of ethnic integration at the time [18]. Women's clothing increasingly emphasized comfort and ease, with the popular ensemble of wide-sleeved robes paired with long skirts. The wide sleeves of the robes fluttered in the wind, giving a graceful and ethereal appearance [19], [20]. It is evident that in the new era, the computer analysis of the Tang Dynasty's clothing symbol system and the dynamic evolution of cultural symbols, through the digitalization of Tang Dynasty clothing, can help understand the deeper meanings of cultural symbols, thereby facilitating the modernization of traditional clothing and cultural heritage [21]-[24].

This paper aims to utilize the advantages of knowledge graphs in knowledge system construction and knowledge representation to conduct research on the dynamic evolution of the Tang Dynasty clothing symbol system and cultural symbols. Based on BiLSTM-CRF, a knowledge graph construction method is proposed, combining BiLSTM (bidirectional long short-term memory neural network) with CRF to achieve named entity recognition. The CRF transition matrix is further utilized to obtain the interrelationships between each position label, enabling the BiLSTM-

CRF to retain contextual information while considering both contextual information and the correlations between labels. Word vectors are trained using word2vec, character-level annotations are performed, and the model is trained using the BIOE pattern. During the construction of the Tang Dynasty clothing symbol knowledge graph, to reduce the impact of irrelevant words on the relationship extraction results, a BiLSTM relationship extraction model with a dual-layer attention mechanism was used for relationship extraction. The processed structured data was batch-imported into the Neo4j graph database, and part of the data was visualized. Finally, the evolution and characteristic changes of Tang Dynasty clothing symbols were explored from multiple aspects, including clothing style, color, and openness.

II. Knowledge Graph Construction Methods

Knowledge graphs are powerful tools for integrating information and symbols related to Tang Dynasty clothing culture, and are widely used in research on Tang Dynasty clothing culture. This chapter will propose a knowledge graph construction method based on BiLSTM-CRF named entity recognition, providing a methodological basis for the construction of a knowledge graph of Tang Dynasty clothing symbols and the analysis of the dynamic evolution of cultural symbols in subsequent sections [25].

II. A. Named entity recognition based on BiLSTM-CRF

II. A. 1) CRF

Formally, we use $x=\{x_1,x_2,\cdots,x_n\}$ to represent a general input sequence, where x_i is the input vector of the i th character, $y=\{y_1,y_2,\cdots,y_n\}$. $Y(x)$ denotes the set of all possible label sequences for x. The probabilistic model of Sequence CRF defines a family of conditional probabilities $p(y\mid x;W,b)$ over all possible label sequences y given the input x, with the following form:

$$p(y\mid x;W,b)=\frac{\prod_{i=1}^{n}\psi_i(y_{i-1},y_i,x)}{\sum_{y'\in\Box(x)}\prod_{i=1}^{n}\psi_i(y'_{i-1},y'_i,x)} \tag{1}$$

where $\psi_i(y',y,x)=\exp(W^T_{y',y'}x_i+b_{y',y})$ is the potential function, and $w^T_{y',y'}x_i$ and $b_{y',y}$ correspond to the weight vector and bias of the label pair (y',y), respectively. A commonly used conditional random field is the linear chain conditional random field. When x and y have the same structure, the CRF is referred to as a linear chain CRF.

The parameter form of a linear chain CRF: Let $P(Y\mid X)$ be a linear chain conditional random field. Under the condition that the random variable X takes the value x, the conditional probability that the random variable Y takes the value y has the following form:

$$P(y\mid x)=\frac{1}{Z(x)}\exp\left(\sum_{i,k}\lambda_k t_k(y_{i-1},y_i,x,i)+\sum_{i,l}\mu_l s_l(y_i,x,i)\right) \tag{2}$$

Among them:

$$Z(x)=\sum_{y}\exp\left(\sum_{i,k}\lambda_k t_k(y_{i-1},y_i,x,i)+\sum_{i,l}\mu_l s_l(y_i,x,i)\right) \tag{3}$$

In the equation, t_k and s_l are feature functions, λ_k and μ_l are the corresponding weights, $Z(x)$ is the normalization factor, and the summation is performed over all possible output sequences.

These two feature functions have two expressions:

Transition feature t_k: A feature function defined on the edge, depending on the current node and the previous node, denoted as:

$$t_k(y_{i-1},y_i,x,i),k=1,2,\ldots K \tag{4}$$

Where K is the total number of transition features defined at that node, and i is the position of the current node in the sequence; state feature s_l: a feature function defined at the node, depending on whether the current node has a certain attribute, and independent of other nodes, denoted as:

$$s_l(y_i,x,i),l=1,2,\ldots L \tag{5}$$

where L is the total number of state features defined at the node, and i is the current node's position in the sequence.

Assume there are K_1 transition features and K_2 state features, with $K = K_1 + K_2$. If the feature functions are uniformly represented by a single symbol, denote it as:

$$f_k(y_{i-1}, y_i, x, i) = \begin{cases} t_k(y_{i-1}, y_i, x, i), k = 1, 2, ..., K_1 \\ s_l(y_i x, i), k = K_1 + l; l = 1, 2, ..., K_2 \end{cases} \tag{6}$$

Then, the sum of the features at each position i is:

$$f_k(y, x) = \sum_{i=1}^{n} f_k(y_{i-1}, y_i, x, i), k = 1, 2, ..., K \tag{7}$$

The feature $f_k(y, x)$ is represented by the weight w_k, that is:

$$w_k = \begin{cases} \lambda_k, k = 1, 2, ..., K_1 \\ \mu_l, k = K_1 + l; l = 1, 2, ..., K_2 \end{cases} \tag{8}$$

Equations (2) and (3) can be expressed as:

$$P(y \mid x) = \frac{1}{Z(x)} \exp \sum_{k=1}^{K} w_k f_k(y, x) \tag{9}$$

$$Z(x) = \sum_{y} \exp \sum_{k=1}^{K} w_k f_k(y, x) \tag{10}$$

If we define an $m \times m$ matrix M (m is the number of values of the label y_i):

$$M_i(x) = [M_i(y_{i-1}, y_i \mid x)] \tag{11}$$

$$M_i(y_{i-1}, y_i \mid x) = \exp(W_i(y_{i-1}, y_i \mid x)) \tag{12}$$

$$W_i(y_{i-1}, y_i \mid x) = \sum_{k=1}^{K} w_k f_k(y_{i-1}, y_i x, i) \tag{13}$$

Introduce the start and end state labels $y_0 = start, y_{n+1} = stop$. Let $P_w(y \mid x)$ denote the conditional probability of the observation sequence x given the label sequence y. Then:

$$P_w(y \mid x) = \frac{1}{Z_w(x)} \prod_{i=1}^{n+1} M_i(y_{i-1}, y_i \mid x) \tag{14}$$

Among them, $Z_w(x)$ is the normalization factor:

$$Z_w(x) = (M_1(x) M_2(x) \cdots M_{n+1}(x))_{start,stop} \tag{15}$$

1) Probability calculation problem

By definition, the parameters that our trained CRF model aims to determine are the weights λ_k and μ_l. The parameter values obtained through training with the given data determine the entire model. However, we need to verify that the trained model is valid. Therefore, we calculate the expected value of the CRF model and the expected value of the sample. If they are equal or close, it indicates that the trained model is valid; otherwise, it is invalid. The conditional probability (2) of CRF and the corresponding mathematical expectation are calculated using the forward-backward algorithm. The forward vector is defined as $\alpha_i(x)$:

$$\alpha_0(y \mid x) = \begin{cases} 1, y = start \\ 0, \text{Otherwise} \end{cases} \tag{16}$$

Assume that the label at position i is y_i, and y_i can take m values, then:

$$\alpha_i^T(y_i \mid x) = \alpha_{i-1}^T(y_{i-1} \mid x) M_i(y_{i-1}, y_i \mid x), i = 1, 2, \cdots, n+1 \tag{17}$$

Therefore, $\alpha_i(x)$ is an m-dimensional column vector, and equation (17) can be expressed as:

$$\alpha_i^T(x) = \alpha_{i-1}^T(x) M_i(x) \tag{18}$$

Similarly, the backward vector is defined as $\beta_i(x)$:

$$\beta_{n+1}(y_{n+1} \mid x) = \begin{cases} 1, y_{n+1} = stop \\ 0, \text{Otherwise} \end{cases} \tag{19}$$

$$\beta_i(y_i \mid x) = M_{i+1}(y_i, y_{i+1} \mid x) \beta_{i+1}(y_{i+1} \mid x) \tag{20}$$

Equation (20) can also be expressed as:

$$\beta_i(x) = M_{i+1}(x) \beta_{i+1}(x) \tag{21}$$

Therefore, based on the definition of forward-backward vectors, we can obtain the conditional probability:

$$P(Y_i = y_i \mid x) = \frac{\alpha_i^T(y_i \mid x) \beta_i(y_i \mid x)}{Z(x)} \tag{22}$$

$$P(Y_{i-1} = y_{i-1}, Y_i = y_i \mid x) = \frac{\alpha_{i-1}^T(y_{i-1} \mid x) M_i(y_{i-1}, y_i \mid x) \beta_i(y_i \mid x)}{Z(x)} \tag{23}$$

The expected value of the feature function f_k with respect to the conditional distribution $P(Y \mid X)$ is:

$$\begin{aligned} &E_{P(Y|X)}[f_k] = \sum_y P(y \mid x) f_k(y, x) \\ &= \sum_{i=1}^{n+1} \sum_{y_{i-1} y_i} f_k(y_{i-1}, y_i, x, i) \frac{\alpha_{i-1}^T(y_{i-1} \mid x) M_i(y_{i-1}, y_i \mid x) \beta_i(y_i \mid x)}{Z(x)} \\ &k = 1, 2, \cdots, K \end{aligned} \tag{24}$$

Among them, the experience distribution is $T(x)$, and the expectation of the characteristic function f_k with respect to the conditional distribution $P(X, Y)$ is:

$$\begin{aligned} &E_{P(X,Y)}[f_k] = \sum_{x,y} P(x, y) \sum_{i=1}^{n+1} f_k(y_{i-1}, y_i, x, i) \\ &= \sum_x T(x) \sum_y P(y \mid x) \sum_{i=1}^{n+1} f_k(y_{i-1}, y_i, x, i) \\ &= \sum_x T(x) \sum_{i=1}^{n+1} \sum_{y_{i-1} y_i} f_k(y_{i-1}, y_i, x, i) \frac{\alpha_{i-1}^T(y_{i-1} \mid x) M_i(y_{i-1}, y_i \mid x) \beta_i(y_i \mid x)}{Z(x)} \end{aligned} \tag{25}$$

$$Z(x) = \alpha_n^T(x) \cdot 1 = 1^T \cdot \beta_1(x) \tag{26}$$

Using forward-backward vectors, the probability and expectation of a linear chain CRF can be calculated.

2) Learning Algorithm

Training the parameters of the CRF model is the learning problem of CRF. The learning method is generally maximum likelihood estimation. In this paper, SGD (stochastic gradient descent) is used to train the CRF parameters [26]. The following is the gradient descent method:

Assuming that the objective function is a convex function $f(x)$, to obtain the global optimum, it should be expressed as:

$$\min f(x) \tag{27}$$

In a multivariate context, the gradient $\nabla f(x)$ of $f(x)$ at a point x_k is a vector composed of the partial derivatives of the components of this fixed point. The direction of the gradient is the direction in which the function rises most rapidly at a given point, so the opposite direction of the gradient is the direction in which the function descends most rapidly at a given point.

To solve (27), choose any initial point x_0 and descend along the negative gradient direction:

$$\nabla^{(0)} = -\nabla f(x_0) \tag{28}$$

Among them, $\nabla^{(0)}$ is the search direction of point x_0. This iteration is performed k times, and the length of each step is called the stride ρ_k, defined as:

$$x_{k+1} = x_k + \rho_k \nabla^{(k)} \tag{29}$$

Starting from x_k, move along $\nabla^{(k)}$ by one step to obtain the point x_{k+1}. At this point:

$$f(x_{k+1}) = f(x_k + \rho_k \nabla^{(k)}) \tag{30}$$

All points form a sequence $x_0, x_1, x_2, \cdots, x_k, x_{k+1}, \cdots$, which converges to a point x^* under certain conditions, where $f(x)$ achieves its minimum value.

Based on the CRF model given by formulas (9) and (10), its log-likelihood function is:

$$\begin{aligned} L(w) = L_T(P_w) &= \log \prod_{x,y} P_w(y \mid x)^{T(x,y)} = \sum_{x,y} T(x,y) \log P_w(y \mid x) \\ &= \sum_{x,y} [T(x,y) \sum_{k=1}^{K} w_k f_k(y,x) - T(x,y) \log Z_w(x)] \\ &= \sum_{j=1}^{N} \sum_{k=1}^{K} w_k f_k(y_j, x_j) - \sum_{j=1}^{N} \log Z_w(x_j) \end{aligned} \tag{31}$$

Our objective is to find a set of optimal parameters that maximize the conditional probability, i.e., maximize (31). Taking the negative of this is our objective function, which is converted into a minimization problem and optimized using SGD to find the approximate optimal parameters.

3) Prediction Algorithm

The prediction problem for CRF is to find the output sequence (label sequence) y^* with the maximum conditional probability given the conditional random field $P(Y \mid X)$ and the input sequence (observation sequence) x, i.e., to label the observation sequence. The well-known prediction algorithm is the Viterbi algorithm.

The Viterbi algorithm for CRF prediction is as follows:

Let w denote the weight vector, i.e.:

$$w = (w_1, w_2, \cdots, w_K)^T \tag{32}$$

Define the global feature vector $F(y,x)$, that is:

$$F(y,x) = (f_1(y,x), f_2(y,x), \cdots, f_K(y,x))^T \tag{33}$$

CRF(32) and (33) can be written in the form of an inner product:

$$P_w(y \mid x) = \frac{\exp(w \cdot F(y,x))}{Z_w(x)} \tag{34}$$

Among them:

$$\delta_1(j) = w \cdot F_1(y_0 = start, y_1 = j, x), j = 1, 2, \cdots, m \tag{35}$$

Input feature vector $F(y,x)$, weight vector w, observation sequence $x = (x_1, x_2, \cdots, x_n)$; the objective is to output the optimal path $y^* = (y_1^*, y_2^*, \cdots, y_n^*)$:

(1) Initialization:

$$\delta_1(j) = w \cdot F_1(y_0 = start, y_1 = j, x), j = 1, 2, \cdots, m \tag{36}$$

(2) Recursively:

$$\delta_i(l) = \max_{1 \le j \le m} \{\delta_{i-1}(j) + w \cdot F_i(y_{i-1} = j, y_i = l, x)\}, l = 1, 2, \cdots, m \tag{37}$$

$$\Psi_i(l) = \arg\max_{1 \le j \le m} \{\delta_{i-1}(j) + w \cdot F_i(y_{i-1} = j, y_i = l, x)\}, l = 1, 2, \cdots, m \tag{38}$$

(3) Termination:

$$\max_y (w \cdot F(y,x)) = \max_{1 \le j \le m} \delta_n(j) \tag{39}$$

$$y_n^* = \arg\max_{1 \le j \le m} \delta_n(j) \tag{40}$$

(4) Return path:

$$y_i^* = \Psi_{i+1}(y_{i+1}^*), i = n-1, n-2, \cdots, 1 \tag{41}$$

Find the optimal path $y^* = (y_1^*, y_2^*, \cdots, y_n^*)$.

II. A. 2) BiLSTM-CRF

The BiLSTM outputs separate label scores for each word in a sentence, retaining contextual information. CRF also considers the mutual relationship between the current position and the label of the previous position. Therefore, adding a CRF layer on top of the BiLSTM structure layer can effectively avoid many label output errors.

First, the word vectors obtained through random initialization are converted into BiLSTM inputs using the word2vec tool, yielding embeddings for each character. The forward LSTM and backward LSTM respectively model the sentence to obtain context information from both preceding and following positions. This context information is then concatenated and passed through a softmax layer to generate individual scores for each character. The softmax function maps inputs to real numbers between 0 and 1, with a sum of 1, satisfying the property that the sum of probabilities equals 1:

$$soft\max(x)_i = \frac{\exp(x_i)}{\sum_{j=1}^{n} \exp(x_j)} \tag{42}$$

Contextual information is used as input to calculate the score for the entire sentence through the CRF layer transition matrix. The final sequence label score is composed of the character label score and the CRF label score, and the annotation sequence with the highest score is used as the final prediction result.

II. B. Relationship and Attribute Extraction

In the process of constructing a knowledge graph, it is necessary to extract the relationships between entities and between entities and attributes in the data information, including the relationships between different entities and the attribute information of entities. A rule-based relationship extraction method is used to achieve the above requirements. The specific implementation process is as follows:

1) Manually observe the entities in the data information, manually extract entities that may have relationships, and construct a relationship set in the form of a dictionary based on relevant knowledge in the field of network security.

2) Use inference rules to infer potential relationships that may exist along the connection paths between two entities, thereby establishing new relationships and attributes.

3) Store the extracted and newly constructed relationships and attribute information in a graph database using py2neo to expand the knowledge graph.

II. C. Experimental Results and Analysis

The experiment was conducted in an environment equipped with Windows 11, a Tesla V100 32GB graphics card, and Python 3.9. This paper employs a web crawling algorithm to extract data from web pages related to Tang Dynasty clothing culture on the internet, creating a self-built dataset containing 1,681 examples of Tang Dynasty clothing culture data, which serves as the experimental data source.

To more intuitively demonstrate the advantages of the knowledge graph construction method proposed in this paper, we compared the recall, precision, and F1 scores of different named entity recognition methods under the same experimental environment. The experimental results are detailed in Table 1. As can be seen, the recall rate, accuracy rate, and F1 score of the BiLSTM-CRF model proposed in this paper reached 92%, 94%, and 94%, respectively, making it the best-performing model among all models and more suitable for entity relationship extraction tasks.

Table 1: Comparison of evaluation indicators

Model	Precision	Recall	F1
RNN	0.43	0.57	0.18
LSTM	0.33	0.59	0.53

BiLSTM	0.62	0.64	0.65
BERT	0.86	0.92	0.58
RNN-CRF	0.76	0.71	0.72
LSTM-CRF	0.77	0.81	0.83
BiLSTM-CRF	0.92	0.94	0.94

Relational extraction was performed on nine different types of relationships, including collar types and pattern designs, in Tang Dynasty clothing. The experimental results are shown in Table 2. As can be seen from the table, the average accuracy rate, recall rate, and F1 value of the relationships obtained using the method described in this paper are all relatively high, reaching 82.22%, 81.04%, and 82.2%, respectively, playing a positive role in relational classification work.

Table 2: Eexperimental results of each relationship category

Relationship	Precision (%)	Recall (%)	F1 (%)
Material	83.14	83.48	83.49
Style	85.46	78.14	79.1
Collar type	87.37	76.17	76.66
Identity class	80	80.81	88.92
Patterns	80.96	88.96	89.22
Type of cuffs	81.02	80.29	80.81
Color	79.82	78.16	78.78
Uses	80.96	80.79	80.86
Pairing	81.24	82.55	81.94
Average	82.22	81.04	82.2

III. Construction of a Corpus of Tang Dynasty Clothing Symbols

The main sources of Tang Dynasty clothing data include published books and CNKI literature, all of which are unstructured. The purpose of this chapter is to construct a corpus of Tang Dynasty clothing entities and relationships, laying the foundation for the subsequent construction of a Tang Dynasty clothing symbol knowledge map.

III. A. Corpus Sources

The distribution of the corpus data sources is shown in Figure 1. The majority of the texts on Tang Dynasty clothing in published journals and CNKI literature are unstructured. The corpus of this paper comes from records on Tang Dynasty clothing in several publications in the special collection of the Xi'an University of Engineering Library, such as “A Comprehensive History of Chinese Clothing,” “Chinese Clothing Art Through the Ages,” and “Clothing in China,” as well as documents related to Tang Dynasty clothing culture in CNKI journals, master's theses, and doctoral dissertations from the past decade (2015-2025). Among these, CNKI literature includes 51 journal articles, 16 master's theses, 8 doctoral dissertations, and references to 26 published journals.

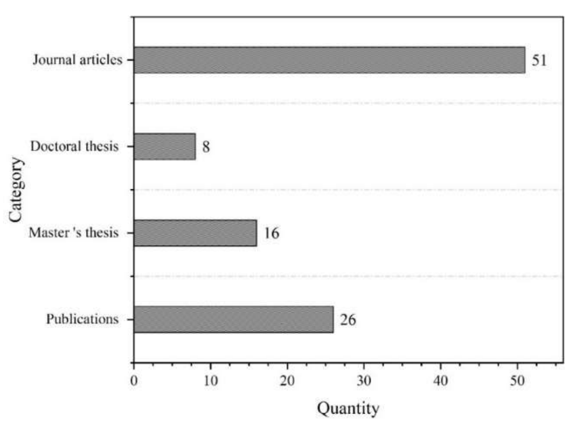

Figure 1: The distribution of corpus sources

III. B. Construction of Entities and Relationships Between Entities

Based on Tang Dynasty clothing literature and characteristics of the field, this paper refers to representative literature (A General History of Chinese Clothing, Chinese Clothing Art Through the Ages, and Clothing in China) and uses a top-down approach to construct the ontology of Tang Dynasty clothing, as shown in Figure 2. A total of 16 ontologies were constructed, including two second-level ontologies, namely ceremonial clothing and everyday clothing. Each of the two second-level ontologies contains eight third-level ontologies: accessories, headwear, footwear, lower body, wearing occasions, components, social status, and upper garments. Among the eight third-level ontologies, wearing occasions and social status are directly instantiated. The remaining third-level ontologies contain different sub-ontologies based on their characteristics. Accessories and headwear, footwear and components each have three fourth-level ontologies: color, pattern, and material. Upper garments have six sub-entities: color, pattern, material, collar, cuff, and style. Lower garments have four sub-entities: color, pattern, style, and material.

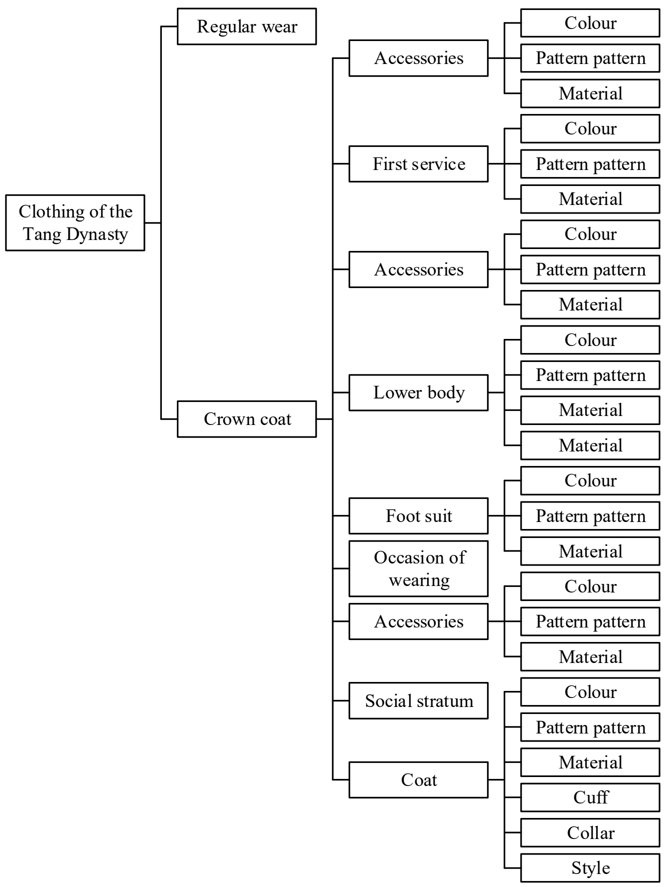

Figure 2: Tang Dynasty clothing ontology construction

After constructing the ontology structure of Tang Dynasty clothing, we can annotate concrete instances based on the ontology and construct and annotate relationships. The results of the relationship construction are shown in Table 3. This paper constructed ten relationships, including “upper garment—cuff” and “upper garment—neckline.” Among them, there are also unrecognizable unknown relationships, which are marked as no relationship in this paper.

Table 3: Relationship between ontology

Type of relationship	Relationship value
Secondary body - Accessories	Pairing
Secondary body - Accessories	Pairing
Secondary body-first clothing	Pairing
Secondary ontology - lower body	Pairing
Secondary body-coat	Pairing

Secondary body - footwear	Pairing
Secondary body-first clothing	Pairing
Second level body - wearing occasion	Uses
Secondary ontology-identity class	Identity class
Three-level ontology (except for wearing occasion and identity class) -color	Color
The third level of body (except for wearing occasion, identity class) - pattern pattern	Patterns
Three level ontology (except for wearing occasion, identity class) - material	Material
Three-level ontology (except for wearing occasion, identity class) - style	Style
Blouse - cuffs	Type of cuffs
Blouse - neckline	Collar type
Does not constitute a relationship	Unknow relationship

III. C. Relationship annotation

This paper annotates the relationships between entities in the corpus. The annotation method combines machine annotation with human review. Machine annotation cannot guarantee accuracy in complex semantic contexts, so human annotation remains indispensable as a means of correction. This paper first uses machine annotation and then performs human correction based on the machine annotation. Combined with human correction, the number of annotated relationship types is shown in Table 4. A total of 10 types of relationships were annotated, with a total of 10,585 entries.

Table 4: Number of relationship types

Type of relationship	Quantity
Material	1947
Pairing	745
Style	305
Collar type	561
Identity class	238
Patterns	1383
Type of cuffs	362
Color	1765
Uses	292
Unknow	2987
Total	10585

IV. Construction of a Knowledge Map of Tang Dynasty Clothing Symbols

Based on the Tang Dynasty clothing symbol corpus constructed in the previous chapter, this chapter will use the knowledge graph construction method proposed in this paper, which is based on BiLSTM-CRF named entity recognition, to build a knowledge graph of Tang Dynasty clothing symbols.

IV. A. Knowledge extraction of clothing cultural symbols

This paper divides the knowledge extraction of unstructured data on clothing cultural symbols into two steps: first, using the BiLSTM+CRF model for entity recognition; second, using a model that combines BiLSTM with a double-layer attention mechanism for relationship extraction. The following is an introduction to the entity recognition process and relationship extraction process for unstructured Tang Dynasty clothing cultural data.

IV. A. 1) Entity Recognition

Entity recognition is an indispensable step in constructing a knowledge graph of Tang Dynasty clothing culture. In the field of Chinese named entity recognition, the identification of personal names, place names, and organization names has achieved satisfactory results. However, in the field of Tang Dynasty clothing, the textual data in this domain contains a large number of specialized terms related to craftsmanship and processes. Conventional named entity recognition models and tools are no longer sufficient to meet the needs of the Tang Dynasty clothing domain. Therefore, this section addresses the characteristics of Tang Dynasty clothing domain data by establishing a Tang Dynasty clothing domain dictionary. The dictionary is used to perform BIO annotation on the original text, and finally, the BiLSTM-CRF model is employed for entity recognition.

1) Creating the dictionary

When constructing the ontology, we have already enumerated the terms in the field of Tang Dynasty clothing. Based on this, we have created a dictionary for the field of Tang Dynasty clothing through manual selection and error correction. The dictionary includes Tang Dynasty clothing names, Tang Dynasty settlement names, Tang Dynasty clothing craft names, Tang Dynasty clothing patterns, ethnic beliefs, etc. The dictionary follows the custom dictionary format requirements, with one word and one annotation per line, separated by spaces.

2) BIO sequence annotation

This paper uses a Python program to load the custom Tang Dynasty clothing culture dictionary and perform BIO annotation on the original text. The BIO tag types are divided into seven categories: place names "LOC," organizations (including ethnic group names) "ORG," time "DATE," skills "TECH," clothing "ClOTHES," patterns "PATTERN," and beliefs "REL."

3) Entity Recognition

Entity recognition employs the BiLSTM-CRF model. The model consists of an input layer, a BiLSTM layer, an output layer, and a CRF layer.

The specific process of entity recognition is as follows:

Since BiLSTM cannot directly process text data, the characters in a sentence must be converted into vectors. In this experiment, the pre-trained Word2Vec model is first used to convert the One-Hot vectors representing characters in a sentence into low-dimensional continuous character vectors using formula (43):

$$x_i = w^{word} v^i \tag{43}$$

Among them, x_i is the vector representation of a character; $W^{word} \in R^{d^w \times |m|}$ represents the text word vector matrix, where m denotes the number of words in a sentence, d^w denotes the dimension of the word vector, and v^i is the One-Hot representation of a word.

Let the word vector representation of the sentence be $x(x_1, x_2, x_3, ..., x_i)$; the word vectors are input into the BiLSTM layer. The BiLSTM layer extracts feature values and learns the mapping between feature values and labels to obtain the probability P_i of the character sequence x_i corresponding to any label. The output layer outputs the label sequence $x(x_1, x_2, x_3, ..., x_i)$ to the corresponding label sequence $y(y_1, y_2, y_3, ..., y_i)$. However, the label sequence may not comply with the BIO annotation rules at this point, so a CRF layer is needed to adjust the sequence to obtain a valid label sequence:

$$s(x, y) = \sum_{n=1}^{i} (M_{y_n, y_{n+1}} + P_{n, y_n}) \tag{44}$$

where M is the transition matrix, and $M_{y_n y_{n+1}}$ represents the probability of each element's label transitioning from y_n to y_{n+1}. P_n, y_n represents the score of the y_n label corresponding to the n th character.

Then, the softmax normalization is used to map the probability of the x sequence to the label sequence y, yielding the predicted classification $S(x, y)$, with the calculation formula shown in (45):

$$p(y \mid x) = \frac{\exp(s(x, y))}{\sum y' \exp(s(x, y'))} \tag{45}$$

Finally, use formula (46) to obtain the optimal set of legal sequences in the predicted classification.

$$y^* = \operatorname{argmax} y' s(x, y') \tag{46}$$

IV. A. 2) Relationship Extraction

In the previous section, we performed entity recognition on the symbolic information resources of Tang Dynasty clothing. Entity recognition merely identified entities within the field of Tang Dynasty clothing culture. To further obtain the relationships between entities, relationship extraction is required.

The entire workflow of relationship extraction is as follows: first, the characters in a sentence and the relative positions of each character to the two entities are represented as vectors. The character vectors and position vectors are then input into a BiLSTM to extract feature vectors. Next, character-level attention mechanisms and sentence-level attention mechanisms are introduced to fully capture semantic changes in the text while reducing text noise. Finally, a softmax classifier is used to obtain the relationship classification results [27].

The following sections will briefly explain the working principles and processes of each layer.

1) Embedding layer

Similar to the entity recognition input layer, the embedding layer uses the Word2Vec method to represent character vectors. That is, all characters w in a sentence S are converted into vectors. Word2Vec converts the word w_i into a vector x_i using formula (47),

$$x_i = w^{word} v^i \tag{47}$$

In order to fully obtain the semantic information of a sentence, this paper considers that the closer a character is to an entity, the greater its influence on semantic information. Therefore, this paper vectorizes the relative position of each character in a sentence to two entities as w_i^q and w_i^b.

The two position vectors are concatenated with the character vector, and the final expression form of a character vector is:

$$e_i = (x_i, w_i^q, w_i^b) \tag{48}$$

2) Network layer

After generating word vectors e_i, input e_i into BiLSTM to extract feature values, then output feature vectors $h_i = [\vec{h}_i + \overline{h}_i], i\grave{o}[0,T]$, where T is the length of the sentence. Finally, different weights are assigned to each character in the sentence, i.e., a character-level attention mechanism is added to fully capture the semantic information of the sentence. The process is as follows:

$$u_i = \tanh(h_i) \tag{49}$$

$$\alpha_i = softmax(\omega^T u_i) \tag{50}$$

Among them, ω is the parameter vector for training and learning.

After adding character-level attention, the weighted sum of the weighted character vectors is calculated to generate the sentence vector s_i. The sentence vector s_i can be expressed as:

$$s_i = \sum_i \alpha_i h_i \tag{51}$$

In real-world relation extraction tasks, sometimes a pair of entities corresponds to multiple sentences. To reduce the impact of noisy sentences on entity relation prediction, this paper uses multi-instance learning to calculate the relevance degree of all sentences containing the same entity pair and predict the relationship, thereby assigning higher weights to sentences with higher relevance degrees,

i.e., introducing sentence-level attention.

The process of introducing the sentence-level attention mechanism can be represented as:

$$\beta_i = softmax(s_i Ar) \tag{52}$$

$$u = \sum_i \beta_i s_i \tag{53}$$

Formula (52) is used to calculate the relevance of sentence s_i to relation r, where β_i is the weight of the prediction for each sentence pair corresponding to the same entity pair. Here, A is a weighted diagonal matrix, and r is the vectorized representation of the sentence-corresponding relation.

3) Classification Layer

Relation extraction is essentially a multi-class classification problem. This paper uses a softmax classifier to obtain the probabilities of all relations:

$$p(y_i) = \mathrm{softmax}(w_c u + b_c) \tag{54}$$

$$J(\theta) = -\frac{1}{n}\sum_{i=1}^{n} \log p(y_i) + \lambda \|\theta\|_F^2 \tag{55}$$

Among them, w_c and b_c are parameters, $J(\theta)$ is the loss function, n is the number of relationship categories, $p(y_i)$ is the probability of each relationship category calculated by the softmax function, and λ is the parameter of L2 regularization.

IV. B. Knowledge Graph Visualization

Based on the scale of data collected in the field of ethnic minority clothing culture and its application characteristics, this paper selects Neo4j graph database as the triplet storage database for the ethnic minority clothing culture knowledge graph. Compared to RDF, RDFS, and OWL knowledge graph storage files, Neo4j offers a user-friendly interface and high visualization capabilities. In terms of data processing, Neo4j is no less capable than other graph databases, with very fast read/write speeds and the ability to quickly retrieve complex hierarchical data structures. Additionally, Neo4j provides the Cypher query language, which is similar to SQL and easy to learn.

Partial visualization results of the Tang Dynasty clothing cultural symbol knowledge graph are shown in Figure 3. The graph contains 8 major entity categories, 7 major relationship categories, 9 major attribute categories, and descriptive text, totaling 12,895 data entries, with 3,491 entity nodes.

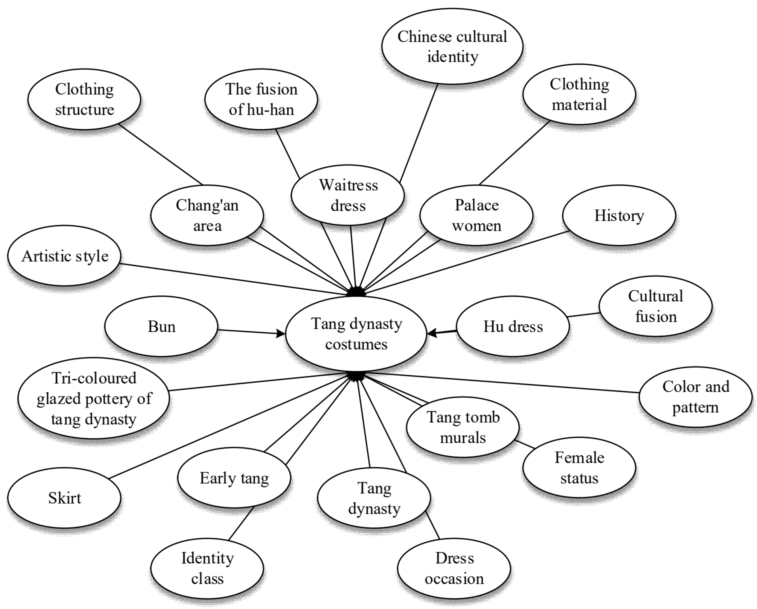

Figure 3: Partial visualization of knowledge graph

V. Analysis of the Evolution of Tang Dynasty Clothing Culture Symbols Based on Knowledge Graphs

This paper utilizes a knowledge graph construction method based on BiLSTM-CRF named entity recognition to construct a knowledge graph of Tang Dynasty clothing symbols, laying a foundational groundwork for the analysis of the evolution of Tang Dynasty clothing symbols in this chapter and enhancing the scientific rigor of the research content. This chapter will use the constructed Tang Dynasty clothing symbol knowledge graph as a foundation to reveal the evolution and characteristic changes of Tang Dynasty clothing symbols from multiple aspects, including clothing style, color, and openness.

V. A. Clothing Style Analysis

The style of clothing essentially describes the state and attributes of objects and people. This paper conducts a comprehensive study on the terms used to describe or modify Tang Dynasty clothing nouns or pronouns in the Tang Dynasty clothing symbol knowledge graph. The specific characteristics of Tang Dynasty clothing styles are shown in Table 5. As can be seen, the most frequently occurring clothing style terms in the knowledge graph corpus are “lavish,” “prosperous,” and “free,” with frequencies of 242, 205, and 183, respectively, and corresponding weights of 22.22, 18.34, and 24.86. Other clothing style terms such as “bold,” “plump,” “graceful,” “confident,” “rich,” and “full-bodied” also exhibit notable word frequency and weight performance.

Table 5: The style characteristics of Tang Dynasty costumes

Vocabulary	Weight	Word frequency statistics	Vocabulary	Weight	Word frequency statistics
Gorgeous	22.22	242	Fatty	14.01	115
Prosperity	18.34	205	Loose	13.82	110
Freedom	24.86	183	Developed	8.56	107
Bold	15.91	159	Beautiful	11.01	96
Rich	16.67	142	Elegant	11.42	93
Fullness	18.28	140	Beautiful	12.68	91

Wide	15.58	129	Hua Gui	11.6	80
Confidence	13.35	121	Yongrong	4.94	49
Huamei	8.64	85	Heyday	4.16	41
Brilliant	9.3	63	Slender	3.44	29
Bustling	11.55	60	Different	2.06	27
Elegant	10.12	44	Short short	2.73	24

To gain a clearer understanding of the stylistic characteristics of Tang Dynasty clothing, this study categorized a portion of the clothing style vocabulary from the knowledge graph corpus into six major categories: characteristics, nature, condition, quality, perception, and appearance. The results are shown in Table 6. As shown in the table, the overall objective style impressions of Tang Dynasty clothing are described as luxurious, graceful, and elegant. The shape, volume, appearance, color, or tactile qualities of the fabric are often described as full-bodied, lightweight, and vibrant. The talent and taste displayed by the people of the Tang Dynasty through their clothing are characterized as graceful, free, and bold. The style of Tang Dynasty clothing reflects the societal backdrop of the era and the prevailing emotional aspirations of the people, which were centered on prosperity and the pursuit of a better life.

Table 6: Clothing style of Tang Dynasty

Category	Synonym
Traits	Gorgeous, rich, beautiful, sexy, elegant, brilliant, brilliant, bright
Properties	Luxurious, noble, wealthy
Morphology	Full, plump, rich, fat, narrow, light and thin
Consciousness	Colorful, bright
Talents	Grace, freedom, self-confidence, boldness, romance
Situation	Developed, beautiful, good.

V. B. Clothing Color Analysis

This section will analyze the structured data of Tang Dynasty clothing images extracted from the Tang Dynasty clothing symbol knowledge graph. The K-means clustering algorithm is used to integrate the RGB values of color nodes in Tang Dynasty clothing images with their secondary node degrees. To reduce color influence between nodes and improve node accuracy, the data is limited to a maximum range of [0,1]. Simultaneously, the length values of adjacent edge pixels between color pixels are measured. To enhance the precision of the measured color pixels and avoid mutual influence between dimensions, the data range is constrained to [0,1]. Based on this data, the thickness of the connections is determined, and the connection relationships between nodes are established, thereby constructing the Tang Dynasty clothing color foundation network, as shown in Figure 4. The historical book "Zhou Li" records, "The painting of achievements involves five colors." This is the earliest record of the "five colors" theory in China, and this far-reaching concept is the basis for the formation of traditional Chinese color concepts. The Book of History also records: "The colors are blue, yellow, red, white, and black, which are applied to silk and cloth." It can be clearly seen from the figure that the colors of Tang Dynasty clothing were deeply influenced by the "five colors" theory, with the colors of clothing mainly concentrated in red, black, and yellow, which embody the color concept that has been passed down in traditional Chinese art and culture.

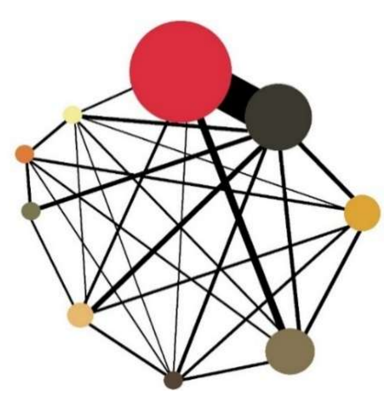

Figure 4: A basic netw ork model of clothingpattern color in the Tang Dynasty

V. C. Clothing Openness Analysis

The degree of openness in clothing is closely tied to the social environment and cultural trends of different dynasties, and the openness of clothing is closely related to its silhouette and level of exposure. Based on the mainstream view in historical studies, the Tang Dynasty is divided into three periods: the Early Tang, the High Tang, and the Late Tang. Combining the structured data of Tang Dynasty clothing images extracted from the Tang Dynasty clothing symbol atlas, an analysis of the fit and exposure levels of Tang Dynasty clothing silhouettes was conducted. The evolution of the fit and exposure levels of Tang Dynasty clothing silhouettes is shown in Figure 5. In the figure, P1 to P3 correspond to the Early Tang, High Tang, and Late Tang periods, respectively. As shown in the figure, from the Early Tang to the High Tang period, the fit and exposure of Tang Dynasty clothing showed a significant increase, reaching their peak during the High Tang period. However, during the Late Tang period, the fit and exposure of Tang Dynasty clothing exhibited a declining trend. During the Early Tang Dynasty, the Tang Dynasty was newly established and still deeply influenced by the Confucian rituals of the Southern and Northern Dynasties. Women's clothing retained the narrow-sleeved robes of the Sui Dynasty, while men's clothing continued the round-collared robes of the previous dynasty. Overall, the clothing remained relatively conservative and less open. However, with the prosperity of the economy during the High Tang Dynasty and the prevalence of foreign influences brought by the Silk Road, Persian merchants engaged in trade introduced clothing styles such as collared robes and front-opening robes. Off-the-shoulder robes became widespread among women, and the trend of women wearing men's clothing became popular. During the late Tang Dynasty, social unrest caused by crises such as the An Lushan Rebellion led to a strengthening of social moral constraints, and clothing became less open. Women's clothing featured higher necklines and wide sleeves, while men no longer exposed their chests and breasts, and clothing sleeves and necklines became tighter. The evolution of clothing openness in the Tang Dynasty was closely tied to the prosperity of the Tang Dynasty, and it was also a dynamic expression of the mutual restraint and balance between foreign cultures, marked by “Hu Feng,” and the indigenous culture of Central China.

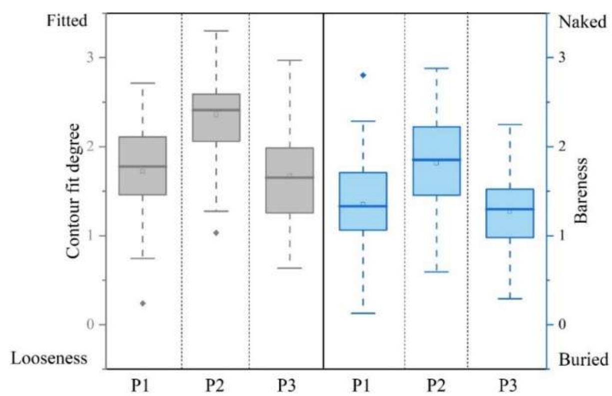

Figure 5: Openness of Tang Dynasty costumes

VI. Conclusion

This paper proposes a knowledge graph construction method based on BiLSTM-CRF named entity recognition, and builds a knowledge graph of Tang Dynasty clothing symbols based on the Tang Dynasty clothing symbol corpus. To verify the advantages of the knowledge graph construction method proposed in this paper, experiments were conducted and compared with other methods in terms of recall, accuracy, and F1 score. The recall rate, accuracy rate, and F1 value of the BiLSTM-CRF named entity recognition method used in this paper reached 92%, 94%, and 94%, respectively, all of which were superior to other methods. In the relationship extraction work of different relationship types, the average accuracy rate, recall rate, and F1 value of the method used in this paper reached 82.22%, 81.04%, and 82.2%, respectively, showing obvious advantages. The evolution and characteristics of Tang Dynasty clothing cultural symbols were analyzed from multiple aspects, including clothing style, color, and openness. In terms of clothing style, the most frequently occurring style terms in the knowledge graph corpus were “lavish,” “prosperous,” and “free,” with corresponding frequencies of 242, 205, and 183, and weights of 22.22, 19.34, and 24.86, respectively. Other clothing style terms such as “plump,” “graceful,” and “confident” also exhibit notable word frequency and weight performance. Based on the clustering results of some Tang Dynasty clothing style terms, it can be concluded that the overall style of Tang Dynasty clothing is characterized by opulence, elegance, and grandeur. The visual impressions of Tang Dynasty clothing in terms of color and volume include fullness, lightness, and vibrancy, while the artistic flair and taste reflected in the clothing are characterized by gracefulness, freedom, and boldness. Based on the structured image data of Tang Dynasty clothing in the knowledge graph, a color foundation network for Tang Dynasty clothing was constructed. It was found that the colors of Tang Dynasty clothing were deeply influenced by the “Five Colors Theory,” with colors primarily concentrated on red, black, and yellow. The openness of Tang Dynasty clothing evolved with the prosperity of the Tang Dynasty. From the early Tang to the prosperous Tang period, the fit and exposure of clothing increased, while the openness of clothing decreased in the late Tang period.

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