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Research on Semantic Network Modeling and Analysis of folk music cultural symbols

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SUMMARY: *The symbols of folk music culture are scattered in audio, lyrics, instrument images, performance scenes and field archives, and it is difficult to realize unified correlation analysis in traditional research. In order to solve the problem, this paper proposes a semantic network modeling method for folk music culture symbols. With the support of computer technology, this paper constructs an analysis framework combining multi-source data feature extraction, semantic relationship calculation, graph calculation optimization and parameter adaptive adjustment, maps heterogeneous cultural information into a unified representation space, and completes symbol node recognition, relationship edge construction and network structure optimization. Based on 4860 multimodal samples, 11372 cultural symbol items and 16894 groups of symbol relations were formed, and the model was systematically verified. The results show that the accuracy of the proposed method in the semantic network task reaches 91.8%, the F1 value of relation recognition reaches 89.6%, and the RMSE of link prediction is reduced to 0.137. The overall performance of the proposed method is better than that of the fixed threshold co-occurrence network, the GCN semantic graph model and the standard GAT model. Under the conditions of small sample size, noise disturbance and cross-region transfer, the model still maintains a relatively stable recognition ability and structural fidelity. The research shows that the introduction of knowledge graph, semantic computing and graph learning methods into the analysis of ethnic music cultural symbols can not only improve the accuracy of cultural relationship recognition, but also help to promote the digital organization, semantic retrieval and structural interpretation of ethnic music resources.*

KEYWORDS: *folk music; Cultural symbol; Semantic network; Graph computation*

1 Introduction

Under the background of deepening digital humanities research, folk music is no longer only regarded as an artistic presentation object of sound form, but gradually enters the research field of computable analysis, structured expression and correlation mining. In particular, with the continuous accumulation of data such as folk music recording materials, musical score texts, instrument images, fieldwork records, performance scene descriptions and intangible cultural heritage archives, conditions for systematic modeling around folk music cultural symbols are being formed [1]. Different from traditional musicology research, which mostly relies on manual discrimination, experience induction and case interpretation, current research is faced with multi-source cultural data with complex sources, heterogeneous forms and interleaved semantic levels, and it is difficult to effectively reveal the deep connections and evolution rules between cultural symbols of folk music by only using single-text close reading or static

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classification methods [2]. How to realize the semantic recognition, relationship organization and network analysis of cultural symbols with the help of computer technology has become an important issue in the research of folk music from descriptive interpretation to structural cognition.

Existing research provides a basis for digital arrangement and knowledge expression of folk music, but there are still some deficiencies in semantic modeling at the level of cultural symbols [3]. On the one hand, many researches remain at the level of track classification, style recognition, melody feature extraction or label management, which can improve the efficiency of music resource retrieval, but rarely deeply deal with the complex relationship between lyric imagery, ritual function, regional identity, instrumental symbol and performance context, resulting in a large number of symbol information with cultural thickness in folk music being compressed into isolated features. On the other hand, although some knowledge graphs or semantic networks have introduced entity association and relationship description mechanisms, they are still prone to problems such as inconsistent node granularity, coarse expression of relationship types, and insufficient context dependence when facing cross-regional, cross-ethnic and cross-media corpora, which affect the explanatory power of network structure and the stability of calculation results. Especially in dynamic context, the same cultural symbol may have semantic drift due to performance occasions, communication media and regional migration. If the model lacks parameter adaptive ability, it is difficult to truly reflect the fluidity and hierarchy of ethnic music cultural symbols [4, 5].

Based on this, this paper proposes a computer-driven analysis method for the semantic network modeling of folk music cultural symbols. Starting from the collaboration of multi-source data, this method integrates audio content, lyric text, instrument representation, performance scene and ethnic culture description into a unified processing framework. Through symbol extraction, semantic annotation, relational computing and graph structure modeling, a semantic network model can be formed for analyzing the internal relationship of ethnic music culture symbols. On this basis, the graph computing and semantic correlation analysis mechanism are further introduced to optimize the node weight, edge connection strength and local substructure of the network, so as to enhance the recognition ability of the model for core cultural symbols, implicit relationship chains and cross-context propagation paths. At the same time, aiming at the problem of unbalanced corpus size, expression habits and symbol distribution in different regions, a parameter adaptive adjustment strategy for dynamic context is set, so that the model can automatically adjust the representation space and relationship threshold according to the change of data structure, so as to improve the robustness and generalization ability of network modeling.

The research focus of this paper is mainly reflected in the following aspects. Firstly, a multi-source feature extraction mechanism for folk music cultural symbols is constructed, which preserves the hierarchical differences of cultural semantics on the basis of unified data expression. Secondly, a network modeling method based on semantic relation computing was designed to transform the originally scattered cultural symbols into analyzable and computable association structures. Thirdly, graph computing optimization and parameter adaptive adjustment are combined to improve the interpretation ability and application scope of the model in complex contexts. Fourth, the effectiveness of the proposed method is systematically verified through corpus statistics, model evaluation, ablation experiments and qualitative interpretation. This paper hopes to establish a closer connection between folk music research and computational methods, and provide a more operational research path for digital cognition, structured expression and intelligent analysis of cultural symbols.

2 Related Research

Focusing on the digital analysis of folk music cultural symbols, the existing research can be generally summarized into three directions: the first is the semantic modeling research for music resource organization and knowledge expression, the second is the knowledge graph and correlation calculation research for music content understanding, and the third is the research on traditional music corpus analysis and cultural interpretation combined with computational methods. The three types of research promoted the method update of folk music research from the aspects of resource description, relationship reasoning and computational analysis, and also provided a technical basis for this paper to carry out semantic network modeling from the perspective of cultural symbols.

In terms of music semantic modeling and ontology construction, related research has paid attention to the structural representation of music resources. Some scholars have introduced semantic Web technology into music classification, retrieval and metadata interoperability scenarios, and improved the standardization of music information organization through ontology design [6, 7]. Such research solves the problem that music objects are "describable, linkable and shareable", and also promotes the formation of musical heritage knowledge infrastructure [8, 9]. In recent years, MusicKG, Polifonia and other works have further incorporated works, characters, regions, Musical Instruments, texts and historical contexts into the unified knowledge representation framework, thus enhancing the connection ability of music cultural data [10, 11]. However, from the perspective of cultural symbol analysis of folk music, this kind of research pays more attention to the intercommunication between the entity layer and the metadata layer, and the depiction of the deep semantic relationships such as symbolic meaning, ritual function and narrative meaning is still not detailed enough to directly support the structural analysis of cultural symbol network.

In the field of knowledge graph and semantic association computation, the research focus has gradually shifted from static description to relation reasoning and semantic discovery. Some works have applied knowledge graph embedding, recommendation algorithms and association retrieval methods to music resource analysis, and verified the effectiveness of graph structure in music semantic computing [12, 13]. These methods have obvious advantages in node representation learning, similarity calculation and relationship completion, and can mine potential associations from large-scale heterogeneous data, which provides a method support for network modeling of complex cultural objects. At the same time, there are also studies trying to improve the music knowledge organization system from the perspective of interoperability, cross-platform link and semantic extension [14, 15]. However, most of the existing methods serve tasks such as recommendation, retrieval or copyright identification, and their modeling goals are still biased toward functional optimization, rather than the explanation of structural relationships between cultural symbols. For the multi-layer coupling relationship of "melodic motif, ritual scene, regional memory and ethnic identity" common in folk music, the existing research still lacks a unified modeling path for cultural interpretation.

In terms of computational ethnomusicology and corpus analysis of traditional music, researchers have begun to quantitatively analyze the structural characteristics and propagation laws of traditional music by means of corpus statistics, pattern recognition and cross-regional comparison methods [16]. For example, the research on Georgian traditional vocal music, European folk song variants and transnational music element distribution shows that the computational method has been able to process a certain scale of traditional music corpus, and has made progress in style comparison, melody memory and cultural transmission analysis [17, 18]. At the same time, the research on Chinese Guqin literature and Chinese folk instrumental music culture communication also shows the application potential of semantic modeling in the research of local music culture [19, 20]. However, in general, this direction is still dominated by feature extraction, pattern comparison and local semantic expression, and the integration of cross-modal cultural symbols is insufficient, especially the lack of system design that integrates text, audio, images and scene descriptions into the graph structure.

In order to more intuitively present the technical path and limitations of the existing research, this paper collates the representative results, as shown in Table 1. It can be seen that the existing methods have made substantial progress in music knowledge representation, semantic computing and traditional music analysis, but there are still gaps in the unified modeling of multi-source cultural symbols, dynamic context adaptation and network structure interpretation. Based on this, this paper focuses on the collaborative design of multi-source feature extraction, semantic relation calculation, graph network optimization and parameter adaptive adjustment, trying to provide a method framework with both computing power and cultural interpretation power for the structural analysis of folk music cultural symbols.

Table 1: Corpus composition and sample distribution statistics of folk music culture symbols

Author(s)	Research Direction / Method	Main Focus / Object	Key Contribution	Limitations
Cannam et al. [5]	Semantic Web & Linked Data	Music research software and data resources	Promoted integration of music data into semantic web environments	Focused on resource linking; cultural symbol semantics limited
Ferrara et al. [6]	Music Ontology Modeling	Music resource classification and retrieval	Enhanced contextual classification and retrieval capabilities	More suitable for standardized resource management
De Berardinis et al. [2]	Polifonia Semantic Network	Multi-source music heritage data	Strengthened interconnection of music heritage knowledge	Limited characterization of deep cultural meanings
Eyharabide et al. [3]	MusicKG Knowledge Representation	Medieval music and sound representation	Enriched music knowledge graph structure	Focused on historical text context
Oramas et al. [10]	Knowledge Graph Recommendation	Music recommendation tasks	Validated relational modeling capability of graph structures	Goal oriented toward functional optimization; limited interpretability
Liu et al. [11]	Knowledge Graph & Multi-task Learning	Music recommendation algorithms	Improved feature fusion and recommendation accuracy	Not directly aimed at cultural symbol analysis
Rosenzweig et al. [12]	Traditional Music Corpus Construction	Georgian traditional vocal music	Provided high-quality computational corpus foundation	Insufficient depth in semantic relationship modeling
Mihelač et al. [14]	Cross-region Computational Comparative Analysis	Musical elements across European countries	Revealed cross-regional differences in musical elements	Limited discussion of symbol network structure
Zhou et al. [15]	Guqin Literature Semantic Modeling	Ancient Chinese Guqin score literature	Demonstrated potential of local music semantic modeling	Cross-modal network framework not yet established
Liu [19]	AI-driven Timbre and Cultural Transmission Analysis	Chinese folk instrumental music	Focused on cultural transmission in music dissemination	Weak relational modeling and network optimization

3 Modeling and analysis of the semantic network of computer-driven folk music cultural symbols

3.1 Multi-source data feature extraction mechanism of folk music cultural symbols

The cultural symbols of folk music do not exist in a single form, and their information is often distributed in multiple carriers such as melody fragments, lyric texts, instrument forms, performance scenes, regional descriptions and intangible cultural heritage records. If the single-channel data processing method is still used, the original semantic involvement between cultural symbols is easy to be separated, which affects the accuracy of subsequent network modeling. Based on this, this paper constructs a multi-source data feature extraction mechanism at the input end, and integrates audio, text, image and scene description into a unified processing flow, so that the symbols of folk music culture can be represented, aligned and aggregated in the same computing framework.

In the stage of data acquisition, the original corpus mainly comes from folk music recording data, lyric text database, instrument image archives, fieldwork records and related cultural interpretation texts. Data from different sources have obvious differences in format, granularity and semantic level. Therefore, it is necessary to complete standardized preprocessing, including audio slicing, noise suppression, text segmentation, image size normalization, and scene description field cleaning. After preprocessing, the acoustic features such as MEL frequency spectrum, rhythm intensity and timbre contour are extracted from the audio data, the cultural imagery words, ritual behavior words and regional identification words are extracted from the text data, and the visual features such as instrument shapes, clothing elements and performance movements are extracted from the image data. The features of different modalities are then mapped into a unified semantic space to ensure that the "heterogeneous presentation of the same cultural symbol in different carriers" can be recognized by the model as relatable objects. Let the multi-source input set of folk music be

$$X = \{x_a, x_t, x_v, x_c\} \tag{1}$$

Here, x_a represents audio features, x_t represents text features, x_v represents image features, and x_c represents cultural context features. To achieve cross-modal fusion, the unified representation vector is defined as in this paper

$$h_i = \sigma(W_a x_a + W_t x_t + W_v x_v + W_c x_c + b) \tag{2}$$

where W_a,W_t,W_v,W_c are the mapping matrices of different modes, b is the bias term, and $\sigma(\cdot)$ is the nonlinear activation function. The function of this formula is not to simply concatenate features, but to compress the originally scattered symbolic cues into the same semantic representation space, so that the melody motif, lyric imagery, utensils symbol and scene information can form a computable joint representation.

Through this mechanism, the cultural symbols of folk music are no longer isolated data fragments, but transformed into characteristic units with both cultural meaning and computational structure. Figure 1 shows the basic process of multi-source feature extraction in this paper. This process provides a unified and stable input basis for subsequent semantic relation calculation, node connection strength determination and cultural symbol network optimization, and also makes it possible for different regions and different types of folk music corpus to enter the same modeling system.

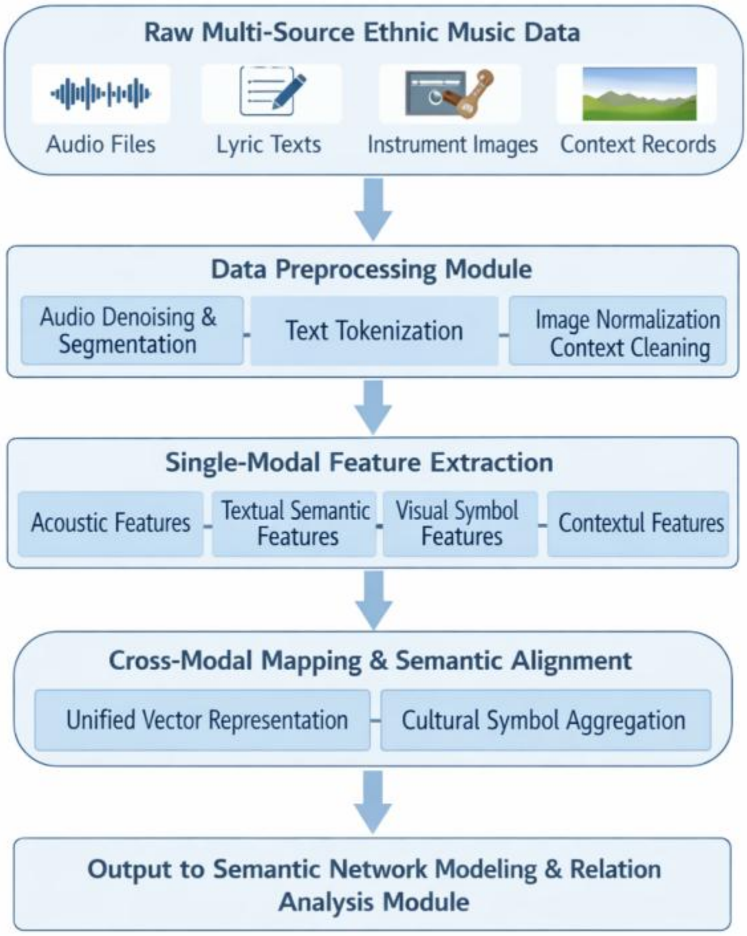

Figure 1: Flow chart of feature extraction from multi-source data of folk music cultural symbols

3.2 Design of cultural symbol network modeling method based on semantic relation computing

After multi-source feature extraction, whether the cultural symbols of folk music can be transformed into structured objects with hierarchical associations is directly related to the effectiveness of subsequent network analysis. Compared with general text entity modeling, cultural symbols in folk music corpora often have musical attributes, regional attributes and ritual attributes at the same time, and the same symbol may also show meaning deviation in different contexts. Therefore, based on the symbol recognition results, this paper introduces a semantic relationship computing mechanism to organize the symbol units scattered in lyrics, track captions, instrument image annotations, field notes, and cultural interpretation texts into a reasonable cultural symbol network.

In the symbol node construction stage, the model firstly identifies and merges the core symbols in the multi-source corpus, including tune names, instrument names, performance scenes, ritual behaviors, regional appellations, image words and ethnic cultural references. Let the set of symbols after recognition be

$$S = \{s_1, s_2, \dots, s_m\} \tag{3}$$

Here, m represents the total number of cultural symbol nodes. Considering the existence of alias coreference, cross-modal mapping and context omission in the folk music corpus, this paper combines semantic similarity matching and rule constraints to align the nodes of symbols with the same meaning or stable pointing relationship, so as to avoid excessive dilution of the network structure due to expression differences.

In the relationship calculation stage, the symbol co-occurrence is not regarded as the only basis, but the context semantic distance, dependency relationship cues and cross-modal correspondence strength are integrated to determine the connection weight between nodes. If symbols s_i and s_j co-occur many times in the same semantic window and their cultural interpretations are obviously related, a relational edge is established between them. Accordingly, the set of cultural symbol relations can be expressed as

$$R = \{(s_i, s_j, r_{ij}, w_{ij}) \mid s_i, s_j \in S\} \tag{4}$$

Here, r_{ij} denotes the relationship type and w_{ij} denotes the relationship strength. The relationship types mainly include "regional affiliation", "ritual association", "instrumental accompaniment", "image co-reference" and "performance scene mapping". In order to improve the stability of relation determination, this paper further defines the comprehensive association score of symbol pairs as

$$w_{ij} = \lambda_1 \cdot \mathrm{Sim}(h_i, h_j) + \lambda_2 \cdot \mathrm{Co}(s_i, s_j) + \lambda_3 \cdot \mathrm{Ctx}(s_i, s_j) \tag{5}$$

$\mathrm{Sim}(h_i, h_j)$ represents the node semantic vector similarity, $\mathrm{Co}(s_i, s_j)$ represents the normalization result of symbol co-occurrence frequency, $\mathrm{Ctx}(s_i, s_j)$ represents the context cultural interpretation consistency score,$\lambda_1, \lambda_2, \lambda_3$ are weight parameters, and meet $\lambda_1 + \lambda_2 + \lambda_3 = 1$.In the network representation layer, this paper abstracts the folk music cultural symbol system as a graph structure

$$G = (V, E) \tag{6}$$

Among them, the set of nodes V corresponds to cultural symbol units, and the set of edges E corresponds to the semantic relations between symbols. In order to enhance the model's ability to identify local strong correlations and global propagation paths, we introduce an attention-based neighborhood aggregation strategy in graph representation learning, so that core symbols can obtain higher expression weights in multi-hop propagation. Through this design, melodic motifs, instrumental symbols, regional memories and ritual functions in folk music are no longer isolated descriptive components, but are organized into a computable and interpretable relationship network. This method provides a stable modeling foundation for subsequent graph computation optimization, key symbol recognition and cultural structure interpretation.

3.3 Network optimization mechanism combining graph computing and semantic association analysis

After the initial construction of cultural symbol network, although basic connections have been formed between nodes, there may still be problems such as relationship redundancy, weak association interference and local structural imbalance. If the initial network is directly used for subsequent analysis, it is easy to amplify the noise caused by accidental co-occurrence and weaken the identification effect of core cultural chain. Based on this, this paper introduces a network optimization mechanism combining graph computing and semantic association analysis based on the results of semantic relationship calculation, and iteratively modifies the symbol network of folk music culture through three steps: relationship re-weighting, neighborhood aggregation and structure constraint. The overall process is shown in Figure 2:

firstly, the edge weights are updated according to semantic similarity and context consistency, and then the influence of key nodes is strengthened by graph attention propagation, and then the low-quality connections are weakened by combining sparse constraints, so that the network structure is further turned from "connectable" to "interpretable".

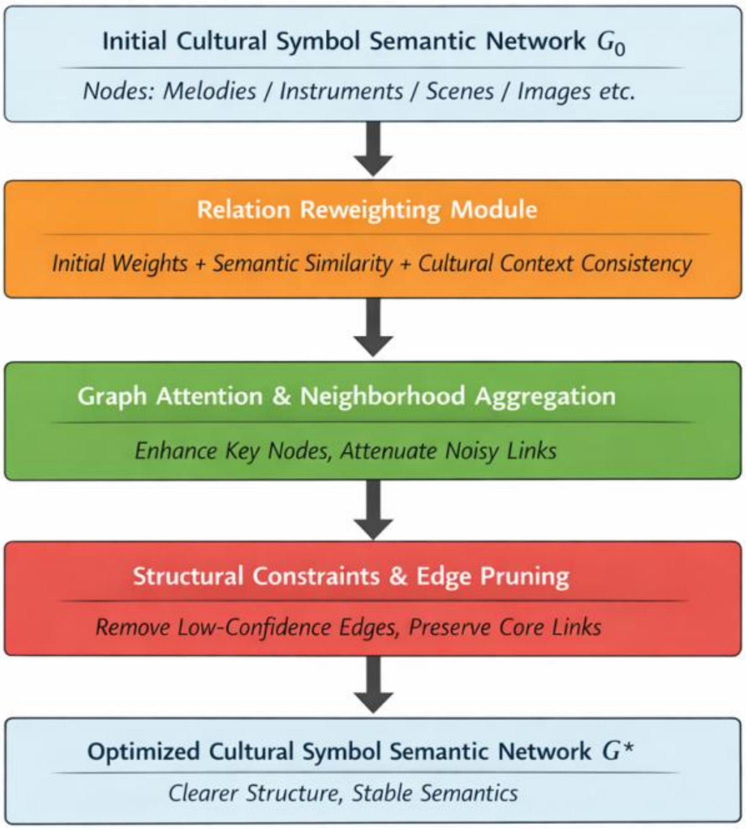

Figure 2: Network optimization process of fusing graph computation and semantic association analysis

In the stage of edge weight optimization, the surface co-occurrence relationship and deep semantic association of cultural symbol pairs are simultaneously included in the calculation, and the optimized connection strength of nodes s_i and s_j is redefined as

$$\widetilde{w}_{ij} = \alpha \cdot w_{ij} + \beta \cdot \cos(z_i, z_j) + \gamma \cdot c_{ij} \tag{7}$$

where w_{ij} is the initial relationship weight, $\cos(z_i, z_j)$ represents the cosine similarity between the semantic representations of nodes, c_{ij} represents the cultural context consistency score, α,β,γ are the learnable coefficients. The function of this formula is to avoid that the network is only dominated by the surface frequency, so that the symbol pairs with "low co-occurrence but stable cultural connection" still have a chance to remain in the graph structure.

In the node representation update stage, we adopt an attention-based neighborhood aggregation strategy to assign differentiated propagation weights to different adjacent nodes. Let the LTH layer node be denoted by $z_j^{(l)}$, then the update procedure can be written as

$$z_i^{(l+1)} = \phi\left(\sum_{j \in \mathcal{N}(i)} a_{ij}^{(l)} W^{(l)} z_j^{(l)}\right) \tag{8}$$

Here, $\mathcal{N}(i)$ represents the neighborhood set of node s_i, $a_{ij}^{(l)}$ is the attention coefficient, $W^{(l)}$ is the transformation matrix, and ,$\phi(\cdot)$ is the activation function. Through this mechanism, key symbols such as Musical Instruments, melodic imagery, regional memory, and ritual behavior are able to obtain clearer structural expression in multi-hop propagation, while the interference of edge noise nodes is compressed.

In order to prevent the network from over-dense connections in the iterative process, we further introduce a structural regularization term to suppress low-confidence edges and control the overall complexity. The integrated optimization objective can be expressed as

$$\mathcal{L}_{\mathrm{opt}} = \mathcal{L}_{\mathrm{rel}} + \lambda\mathcal{L}_{\mathrm{sem}} + \eta||A||_1 \tag{9}$$

Here, $\mathcal{L}_{\mathrm{rel}}$ is used to preserve the discriminative power of the identified relations, $\mathcal{L}_{\mathrm{sem}}$ is used to constrain the consistency of semantic neighbors, and $||A||_1$ denotes the adjacency matrix sparsity penalty term. After the above optimization, the local clustering characteristics, cross-regional connection ability and core symbol recognition accuracy of the folk music cultural symbol network are improved, and a more stable graph foundation is provided for subsequent parameter adaptive adjustment and cultural structure interpretation.

3.4 Adaptive adjustment method of semantic network parameters for dynamic context

The semantic expression of cultural symbols of folk music is not constant. When the same melody motif, instrument name or ritual image is used in different regions, different performance scenes and different narrative texts, there are often some phenomena such as semantic boundary expansion, relationship strength fluctuation and symbol pointing transfer. If the fixed window, fixed threshold and fixed training parameters are still used, the model can complete the general modeling, but it is difficult to accurately capture the subtle differences in dynamic context. Based on this, this paper introduces a dynamic context oriented parameter adaptive adjustment method, so that the semantic network can automatically adjust the key parameters according to the statistical characteristics of the corpus and the context complexity during the modeling process, so as to enhance the adaptation ability of the model to cross-regional folk music corpus.

In terms of context window adjustment, this paper sets the semantic window length and the current context complexity jointly. Let the window size in the t-th context be w_t, then there is

$$w_t = w_0 + \alpha \cdot \ln(1 + l_t) + \beta \cdot d_t \tag{10}$$

where w_0 is the basic window length, l_t represents the average sentence length of this kind of corpus, d_t represents the distribution density of cultural symbols, and α and β are the adjustment coefficients. For field texts and ritual records with long narratives and dense cultural explanations, the window will be moderately extended to retain a more complete semantic chain. In the lyrics corpus with short sentences and strong fragmentation, the window is correspondingly shrunk to reduce the interference of redundant connections on relation determination.

In terms of relation threshold and regularization adjustment, we further consider the joint influence of semantic ambiguity and network density. If there are many homonyms in a certain context, the model needs to increase the relation retention threshold to avoid a large number of weak referential connections entering the network. To this end, the relation filtering threshold is defined as

$$\tau_t = \tau_0 + \gamma \cdot H_t \quad (11)$$

Here, τ_0 is the initial threshold, H_t represents the information entropy of the semantic distribution of symbols in the current context, and γ is the regulation coefficient. The higher the information entropy is, the more obvious the semantic differentiation is, and the more strict the model should be in preserving edge connections. At the same time, aiming at the possible overfitting problem in high-density semantic networks, this paper synchronously adjusts the Dropout ratio to keep the node propagation in complex contexts moderately sparse, so as to improve the stability of network representation.

In the training phase, the learning rate no longer adopts a single fixed value, but dynamically decays with the gradient fluctuation. The early training retains a high update amplitude, so as to quickly establish the overall structure between cultural symbols. In the middle and later stages, the learning rate is gradually reduced according to the gradient variance, so that the model can obtain a smoother convergence process at the local details. Through the above adjustment mechanism, the semantic network can form a more flexible parameter response between different folk music corpora, different cultural scenes and different expression scales, which not only reduces the burden of manual parameter adjustment, but also provides a more reliable technical support for subsequent network evaluation, structure interpretation and cross-regional expansion.

4 Analysis of results

4.1 Corpus construction and sample distribution statistics of folk music Culture symbols

In order to verify the applicability of the semantic network modeling method in the analysis of folk music cultural symbols, this study first constructs a corpus of folk music cultural symbols for multi-source heterogeneous data. Instead of only collecting melody or lyric texts, the corpus integrates audio samples, lyric materials, instrument images, performance descriptions and fieldwork records into the computational framework to ensure that cultural symbol extraction, relationship recognition and network modeling have a relatively complete data foundation. All samples cover 12 provinces of Southwest, northwest, North China and South China, involving 27 categories of folk music, and are divided into training set, validation set and test set according to 7:1.5:1.5.

From the perspective of data composition, lyrics text and audio samples accounted for a high proportion, which were the main sources of cultural image recognition and melody semantic matching. Instrument images and instrument descriptions help to extract visual symbols and instrumental cultural references. Although the number of scene descriptions and field archives is relatively small, they carry deep information such as ritual function, regional memory and communication context. Table 1 presents a statistical summary of the corpus composition. It can be seen that there are obvious differences in the number, semantic density and structural features of different types of samples, which exactly provides an experimental basis for testing the stability of the model under cross-modal, cross-regional and cross-context conditions. On the whole, the constructed corpus not only retains the hierarchical complexity of folk music cultural symbols, but also meets the computational requirements of subsequent semantic annotation, graph structure generation and model evaluation.

Table 1: Corpus composition and sample distribution statistics of folk music culture symbols

Corpus Type	Number of Samples	Content Coverage	Number of Cultural Symbol Entries	Main Usage
Audio Samples	1,280	Folk songs, instrumental music, ensembles, ritual music	3,020	Extract melody, rhythm, timbre features
Lyrics Text	1,540	Folk song lyrics, singing texts, track descriptions	3,486	Identify imagery words, regional terms, ritual semantics
Instrument Images & Artifact Descriptions	860	Instrument shapes, components, usage scenarios	1,725	Extract visual symbols and instrumental cultural information
Performance Scene Descriptions	720	Festivals, weddings/funerals, production/labor scenes	1,864	Establish scene–symbol associations
Field Surveys & Intangible Heritage Archives	460	Interview records, inheritor materials, archival texts	1,277	Supplement historical context and transmission chains
Total	4,860	12 provinces/regions, 27 types of ethnic music	11,372	Support semantic network modeling and evaluation

4.2 Data preprocessing process and symbol semantic annotation specification

Based on the 4860 folk music samples constructed in 4.1, this paper further completes the unified preprocessing and symbolic semantic annotation to ensure that different modal data can enter the same modeling process. After preprocessing, 1342 residual symbols, repeated fields and invalid tags were cleaned up, and 287 field translation inconsistencies and OCR recognition errors were corrected. The 1280 audio samples are segmented into 9120 valid segments with a cumulative effective duration of 216.4 hours. 1540 lyrics and captions are normalized into 18340 sentence units. 860 musical instrument images were unified in resolution and mapped into categories. After the above processing, the multi-source data is consistent in encoding format, timestamp, naming rules and index number, which reduces a lot of noise interference for subsequent semantic relation calculation.

In the stage of symbol semantic annotation, this paper adopts the three-layer specification of "symbol category, relationship type and context attribute" to jointly annotate all the samples. Finally, 11372 cultural symbol items were identified and confirmed, including 2184 in melody and tune categories, 1725 in instrument categories, 2641 in lyrics and imagery categories, 1438 in regional appings, 1286 in ritual behavior categories, and 2098 in performance scenes categories. Furthermore, 16894 groups of symbolic relations are extracted, which mainly include five categories: co-occurrence, attribution, mapping, co-occurrence enhancement and semantic reference. The labeling process was completed by combining automatic recognition and manual review. The manual sampling samples accounted for 12.0% of the total. The correction rate of automatic labeling results was 6.8%, the consistency coefficient of symbol category labeling was 0.84, and the consistency coefficient of relation label was 0.81. It can be seen that the preprocessed corpus achieves a good level of format standardization, semantic boundary clarity and label stability, which can provide reliable input for subsequent semantic network model evaluation.

4.3 Semantic Network model evaluation and modeling effect analysis

After completing the corpus cleaning, symbol tagging and network construction, this paper conducts a systematic evaluation of the proposed semantic network model. The experiment was carried out under uniform data division, the ratio of training set, validation set and test set was kept at 7:1.5:1.5, the embedding dimension was set to 256, the initial learning rate was set to 1×10^{-4}, and the batch size was 64. In order to ensure the interpretability of the comparison results, this paper selects the fixed threshold co-occurrence network, the GCN semantic graph model and the standard GAT model as the control methods, and takes the symbol category determination accuracy, the F1 value of relationship recognition, the link prediction error and the training time as the core indicators. For the classification task, we adopt in this paper

$$F_1 = \frac{2PR}{P + R} \tag{12}$$

Measure the comprehensive performance of the model between precision P and recall R; For the task of network edge weight prediction, the root mean square error is used:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{13}$$

The deviation between the predicted edge weights and the true annotated edge weights is evaluated. As shown in Table 2, the proposed method achieves better results in multiple indicators. Among them, the recognition accuracy of symbol category reached 91.8%, which was 8.9 percentage points higher than that of fixed threshold co-occurrence network and 3.2 percentage points higher than that of standard GAT. The F1 value of relationship recognition reaches 89.6%, indicating that the model has more stable discrimination ability in identifying complex relationships such as "regional affiliation", "instrumental music accompaniment" and "ritual mapping". At the same time, the link prediction RMSE of the proposed method is reduced to 0.137, which indicates that after the semantic association constraint and graph calculation optimization, the network edge weights are closer to the manual labeling results, and the weak association noise is effectively compressed. In terms of training efficiency, a single round of the proposed model takes 10.8 s. Although the adaptive adjustment of parameters and the attention propagation mechanism are introduced, the overall time cost is not significantly increased and is lower than that of the standard GAT model.

Table 2: Evaluation results of different models in the semantic network task of folk music culture symbols

Method	Accuracy (%)	Relation Recognition F1 (%)	Link Prediction RMSE	Training Time (s/epoch)
Fixed-Threshold Co-occurrence Network	82.9	80.7	0.214	8.6
GCN Semantic Graph Model	87.4	85.1	0.176	10.2
Standard GAT Model	88.6	86.8	0.161	11.4
Our Method (Full Model)	91.8	89.6	0.137	10.8

From the perspective of modeling effect, the advantage of the proposed method is not only reflected in the numerical improvement, but also in the stronger retention ability of the core cultural chain. In the test samples, the high-order relations related to the sacritional scene, regional migration and instrumental music composition are easy to be simplified to general co-occurrence edges in the control model. However, the proposed model can preserve such implicit structures completely through the joint calculation of semantic similarity, context consistency and neighborhood propagation weight. From the changes of the indicators during the training process, the model has reached a high accuracy level within the first 10 rounds, and the overall fluctuation in the subsequent stages is small, indicating that its convergence process is relatively stable. This shows that the introduced adaptive adjustment mechanism can improve the stability and cross-context adaptation ability of semantic network modeling while ensuring the convergence speed.

4.4 Ablation experiment and model robustness verification

In order to further test the actual contribution of each component module of the model in this paper, the ablation experiment is carried out under the uniform corpus and the same parameter setting, and the robustness verification is carried out on this basis. In the ablation part, the four modules of multi-source feature extraction, cultural symbol network modeling, graph calculation optimization and parameter adaptive adjustment were removed in turn, and the other conditions remained unchanged. The results are shown in Figure 3, and the complete model remains optimal in the three indicators of accuracy, F1 value of relationship recognition and link prediction error, where the accuracy is 91.8%, F1 value is 89.6%, and RMSE is 0.137. In contrast, after removing the adaptive adjustment of parameters, the model showed the most obvious decline, F1 value decreased to 84.9%, and RMSE increased to 0.181. After removing multi-source feature extraction, the ability to maintain symbolic semantic boundaries is significantly weakened, indicating that the information integrity of the input layer plays a fundamental role in subsequent relation inference. Removing the network optimization mechanism and the initial modeling module also causes performance degradation, but the magnitude is relatively slow, indicating that they mainly affect the ability of fine expression and implicit association retention of network structure.

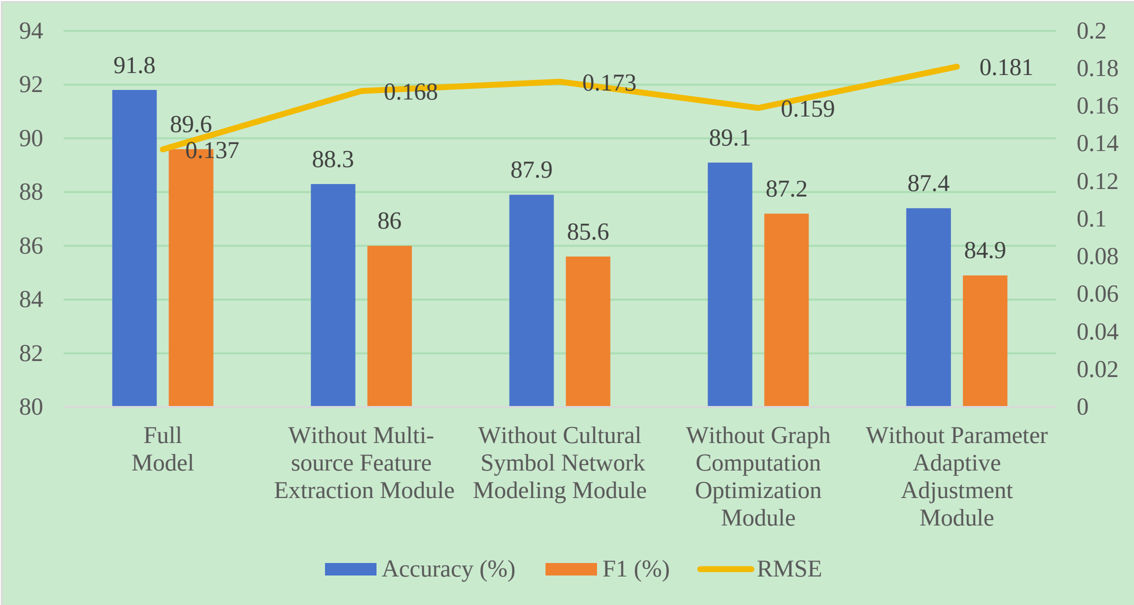

Figure 3: Results of ablation experiments

The robustness experiment is carried out in three dimensions: small sample training, noise perturbation and cross-region transfer, and the performance of the proposed method is compared with that of the fixed-parameter baseline model under complex conditions. As shown in Figure 4, when the training set is compressed to 30% of the original scale, the F1 value of the proposed model still reaches 88.1%, which is only 1.5 percentage points lower than that of the complete data, while the baseline model has dropped to 82.4%. Under 5% and 15% noise interference, the F1 value of the proposed model is 87.6% and 84.8%, respectively, and the overall fluctuation is small. In the cross-region transfer test, the F1 value of the model on the corpus of unfamiliar regions is still 86.9%, indicating that it has good adaptability to different ethnic music cultural contexts. In general, ablation experiments verify the irreplaceable ability of each sub-module in the overall framework, and the robustness results show that the proposed method does not rely on a single data environment and has stable generalization ability.

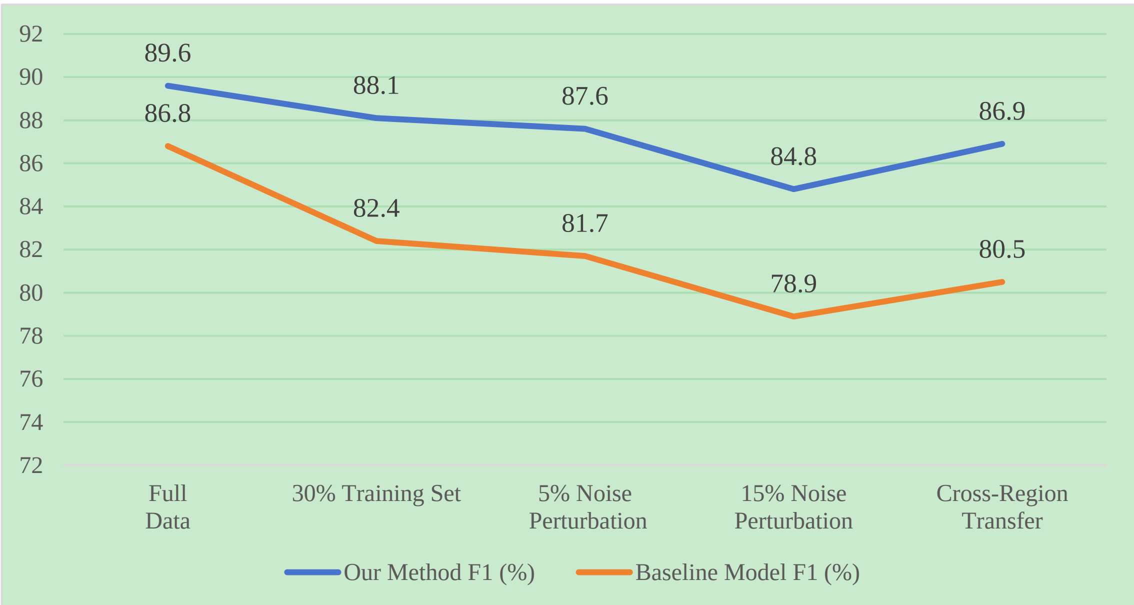

Figure 4: Results of the robustness verification

4.5 Qualitative analysis and explanation of cultural symbol structure correlation

In order to further test the interpretability of the model, this paper extracts representative cultural symbol pairs from the test set and makes qualitative comparison with the manual annotation results. As shown in Table 3, when two symbols have stable correspondence in performance scene, regional memory and ritual function, the association scores given by the model are generally high. On the contrary, if the two only exist surface co-occurrence without cultural isomorphism foundation, the score is obviously low. This indicates that the method in this paper does not stay at the level of word proximity or simple co-occurrence, but can integrate melody carrier, instrumental symbol, ritual scene and ethnic narrative into the same semantic structure.

From the perspective of network structure, the relationships between Lussheng and ritual scene, Matouqin and grassland narrative, and bronze drum and festival collective activities are all stably preserved, and show clear clustering characteristics in the local subgraphs. These results are basically consistent with the empirical understanding in the study of folk music, indicating that the model has good reliability in identifying the backbone chain of cultural symbols. In contrast, symbol pairs lacking direct cultural correspondence, such as "Suona-grassland migration narrative", have significantly lower correlation scores, which also indicates that the model can distinguish strong correlation from weak correlation. It can be seen that the constructed semantic network can not only complete the structural connection, but also provide a more convincing basis for the computational interpretation of the cultural connotation of folk music.

Table 3: Representative folk music cultural symbol relations and model association results

Cultural Symbol A	Cultural Symbol B	Predicted Relation Type	Association Score	Structural Interpretation
Lusheng	Ritual Scene	Ritual Mapping	0.93	Instrument usage is highly coupled with ritual space
Morin Khuur	Grassland Narratives	Regional Cultural Reference	0.91	Instrument imagery closely linked to regional memory
Bronze Drum	Festival Collective Activities	Scene Co-occurrence	0.89	Artifact symbols consistently co-occur with group performance scenes
Hua’er	Mountain Duet Singing	Performance Mapping	0.87	Song characteristics correspond clearly with singing context
Suona	Grassland Migration Narratives	Weak Semantic Association	0.34	Only sporadic co-occurrence, lacking stable cultural correspondence

5 Discussion

5.1 Comparison between the proposed method and existing cultural symbol analysis methods

Around the analysis of folk music cultural symbols, the existing methods can be roughly divided into three categories: manual interpretation type, statistical co-occurrence type and graph structure construction model. Manual interpretation can deeply reveal the meaning and historical context of etiquette and customs, but the processing scale is limited, and it is difficult to stably identify the implicit relationships in cross-regional corpora. Statistical co-occurrence method is easy to calculate and suitable for preliminary association discovery, but it is easy to misjudge short-term co-occurrence as stable cultural association. Although the fixed-parameter graph model improves the relationship expression ability, it still has the problems of rigid edge weights and large transfer fluctuations in the face of multimodal samples and dynamic contexts. Compared with these paths, the proposed method combines multi-source feature extraction, semantic relation calculation, graph attention aggregation, and parameter adaptive adjustment into a unified process, thus achieving a more balanced effect between structure preservation and semantic interpretation.

As shown in Table 4, the proposed method is superior to the existing calculation methods in relation recognition F1 value and link prediction error, where F1 reaches 89.6% and RMSE decreases to 0.137, indicating that the model can not only more accurately distinguish relationship types such as "instrumental music accompaniment", "ritual mapping" and "regional affiliation", but also maintain a high stability of edge weight judgment in complex contexts. It is worth noting that the single-round training time of the proposed method is 10.8 s, which is lower than the 11.4 s of the standard GAT model, indicating that the parameter adaptation mechanism does not bring additional computational drag, but improves the convergence efficiency. From this point of view, the advantage of the method in this paper is not only the improvement of indicators, but also the fact that it can integrate the sound characteristics, text imagery and cultural scene in folk music into the same network space, so that "computable analysis" can be truly transformed into "interpretable comparison".

Table 4: Comparison between the proposed method and existing cultural symbol analysis methods

Method	Data Scope	Relational Expressiveness	Dynamic Context Adaptation	F1 (%)	RMSE	Notes / Description
Manual Interpretation	Small-scale texts and case materials	Stronger than deep explanation, weaker than computational structure	Weak	—	—	Suitable for close reading of cases, not suitable for large-scale comparison
Statistical Co-occurrence	Text or label data	Can identify surface-level associations	Weak	80.7	0.214	Sensitive to high-frequency co-occurrence noise
GCN Semantic Graph Model	Multi-source texts and symbolic nodes	Relational modeling relatively stable	Moderate	85.1	0.176	Insufficient response to complex context changes
Standard GAT Model	Multi-source heterogeneous data	Strong local relational expressiveness	Good	86.8	0.161	Edge weight updates are flexible, but parameter tuning is highly dependent
Our Method (Full Model)	Multimodal Ethnomusic Corpus	Strong	Strong	89.6	0.137	Balances structural interpretability, cross-context adaptation, and efficiency

5.2 Analysis of semantic network modeling complexity and computing resource consumption

In the task of folk music cultural symbol analysis, the effectiveness of the model is not only reflected in the recognition accuracy and relationship judgment ability, but also reflected in the complexity control and the rationality of resource overhead. Although the existing manual statistics or co-occurrence analysis methods have low computational burden, they are difficult to support multi-modal symbol association and high-order semantic propagation. The standard graph model can deal with structural relationships, but it often faces significant time and memory pressure with the increase of node scale and edge connection number. In contrast, the proposed method achieves cross-modal alignment at the feature level, and introduces parameter adaptive adjustment and edge sparsity constraints in the propagation stage, which reduces the repeated calculation caused by low-quality connections, so that the model avoids invalid expansion while maintaining the expressive ability of the model.

Theoretically, the fixed co-occurrence network is mainly consumed in the construction of statistical adjacency relations, which has relatively low complexity, but its structural expression is limited. GCN and GAT methods need to update node representations repeatedly in multi-layer neighborhood propagation. When the network scale expands, the computational cost will increase significantly with the growth of edge set. Although the semantic re-weighting and dynamic adjustment modules are added to the proposed method, the overall running pressure does not increase synchronously because the redundant edges are screened and some parameter updates are restricted to the local subgraphs with high confidence. Table 5 shows the comparison results of different methods in terms of training time, video memory footprint, and convergence rounds. It can be seen that the single-round training time of the proposed method is 10.8 s, which is lower than 11.4 s of the standard GAT model. The video memory occupation is 8.6GB, which is also significantly lower than the 9.8GB of the standard GAT model. In terms of convergence speed, the proposed method can reach a stable state in about 19 rounds, indicating that it achieves a relatively balanced control effect between complexity and efficiency.

Table 5: Comparison of complexity and computational resource consumption of different methods

Method	Main Computed Features	Average Training Time (s/epoch)	GPU Memory Usage (GB)	Convergence Epochs
Statistical Co-occurrence Network	Adjacency Statistics and Frequency Calculation	8.1	5.4	25
GCN Semantic Graph Model	Fixed Neighborhood Propagation	10.2	8.9	23
Standard GAT Model	Attention Propagation and Edge Weight Update	11.4	9.8	22
Our Method (Full Model)	Semantic Reweighting + Adaptive Adjustment	10.8	8.6	19

It can be further seen from Table 5 that the proposed method does not trade additional resource consumption for performance improvement, but improves the training efficiency while optimizing the quality of graph structure. This result shows that the semantic network modeling for folk music cultural symbols does not necessarily mean high cost operation. As long as the relationship screening, parameter adjustment and propagation path control are properly designed, a computational scheme with a balance of accuracy, stability and implementability can still be formed.

5.3 Applicability and expansibility of the model in cross-regional folk music corpus

The experimental results show that the performance of the proposed method is relatively stable in folk music corpora from different regions, indicating that it does not rely on a fixed text style or a single performance tradition, but can maintain good structural modeling ability under the condition of multi-source symbol input. From the network distribution characteristics of cross-regional test samples, some corpus in southwest China is more likely to form a local clustering structure centered on ritual scenes, group songs and dances, and instrumental music co-occurrence relationships, while some corpus in northern grassland highlights the cross-node association between melody motifs, instrument images and regional narratives. In contrast to the fixed-parameter model, which is prone to edge weight drift and relation misconnection when context switching, the proposed method can dynamically adjust the modeling strategy according to the symbol density, text length and relation sparsity with the help of semantic alignment and parameter adaptive adjustment mechanism, so that it can still maintain high consistency of relation recognition in cross-region samples.

This applicability is also reflected in the cross-modal transfer capability. For samples mainly composed of lyrics and scene descriptions, the model can accurately capture the correspondence between image words and cultural functions. For samples with audio and instrumental images as the core, the system can also complete symbol mapping through a unified representation space to reduce the structural break caused by modal differences. More importantly, the proposed method has the potential to scale to larger corpora. With the continuous accumulation of regional archives, intangible cultural heritage databases and multimedia folk song resources, the study of folk music is no longer limited to case analysis, but gradually turns to cross-regional, cross-ethnic and cross-media comparative analysis. In this context, the semantic network framework constructed in this paper can provide a scalable computing foundation for large-scale cultural symbol sorting, regional transmission path tracking and folk music knowledge graph generation, and also reserve a method space for subsequent fine-grained cultural comparative research.

5.4 Application Value and research enlightenment in the dissemination of folk music culture

The semantic network of ethnic music culture symbols constructed in this paper not only serves the identification and analysis at the model level, but also provides a new technical fulpoint for the reconstruction of the transmission mode of ethnic music culture. Traditional communication paths are often based on repertoire display, text introduction or video recording, and information presentation is relatively scattered. Audiences can access sound materials, but they may not be able to synchronously understand the regional memory, ritual structure and symbolic meaning carried by them. After the introduction of semantic network modeling method into the organization of folk music resources, the relationship between melody motif, instrument shape, lyric imagery, performance scene and cultural context can be transformed into searchable, related and visual structural units, which not only helps to improve the efficiency of resource integration in the digital platform, but also helps to enhance the sense of hierarchy and interpretation of folk music communication content.

From the application level, this method can provide computational support for the construction of digital archives of folk music, the indexing of intangible cultural heritage resources, intelligent retrieval recommendation and cross-regional communication analysis. With the help of graph structure representation, the platform can automatically expand its association chain around a core symbol, helping researchers or general audiences to enter a more complete cultural context from a single track. For educational scenarios, this method can also transform abstract cultural knowledge into a cognitive path with clear structure, so that the teaching of folk music can further move from "hearing works" to "understanding symbols". At the research level, the significance of this paper is not only to propose a technical model, but also to show that the research of folk music can introduce computer methods such as knowledge graph, semantic computing and graph learning while retaining the depth of cultural interpretation, and form an analysis framework with both humanistic care and data support. Its subsequent value may be reflected in the direction of cross-ethnic music comparison, regional transmission path tracking and multi-modal cultural resources integration, which provides a more malleable idea for the research of digital humanities of ethnic music.

6 Conclusions

Focusing on the structural expression and correlation analysis of folk music cultural symbols, this paper constructs a semantic network modeling framework that integrates multi-source feature extraction, semantic relationship calculation, graph calculation optimization and parameter adaptive adjustment. In this study, audio samples, lyrics texts, instrument images, performance descriptions and field research archives are integrated into a unified representation space. Based on 4860 samples, 11372 cultural symbol items and 16894 groups of symbol relations, a computational model for the analysis of folk music cultural symbols is formed. The results show that the proposed method can better preserve the complex relationship between "instrumental music, scene, region and etiquette and customs" in folk music, and transform the cultural information originally scattered in different carriers into a computable, comparable and interpretable network structure. The experimental results show that the accuracy of the proposed method in the semantic network task reaches 91.8%, the F1 value of relation recognition reaches 89.6%, and the RMSE of link prediction is reduced to 0.137. The overall performance of the proposed method is better than that of the fixed threshold co-occurrence network, GCN semantic graph model and standard GAT model. The training time of a single round is 10.8 s, which ensures the performance improvement while maintaining good computational efficiency. Ablation experiments further show that the adaptive parameter adjustment and multi-source feature extraction module make the most obvious contribution to the overall performance. In the robustness test, when the training set is compressed to 30% of the original scale, the F1 value of the model still remains at 88.1%, and it still has 84.8% under the condition of 15% noise interference. The F1 value of the cross-region transfer test reaches 86.9%, which indicates that the method has a stable generalization ability. From the perspective of research significance, this paper is not just introducing a computer technology, but trying to provide an analysis path for the research on the cultural connotation of folk music that takes into account both cultural interpretation and data support. The framework can provide methodological support for digital archive arrangement of folk music, semantic indexing of intangible cultural heritage resources, cross-regional transmission path tracking and knowledge graph organization. Of course, there are still some limitations in this paper, such as some hidden cultural relations still need to rely on manual verification, and the problem of symbol escape in complex historical context needs to be deepened. Future research can continue to expand the scope of cross-language and cross-media corpus verification, and strengthen the interpretability and lightweight deployment ability of the model.

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