International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 1500-1517

https://doi.org/10.70517/ijhsa464135

Knowledge Map Construction and Application for the Dissemination of Opera Art in the Internet Age

Lele Zhu[1,*]
[1] College of Music, Jilin Normal University, Siping, Jilin, 136000, China
Corresponding authors: (e-mail: myyongxi2016@163.com).

Abstract Drama communication is an important path for the inheritance and development of drama art. In order to clarify the research development trend of the innovative communication of Ji opera art in the era of Internet+, this paper combines the principles of graph theory and data mining technology, and proposes the knowledge graph relationship extraction based on graph neural network, which utilizes the BERT model to encode the input sentences, and constructs the graph structure through the Gaussian graph generator. On this basis, the knowledge graph of Jiyu Opera art innovation dissemination is constructed. The Ontology Model of the Knowledge Graph was constructed using the Protégé tool, which covered 4 event entity categories such as "Art Creation Event", "Stage Presentation Event", "Communication and Promotion Event", and "Inheritance Education Event" and 9 event element entity categories such as "Time", "Place" and "People". In the analysis of the key words of the knowledge graph, the research hotspots and their evolution in the field of Jiqu art innovation and communication are obtained. The intensity of the keywords "digital inheritance" and "cross-border integration" reached 2.45 and 2.23, respectively, which were research hotspots in the field. The research interests of policy support and "international communication" have lasted for a long time, while "IP development" and "short video marketing" will be highlighted in 2021-2024.

Index Terms graph theory, graph neural network, relational extraction, knowledge graph, innovative communication of Ji opera art

I. Introduction

As a representative project of national intangible cultural heritage of Jilin Province, and also one of the traditional Chinese musical theater, Ji-ju opera has a long history and unique artistic charm, however, in the rapid development of modern society, Ji-ju opera faces the dilemma of survival and inheritance [1]-[4]. With the popularization and development of Internet technology, the inheritance of Ji opera ushered in a new opportunity, through the Internet, people can more conveniently access to information and knowledge of Ji opera, improve the cognition and understanding of Ji opera, and at the same time, the Internet also provides a broader stage for the inheritors of Ji opera, so that the Ji opera can obtain more opportunities for dissemination and exchange [5]-[8].

The Internet of Things provides a platform for the inheritance and protection of ji opera, while how to search in the complicated data and present the association relationship between the non-heritage in a visual way is a hot spot of research [9], [10]. Knowledge graph, as the main application tool for visualization of intangible cultural heritage, and its related technology provide support for the knowledge organization and display of knowledge relations in Ji opera [11], [12]. Knowledge graph is a new type of graph used to represent information, which focuses on entities, integrates multiple information and forms a structured knowledge network by describing the relationships and attributes between entities [13]-[15]. In the dissemination of Internet+Ji Opera, knowledge mapping displays complex ji opera singing and song styles through data mining, information processing, knowledge measurement and graphic drawing, reveals the dynamic development law of ji opera, automatically analyzes its characteristics, and thus provides fast indexing technology for the customers who like ji opera to achieve the purpose of rapid dissemination [16]-[19].

In order to build up the knowledge map of the innovative communication of Ji opera art and realize the academic support for the research on the inheritance development and innovative communication of Ji opera, this paper introduces the relevant principles of graph theory and data mining, and proposes the knowledge map relationship extraction method based on graph neural network. The implicit graph structure features are mined from the text, and the input sentences are encoded using the BERT model. Taking each word in the text sequence as a node, the Gaussian graph generator is used to construct the edges between the nodes from multiple viewpoints in order to represent the hidden relationships between the texts. Under different perspectives, different graph attention networks are used to learn the relationship weights between each node, so that it has the ability to automatically select the correct relationship, and then the weight information and feature information are input to the graph convolutional network for feature fusion, in order to obtain more contextual information and improve the generalization ability. Using the relationship extraction method in this paper, we constructed a knowledge map of the innovative communication of Ji opera art, and analyzed the keywords in terms of keyword co-occurrence, clustering and convexity to explore the changes of research hotspots in the field of innovative communication of Ji opera art.

II. Knowledge graph relationship extraction based on graph neural network

With the arrival of the Internet+ era and the rapid development of new media Internet, the artistic innovation and communication development of traditional theater has also ushered in a brand new opportunity. Ji opera is a unique local theater rooted in the fertile soil of Jilin Province, China, which is not only a bright pearl of non-legacy in Jilin Province, but also a cultural bond closely connected with the daily life of local people. In this chapter, the knowledge extraction method of knowledge graph will be proposed by combining the principles of graph theory and data mining technology to facilitate the construction of the knowledge graph of JI Opera's artistic innovation and dissemination later.

II. A.Principles of graph theory

Graph theory is an important tool for studying the structural energy control of complex network systems, as well as a common method for solving structured network energy control problems [20]. For a complex network system, graphs can be used to concisely portray the basic information inside it and analyze the various properties of the network system by the nature of the reaction on the graph.

II. A. 1) Simple classification and matrix representation of graphs

Graph theory takes graphs as its object of study, where a graph is a figure consisting of a number of points and line segments (also called edges) connecting the points. In practice, if the points represent some specific things, then the line segments (edges) represent the relationships between the connected things, and the interactions between the things and the things constitute a topological graph.

FIGURE: Figure G is a combination of node set V and edge E, denoted as $G=(V,E)$, where, $V=\{v_1,\dots,v_n\}$, $E=\{(v_j,v_i)\in V\times V\}$ denote the connectivity between the nodes. $|V|$ and $|E|$ denote the total number of elements in node set V and edge set E, respectively, and also, $|V|$ denotes the order of graph G.

Subgraph: For a graph $G'=(V',E')$, a graph G' is said to be a subgraph of a graph G if $V\subset V$, $E\subset E$.

Undirected graph: A graph G is said to be an undirected graph if each edge in the graph G has no direction. In an undirected graph, each edge is represented by an unordered pair, and edge (v_i,v_j) and edge (v_j,v_i) are the same edge.

Directed Graphs: A graph G is said to be a directed graph if every edge in graph G has a direction. Unlike undirected graphs, each edge in directed graph G is represented by an ordered pair, where edge (v_i,v_j) represents a directed edge pointing from node v_i to node v_j and edge (v_j,v_i) represents a directed edge pointing from node v_j to node v_i.

A graph G can be represented by a set of nodes V and a set of edges E. Alternatively, a graph G can be represented by an adjacency matrix and a topological graph G has a unique counterpart of an adjacency matrix.

Adjacency Matrix: An adjacency matrix A is a matrix that represents the adjacency between nodes in a corresponding topological graph.

For a n-order directed graph $G=(V,E)$, its corresponding n-dimensional adjacency matrix $A=(a_{ij})_{n\times n}\in\mathbb{R}^{n\times n}$ is defined as follows:

$$a_{ij}=\begin{cases} w_{ij} & e_{ij}\neq 0 \\ 0 & Other \end{cases} \tag{1}$$

where w_{ij} denotes the weight of edge $e_{ij}=(v_j,v_i)$.

In the study of energetic control of dynamic systems of complex networks, the energetic control of the network is generally realized by using the addition of external control inputs u_j to the corresponding topological graph of the network, $j=1,\ldots,m$. Therefore, it is common to use the input matrix B to represent the connection relationship between each external input and the nodes in the network, which is now defined as follows: input matrix $B=\left(b_{ij}\right)_{n\times m}\in\mathbb{R}^{n\times m}$:

$$b_{ij}=\begin{cases} w_{ij} & \left(u_j,v_i\right)\neq 0 \\ 0 & \text{Other} \end{cases} \tag{2}$$

where, w_{ij} denotes the input node u_j control node v_i.

In the undirected graph, the set of nodes $\mathrm{V}=\{v_1,v_2,v_3,v_4,v_5,v_6,u_1\}$ and the set of edges $\mathrm{E}=\{(v_1,v_2),(v_1,v_3),(v_2,v_3),(v_2,v_4)(v_2,v_5),(v_3,v_4),(v_3,v_6),(v_4,v_5),(v_4,v_6),(u_1,v_6)\}$, where the edges (u_1,v_6) denote only the input nodes u_1 control nodes v_6.

In addition, the adjacency matrix A and the input matrix b corresponding to the graph are shown below, respectively:

$$A=\begin{pmatrix} 0 & a_{12} & a_{13} & 0 & 0 & 0 \\ a_{21} & 0 & a_{23} & a_{24} & a_{25} & 0 \\ a_{31} & a_{32} & 0 & a_{34} & 0 & a_{36} \\ 0 & a_{42} & a_{43} & 0 & a_{45} & a_{46} \\ 0 & a_{52} & 0 & a_{54} & 0 & a_{56} \\ 0 & 0 & a_{63} & a_{64} & a_{65} & 0 \end{pmatrix} b=\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ b_6 \end{pmatrix} \tag{3}$$

It can be noted that since the edges in an undirected graph are represented by unordered pairs, the corresponding adjacency matrix A of the undirected graph is a symmetric matrix.

The graph is directed if each edge has a direction. In a directed graph, the set of nodes $\mathrm{V}=\{v_1,v_2,v_3,v_4,v_5,v_6,u_1,u_2\}$ and the set of edges $\mathrm{E}=\{(v_1,v_2),(v_2,v_3),(v_2,v_4),(v_3,v_1)$, $(v_3,v_6),(v_4,v_3),(v_4,v_5),(v_5,v_2),(v_6,v_4),(v_6,v_5),(u_1,v_6),(u_2,v_2),(u_2,v_5)\}$.

In addition, the corresponding adjacency matrix A and input matrix B of the directed graph are shown below, respectively:

$$A=\begin{pmatrix} 0 & 0 & a_{13} & 0 & 0 & 0 \\ a_{21} & 0 & 0 & 0 & a_{25} & 0 \\ 0 & a_{32} & 0 & a_{34} & 0 & 0 \\ 0 & a_{42} & 0 & 0 & 0 & a_{46} \\ 0 & 0 & 0 & a_{54} & 0 & a_{56} \\ 0 & 0 & a_{63} & 0 & 0 & 0 \end{pmatrix} B=\begin{pmatrix} 0 & 0 \\ 0 & b_{22} \\ 0 & 0 \\ 0 & 0 \\ 0 & b_{52} \\ b_{61} & 0 \end{pmatrix} \tag{4}$$

It can be noted that since edges in a directed graph are represented by ordered pairs, their corresponding adjacency matrices are not necessarily symmetric matrices, e.g., the adjacency matrix A in Eq. (4) is an asymmetric matrix.

II. A. 2) Simple classification of networks and nodes

Based on whether the network is controlled by external inputs or not, this paper provides a simple categorization of networks.

Initial network: define the complex network without adding external inputs as the initial network, denoted as $\mathrm{G}_A(\mathrm{V}_A,\mathrm{E}_A)$.

Controlled network: define the network after adding several external inputs to the initial network G_A as the controlled network, denoted as $\mathrm{G}_C(V_{AB},\mathrm{E}_{AB})$.

According to the different properties of the nodes, this paper provides a simple categorization of the nodes in networks of different natures.

State nodes: define all nodes in the initial network G_A as state nodes.

Input nodes: define the nodes in the controlled network G_C that can generate signal input sources as input nodes.

Controlled nodes: a state node that is directly acted upon by at least one input node is defined as a controlled node and the set of controlled nodes is denoted as V_C. Further, a set of controlled nodes that enables the network system to be controlled is defined as the set of controlled nodes, denoted as v_{SC}, and a set of controlled nodes having a minimum number of nodes is defined as the set of minimum controlled nodes, denoted as $v_{SC_{\min}}$, such that N_I denotes the minimum number of inputs required to enable the system to be controlled.

Driver node set: define the set of controlled nodes that do not enjoy a common input node and enable the network to be controlled as the driver node set, denoted as V_D; further, define the set of driver nodes with the minimum number of nodes as the minimum driver node set, denoted as v_{SD}, and define N_D to denote the number of nodes in set v_{SD}.

II. A. 3) Basic concepts in graph theory

Directed path: define a directed path as a sequence of nodes $v_{i1},\dots,v_{im}$ satisfying $\left(v_{ik},v_{i(k+1)}\right)\in\mathrm{E}_P$, denoted as $P(V_P,\mathrm{E}_P)$, $k=1,2,\dots,m-1$. In addition, define node v_{i1} as the initial node, node v_{im} as the terminal node, and $|\varepsilon_P|$ denotes the length of the directed path.

Unidirectional graph: Based on the directed path P, define the directed graph obtained by adding directed edges (v_{im},v_{i1}) as a unidirectional graph, denoted as $C(V_C,\varepsilon_C)$.

Ancestor node, parent node, child node: in a directed graph, a node v_i is said to be the parent node of node v_j if there exists a directed edge $e_{ji}=\left(v_i,v_j\right)\in\mathrm{E}$ and, accordingly, node v_j is the child node of node v_i. In particular, node v_i is said to be an ancestor node of node v_j when there is a directed path (of length not less than 2) from node v_i to node v_j.

In addition, define set $M_{\{v_i\}}$ as the set of child nodes of node v_i, where, $M_{\{v_i\}}=\left\{v_j\in\mathrm{V}\,|\,e_{ji}\in\mathrm{E},i\neq j,i,j=1,\dots,n\right\}$; accordingly, define set $N_{\{v_j\}}$ as the set of parent nodes of node v_j, and also call set $N_{\{v_j\}}$ as the set of neighboring nodes of node v_j, where, $N_{\{v_j\}}=\left\{v_i\in\mathrm{V}\,|\,e_{ji}\in\mathrm{E},i\neq j,i,j=1,\dots,n\right\}$. $\left|N_{\{v_j\}}\right|$ and $\left|M_{\{v_i\}}\right|$ denote the in-degree and out-degree of node v_j and node v_i, respectively.

For a set $S\subset\mathrm{V}$, set $F_S=\left\{v_j\in S\,|\,e_{ji}\in\mathrm{E},v_i\in S,i=1,\dots,|S|\right\}$ denotes the concatenation of all the parents of each node in set S contained in set S, set $W_S=\left\{v_j\in\{\mathrm{V}\setminus S\}\,|\,e_{ji}\in\mathrm{E},v_i\in S,i=1,\dots,|S|\right\}$ denotes the concatenation of all the parents of each node in set S contained in set $\{\mathrm{V}\setminus S\}$, and set N_S is defined to be the concatenation of all the parents of each node in set S, denoted as $N_S=F_S\cup W_S$.

Connected graph: In a graph G, a graph G is said to be a connected graph if there exists no subgraph G' that is independent of any node or edge in the graph.

Directed Tree: In a directed graph $\mathrm{G}=(\mathrm{V},\mathrm{E})$, if there exists only one node $v_i\in\mathrm{V}$ with incidence 0, and for the rest of the nodes $v_j\in\{\mathrm{V}\setminus v_i\}$, there exists only one directed path from node v_i to node v_j, then such a directed graph is said to be a directed tree, denoted $T=(v_T,\mathrm{E}_T)$, and node v_i is defined to be the root node of the directed tree T, denoted v_r. In a directed tree T, every node $v_j\in\{\mathrm{V}\setminus v_i\}$, except for the root node v_r, has incidence 1.

Directed forest: $m\,(m\geq 0)$ directed trees form a directed forest, denoted $F=(V_{Fr},\mathrm{E}_{Fr})$, and furthermore, when $m\geq 2$, any two directed trees are independent of each other.

Directed Spanning Tree: For a directed graph $\mathrm{G}=(\mathrm{V},\mathrm{E})$, if there exists a directed tree $T'=(\mathrm{V}_T',\mathrm{E}_T')$ satisfying $\mathrm{V}_T'=\mathrm{V}$, $\mathrm{E}_T'\subset\mathrm{E}$, then the directed tree is said to be a directed spanning tree of the directed graph G.

Directed spanning forest: If there exists a directed forest F consisting of $m\,(m\geq 1)$ directed trees satisfying $\mathrm{V}_{Fr}=\mathrm{V}$, $\mathrm{E}_{Fr}\subset\mathrm{E}$, then the directed forest is said to be a directed spanning forest of the directed graph G.

Sibling nodes, leaf nodes: in a directed tree T, node v_i and node v_j are said to be sibling nodes of each other if $N_{\{v_i\}}=N_{\{v_j\}}$. For a node v_k, if $\left|M_{\{v_k\}}\right|=0$, call node v_k a leaf node in T.

Degree of a tree, t-forked directed tree: denote the degree of a tree by t, define $t=\max\left\{\left|M_{\{v_q\}}\right|,v_q\in v_T,q=1,\dots\right\}$, and call a directed tree with no more than t branches a t-forked directed tree, denoted $t-T=(V_T,\mathrm{E}_T)$.

II. B.Principles of graph neural networks

Graph neural networks are an important development in neural networks in the last few years, graph structures are commonly used in various areas of computing and there have been many advances in the study of graphs for a long time, however, before the rise of graph neural networks, conventional neural networks were not suitable for modeling graph-structured data, and thus the importance of graph neural networks has been growing [21].

II. B. 1) Basic framework of graph neural networks

The basic graph neural network model is defined from several different perspectives: the generalization of the convolution on non-Euclidean data can also be derived from classical graph isomorphism tests.The GNN uses a new approach to neural message passing that allows messages to be exchanged among nodes, propagated, and updated using neurons for message updating.

During the iteration of the graph neural network, each node $u \in V$ in Fig. $G = \{V, E\}$ has its own hidden state $h_u^{(k)}$, where k represents the number of iterative layers of the graph neural network, the mechanism of message passing in its neural network can be expressed as:

$$h_u^{(k+1)} = update^{(k)}\left(h_u^{(k)}, agg^{(k)}\left(\left\{h_v^{(k)}, \forall v \in \mathrm{N}(u)\right\}\right)\right) \tag{5}$$

$$h_u^{(k+1)} = update^{(k)}\left(h_u^{(k)}, m_{\mathrm{N}(u)}^{(k)}\right) \tag{6}$$

where the $update(\ )$ and $agg(\ )$ functions represent the update and aggregation operations, respectively, and can represent arbitrary differentiable functions, commonly a linear mapping function or a multilayer perceptron, and $\mathrm{N}(u)$ represents the set of neighboring nodes of the u node, then $m_{\mathrm{N}(u)}^{(k)}$ represents the message delivered by the set of neighbors of the kth layer u. In each iteration of the graph neural network at each layer, the aggregation function takes as input the representation of the set of neighbor nodes and generates a message based on the representation of the aggregated neighborhood as the message received by the node u at that iteration. Subsequently, the update function combines the received message $m_{\mathrm{N}(u)}^{(k)}$ with the hidden state $h_u^{(k-1)}$ of the node's previous layer to obtain $h_u^{(k)}$ as the u node's hidden state for that layer. $h_u^{(0)}$ is the input feature of the node, and in some tasks where there is no input node feature, the unique thermal encoding of the node is generally used as the node feature representation.

II. B. 2) Common graph neural networks

Since the node information is accumulated between each layer, resulting in the hidden state of the node is not stable and its highly sensitive to the degree of each node, which may lead to an explosion of values, a more efficient approach is to use an average pooling based approach instead of adding up the neighboring node states:

$$m_{\mathrm{N}(u)} = \frac{\sum_{v \in \mathrm{N}(u)} h_v}{\left|\mathrm{N}(u)\right|} \tag{7}$$

A symmetric normalization based approach was further used to balance the features of node aggregation to obtain the popular Graph Convolutional Network (GCN):

$$h_u^{(k)} = \sigma\left(W^{(k)} \sum_{v \in \mathrm{N}(u) \cup \{u\}} \frac{h_v}{\sqrt{\left|\mathrm{N}(u)\right|\left|\mathrm{N}(v)\right|}}\right) \tag{8}$$

The contribution of the neighbors of each node in the GCN graph to their own information is the same and fixed, and the importance cannot be distinguished, and there are certain limitations, while the graph Attention Network (GAT) uses an attention-based method, the importance of the information transmitted by each edge is determined by the weight of the edge, and the weight of each edge is calculated according to the hidden state of the node connected by the edge of the previous layer, and for an edge from i node to j nodes, its weight is calculated by a single-layer feedforward neural network. And through the LeakyReLU activation function and Softmax normalization operation, the following results are obtained:

$$a_{ij} = \frac{\exp\left(Leaky\,\mathrm{Re}\,LU\left(\vec{a}^T\left[W\vec{h}_i \,\|\, W\vec{h}_j\right]\right)\right)}{\sum_{k \in \mathrm{N}_i} \exp\left(Leaky\,\mathrm{Re}\,LU\left(\vec{a}^T\left[W\vec{h}_i \,\|\, W\vec{h}_k\right]\right)\right)} \tag{9}$$

The research on generalized graph neural network representation learning is not limited to the propagation method, some other shortcomings of GNNs are also being improved in the research, an important limitation is that graph neural networks are difficult to extend to deeper structures due to the problem of over-smoothing, most of the models achieve the best results in 2 layers, and an increase in the number of layers instead leads to the features between nodes converging, and decreases the effectiveness of the classification This limitation of the number of layers also restricts the message passing range of most graph neural networks to about 2 bars, which cannot spread the message farther. To solve this problem, GCNII constructs a jump connection from the input layer by adding an initial residual connection, and uses a constant mapping to add the unit matrix to the graph's adjacency matrix, which is propagated in each layer:

$$H^{(\ell+1)}=\sigma\left(\left(\left(1-\alpha_{\ell}\right)\tilde{P}H^{(\ell)}+\alpha_{\ell}H^{(0)}\right)\left(\left(1-\beta_{\ell}\right)I_{n}+\beta_{\ell}W^{(\ell)}\right)\right) \tag{10}$$

where α_f denotes the residual connection coefficients of layer 1 and β_ℓ denotes the constant mapping coefficients of layer 1. GCNII further investigated the GCN model with over-smoothing and found that the classification accuracy of nodes with large node degrees decreases rapidly as the number of network layers increases, suggesting that over-smoothing has a greater impact on nodes with high degrees.

II. B. 3) Graph Structure Learning

Structure learning of graphs can be divided into three steps: graph construction, graph structure learning and message passing on graphs.

1) Graph Construction. Initially, when a given graph structure is incomplete or even not available at all, an initial graph needs to be constructed as a starting point. There are several ways to construct an initial graph, two of the most common methods are k nearest neighbor and ò distance thresholding methods (ò graphs). Both methods first use a kernel function to compute distances to pairs of node features. The former takes the first few extremes from the distances, while the latter uses a fixed threshold.

2) Graph Structure Learning. The core of graph structure learning is a structure learner that models the connectivity of nodes, and consists of three different approaches: metric-based approaches that obtain edge weights based on pairs of node representations; and neural approaches that use neural networks to obtain edge weights from node representations; The direct approach optimizes the graph structure by considering the adjacency matrix of the graph as a parameter that can be learned directly through the training of graph neural networks.

3) Message passing on the graph. After obtaining the adjacency matrix of the graph, a graph neural network is generally used for representation learning to optimize the representation of nodes.

In the process of structure learning some regularization methods are generally used to constrain the optimization direction of the graph structure, such as sparsity, smoothness and community. Sparsity is generally achieved by applying a regularization loss to the adjacency matrix of the graph, and a common approach is to use L_0-regularization to limit the number of nonzero values in the adjacency matrix, i.e., to limit the number of edges in the graph:

$$\mathrm{L}_{sp}\left(A\right)=\left\|A\right\|_{0} \tag{11}$$

For graph smoothness, the learning of a representation on a graph is generally viewed as a signal propagation process, and a widely used assumption is that the propagation of the signal between nodes is smoothly varying. To enhance the smoothness of the signal on the graph, a regularization term is generally used:

$$\mathrm{L}_{sm}\left(X,A\right)=\frac{1}{2}\sum_{i,j=1}^{N}A_{ij}\left(x_{i}-x_{j}\right)^{2}=tr\left(X^{T}LX\right) \tag{12}$$

where $L=D-A$ denotes the graph Laplacian matrix, D is the degree matrix of the adjacency matrix, and there is an alternative approach that uses a symmetrically normalized Laplacian matrix $\hat{L}=D^{-\frac{1}{2}}LD^{-\frac{1}{2}}$ that is able to make the smoothing of features independent of the degree of the nodes. However this penalty term leads to a decrease in the connectivity of the nodes, so this constraint is generally aided by penalizing the nodes with each additional connectivity penalty term:

$$\mathrm{L}_{con}\left(A\right)=-1^{T}\log\left(A1\right) \tag{13}$$

where the logarithmic component will be constrained to make the adjacency matrix positive.

In the theory of graph spectra, the rank of the adjacency matrix is related to the number of connected components in the graph, and low-rank graphs will generally have dense connected components. Thus a low-rank positive lateralization term can be used to ensure the clustering properties of the graph:

$$\mathrm{L}_{cp}\left(A\right)=rank\left(A\right) \tag{14}$$

II. C.Relationship Extraction Algorithm Design

II. C. 1) BERT coding module

BERT has shown good results in word vector representation, so in this section, the pre-trained language model BERT is used to encode the input text.The input of BERT consists of three parts: word embedding tensor, utterance chunking tensor, and position encoding tensor. The word embedding tensor represents the vectors corresponding to the words in the text sequence, the utterance chunking tensor is used to differentiate paragraphs, and the position encoding tensor takes into account the positional information of different words in the sequence. The sum of these three partial vectors is output as the final vector representation. For a given text sequence $x=\{w_0,w_1,w_2,...,w_n,w_{n+1}\}$, where w_0 denotes the start marker "[CLS]" and w_{n+1} denotes the end marker "[SEP]", the BERT encoded output is $h=\{h_0,h_1,h_2,...,h_n,h_{n+1}\}$. Conventional extraction methods generally use h_o as the input to the SoftMax function to predict the relationship between entities. as the input to predict the relationship between entities, which ignores the implicit latent graph feature information in the sentence.In this chapter, auxiliary edges will be constructed for the relationship between node $h_0,h_1,h_2,...,h_n,h_{n+1}$ to capture the implicit features in it [22].

II. C. 2) Graph Neural Network Module

The graph neural network module consists of three main parts: a Gaussian graph generator, a Multi-View Graph Attention Network (MVGAN) and a graph convolutional neural network. The main role of this part is to perform feature extraction on the encoded sentence to capture the potential graph structure in the sentence.

1) Gaussian graph generator

The input text sequence is encoded by BERT to get the output $h=\{h_0,h_1,h_2,...,h_n,h_{n+1}\}$, the Gaussian graph generator will use $\{h_0,h_1,h_2,...,h_n,h_{n+1}\}$ as a node to generate a potential graph, for which the edges constructed represent the relationship between words. The node is initialized as $V^0=\{v_0^0,v_1^0,v_2^0,...,v_n^0,v_{n+1}^0\}$, and the Gaussian graph generator will take V^0 as the basis to construct potential edges in the graph from multiple perspectives, which is manifested by encoding each node v_i^0 into multiple Gaussian distribution representations using Eq. (15) and Eq. (16):

$$g_\theta(v_i^0)=\{\mu_i^1,\mu_i^2,...,\mu_i^K\} \tag{15}$$

$$\varnothing(g_\theta^{'}(v_i^0))=\{\sigma_i^1,\sigma_i^2,...,\sigma_i^K\} \tag{16}$$

where g_θ and $g_\theta^{'}$ denote two trainable neural networks, $\varnothing$ denotes the nonlinear activation function, K denotes the number of potential relationships in the latent graph, and the Gaussian distribution for node v_i^0 in one view can be expressed as $N_i(\mu_i,\sigma_i^2)$, so each node v_i^0 in the latent graph will get multiple Gaussian distributions $\{N_i^1,N_i^2,...,N_i^K\}$. The purpose of the multiple views is to capture as many relationships in the latent graph of the sentence as possible, and therefore it is considered that the existence of a relationship between the words that have large differences in information is are more likely, so the relative entropy (also known as Kull back-Leibler scatter) formula will be used next to model the relationship of edges between different nodes as in Eqs. (17) and (18):

$$e_{ij}^k=KL(N_i^k(\mu_i^k,(\sigma_i^k)^2)\,||\,N_j^k(\mu_j^k,(\sigma_j^k)^2)) \tag{17}$$

$$KL(P\,||\,Q)=\sum P(x)\log\frac{P(x)}{Q(x)} \tag{18}$$

where e_{ij}^n denotes the edge weights between the i rd and j th nodes on the knd view, and $KL(P\,||\,Q)$ denotes the formula for the dispersion. The Gaussian distribution of any two nodes in a view is used to calculate the KL dispersion using the relative entropy formula. After the computation is completed, multiple adjacency matrices $\{A^1,A^2,...,A^K\}$ are obtained to represent the potential graph relationships under different viewpoints, respectively. Therefore, the graph constructed by the Gaussian graph generator can be defined as $G=(V^0,A^1,A^2,...,A^K)$, and G is a directed graph due to the KL dispersion asymmetry.

2) Multi-viewpoint graph attention network

In this paper, we use the attention mechanism based on graph neural network to learn the different weights of each neighboring node from multiple views, which makes it focus only on those nodes with larger roles in the aggregation process. The inputs to this layer are the feature information of the nodes $h=\{h_0,h_1,h_2,...,h_n,h_{n+1}\}$ and the adjacency matrix representing the potential relationship between the nodes in different views $\{A^1,A^2,...,A^K\}$. In order to learn the weight parameters of different views from different perspectives, this paper uses the weight information of the edges generated by the Gaussian graph generator $\{A^1,A^2,...,A^K\}$ to initialize the weight parameters of the graphic attention network $\{W^1,W^2,...,W^K\}$ as shown in Eqs. (19) and (20):

$$e_{ij}^k=\sigma(W^kh_i,W^kh_j) \tag{19}$$

$$\alpha_{ij}^{k}=\frac{\exp(e_{ij}^{k})}{\sum_{j\in N_i}\exp(e_{ij}^{k})} \tag{20}$$

where W^k is the weight matrix under the knd viewpoint, initially, let $W^k = A^k$, N_i denote the number of nodes, $\sigma(\cdot)$ denotes the activation function, e_{ij}^{k} denotes the importance of node j to node i, and α_{ij}^{k} is the final weight parameter, at this time, we can use the formula (21) to compute the characteristics of node i under the k th importance angle as:

$$h_i^k = \sum_{j\in N_i}\alpha_{ij}^{k} h_j \tag{21}$$

Finally, the eigenvectors under each importance angle can be summed to get the eigenvector $h_i^{'}$ of each node, as shown in Equation (22):

$$h_i^{'} = \sum_{k=1}^{K} h_i^k \tag{22}$$

3) Graph Convolutional Neural Network

In order to better extract the feature information between entity pairs and other words in a sentence, this paper adds a layer of graph convolutional neural network at the end of the graph network module in order to capture the graph structure information in the sentence more deeply. The nodes get the output $h^{'} = \{h_1^{'}, h_2^{'}, \ldots, h_{n+1}^{'}\}$ after feature extraction by the multi-view graph attention network as well as the learned weight parameter matrix $\{W_a^0, W_a^1, \ldots, W_a^k\}$ as the input to this layer of neural network, which can be regarded as the importance of the relationship between the nodes in the graph. After the extraction of graph convolutional network, node i will aggregate the feature information of its neighboring nodes as the output of this layer, and in this paper, the node representation corresponding to the entity in the output is selected as the output of the whole graph module, as shown in Equation (23):

$$h^{''} = \sigma(\hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}}h^{'}W_b) \tag{23}$$

where $\hat{A} = I + W_a, W_a = \Sigma_{k=1}^{K} W_a^{k}$, I is the unit matrix indicates that the network can retain the information of its own nodes in the process of information dissemination, W_a is the adjacency matrix of Fig. G, $\hat{D}_{ii} = \sum_j \hat{A}_{ij}$ denotes the degree matrix of $\hat{A}$, which mainly serves to do normalization of matrix $\hat{A}$ to ensure that the values taken in the matrix are in the range of (0, 1), and w_b is the parameters of the matrix to be learned.

II. C. 3) Small Sample Relationship Extraction Methods

In the small-sample learning approach, the dataset is divided into support set S and query set Q, and the text sequence in the support set required for one NwayKshot's relation prediction during model training can be denoted as $S_i = \{(x_{ij}, r_i) \mid i = 1, 2, \ldots N; j = 1, 2, \ldots, K; r_i \in R\}$, where x_{ij} denotes the j th instance in the i th relation, and r_i denotes a relation in the relation set R; a query instance in the query set can be denoted as q_i, and the type of relation of the query instance belongs to one of the N relationships. The text sequences x_{ij} and query instances q_i in the support set can be encoded by the BERT module to obtain the vector representations $H_{ij} = \{h_{ij}^0, h_{ij}^1, \ldots, h_{ij}^{n+1}\}$ and $H_q = \{h_q^0, h_q^1, \ldots, h_q^{n+1}\}$ of the corresponding instances, which are then inputted into the graph module to extract the features to obtain the states $h_{ij}^{''}$ and $h_q^{''}$ of all the nodes as shown in Eqs. (24) and (25):

$$H_{ij}^{''} = \{h_{ij}^{0''}, h_{ij}^{1''}, \ldots, h_{ij}^{n+1''}\} \tag{24}$$

$$H_q^{''} = \{h_q^{0''}, h_q^{1''}, \ldots, h_q^{n+1''}\} \tag{25}$$

Subsequently, the node feature vectors corresponding to the text sequences of the support set and the query instance are averaged to represent the structural feature representations of the instance extracted by the graph module, and the symbols are denoted as $h_i^{j''}$ and $h_q^{''}$, as shown in Eqs. (26) and Eq. (27):

$$h_i^{j''} = mean(h_{ij}^{0''}, h_{ij}^{1''}, \ldots, h_{ij}^{n+1''}) \tag{26}$$

$$h_q^{''} = mean(h_q^{0''}, h_q^{1''}, \ldots, h_q^{n+1''}) \tag{27}$$

where $h_i^{j''}$ denotes the feature vector of the j rd instance under the i nd relationship category, $h_q^{''}$ denotes the final vector representation of the query instance, and $mean(\cdot)$ denotes the average function. Subsequently, the structural feature vectors extracted from the graph module part are spliced with the initial BERT-encoded semantic feature vectors as shown in Eqs. (28) and (29):

$$h_i^{j'''} = Cat(h_i^{j''}, H_{ij}) \tag{28}$$

$$h_q^{'''} = Cat(h_{q''}, H_q) \tag{29}$$

where $Cat(\cdot)$ denotes the splicing operation of the two vectors, and h_i^j and h_q denote the initial vectors of the support set and query instance encoded by BERT, respectively. The feature vector c_i representing the class of the relation is subsequently computed by inputting it into the prototype network using Eq. (30):

$$c_i = \frac{1}{k}\sum_{j=1}^{K} h_i^{j'''}, i = 1, 2, ..., N \tag{30}$$

where K represents the number of instances. Finally, when performing relationship prediction, the prototype network uses $Softmax(\cdot)$ to compute the probability of a query instance q being in the set of relationships R, as shown in the formula in (31):

$$p_\phi(y = r_i \mid h_q^{'''}) = \frac{\exp(-d(h_q^{'''}, c_i))}{\sum_{j=1}^{N}\exp(-d(h_q^{'''}, c_j))} \tag{31}$$

where $-d(h_q^{''}, c_j)$ denotes the function that computes the distance between two vectors, and $p_\phi(y = r_i \mid h_q^{''})$ denotes the probability that query instance q is of relation type r_i. The distance function uses the Euclidean distance formula to outperform other distance formulas.

III. Knowledge graph relationship extraction performance experiments

In this chapter, the effectiveness of the knowledge graph relationship extraction method proposed in this paper will be evaluated.

III. A. Introduction to the data set

In this paper, experiments are conducted on four widely used public datasets, namely SemEva, TACRED, TACREV, and Re-TACRED. The detailed information of each dataset is specifically shown in Table 1.

Table 1: Dataset

Dataset	Train	Val	Test	Rel
SemEval	6,503	1,496	2,720	18
TACRED	68,123	22,637	15,517	40
TACREV	68,126	22,621	15,511	40
Re-TACRED	58,467	19,593	13,417	42

III. B. Baseline Comparative Analysis

Graph Neural Network (GNN), Prototype Network Model (Proto), and KnowPrompt model are selected as comparisons to compare the performance with the knowledge graph relationship extraction method proposed in this paper. In this paper, each dataset is set up as three different low-resource scenarios for experiments respectively. In this paper, a total of three different scenarios are set up, specifically including the sample size K=8, K=16, K=32, the comparison results of different models on different datasets are specifically shown in Table 2. The results show that the method in this paper performs well on all four datasets and achieves good performance. In the low-resource scenario with K=8, this paper's method also still produces good performance.

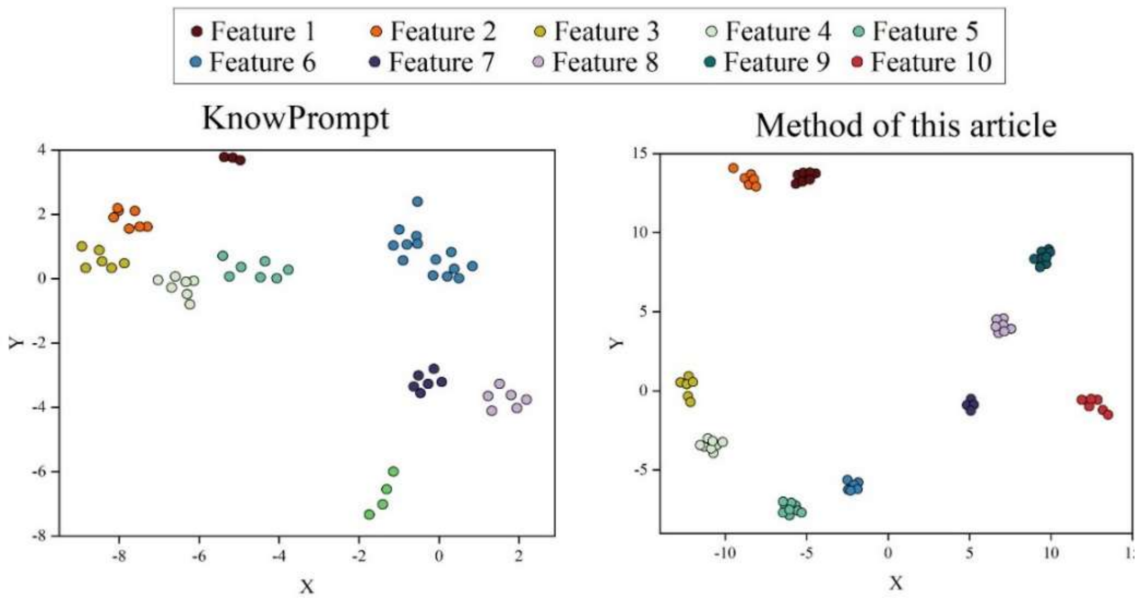
Table 2: Comparison result

Mehtod	TACRED			TACREV			Re-TACRED			SemEval		
	K=8	K=16	K=32	K=8	K=16	K=32	K=8	K=16	K=32	K=8	K=16	K=32
GNN	28.9	32	32.4	27.6	31.2	32	8.4	17.5	17.9	5.2	5.7	18.6
Proto	28.1	30.7	32.1	28.7	31.4	32.4	9.5	21.5	28.7	9.8	22	29.3
KnowPrompt	32	35.4	36.5	32.1	33.1	34.7	11.8	22.5	28.8	8.3	20.8	28.1

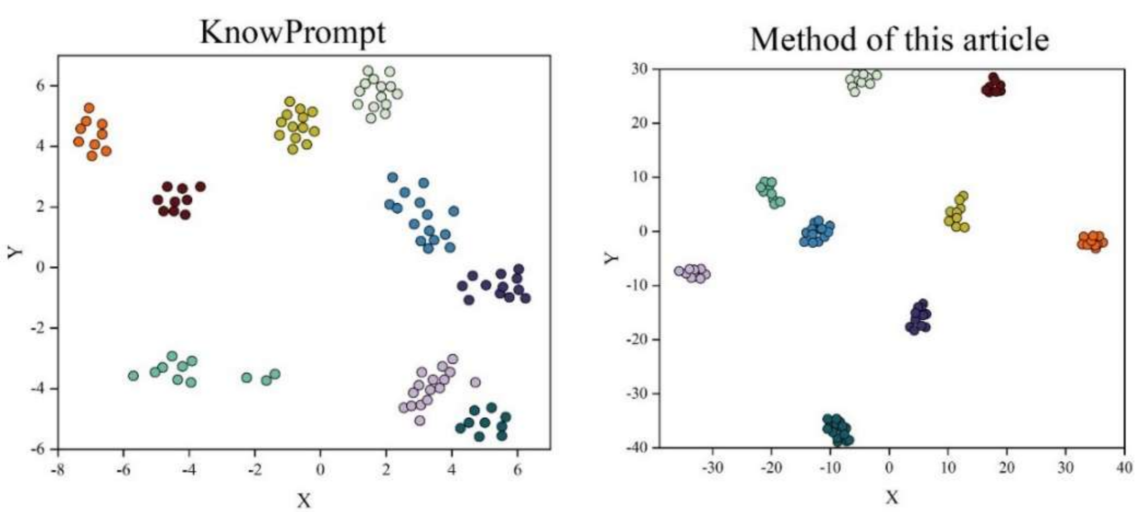
Ours	34.1	37.2	40.3	34.9	37.4	39.2	18.1	27.6	32.1	18.6	28.8	32.2

III. C. Feature visualization and analysis

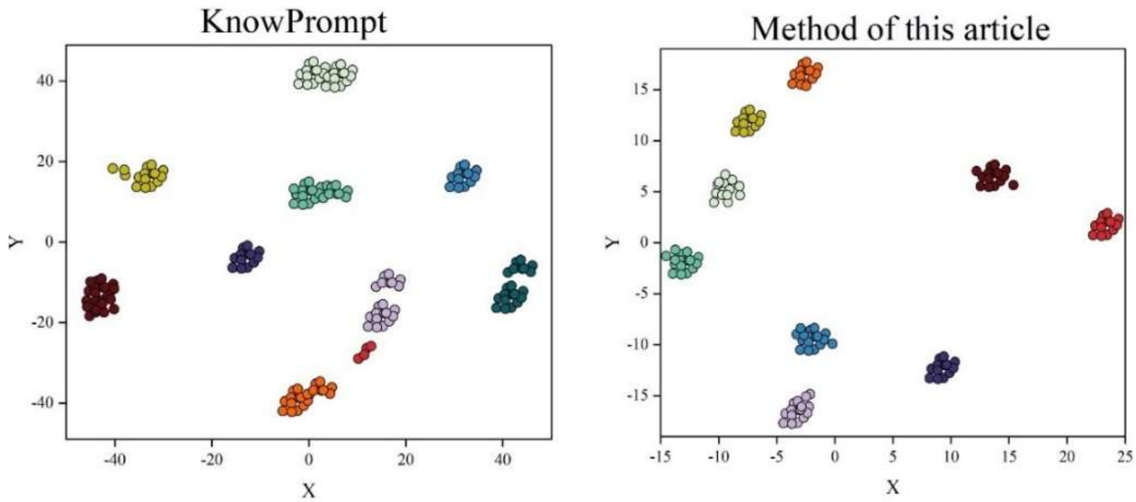
In order to more intuitively see the changes of feature distribution, this paper uses the high-dimensional data downscaling algorithm t-SNE on the Re-TACRED dataset to map the feature distribution in the two-dimensional space, which is compared with the KnowPrompt method in detail. Three cases of K=8, K=16 and K=32 are set respectively to compare the visualization results of this paper's method with KnowPrompt method, as shown in Fig. 1. Figures (a)~(c) correspond to the three cases of K=8, K=16 and K=32, respectively. The results show that the present method shows better aggregation phenomenon compared with KnowPrompt method in the two cases of K=8 and K=16, while both methods show better performance at K=32. This is because the number of samples for each type of relationship has reached 32, and both methods have enough sample size to learn better feature representations.



(a)K=8



(b)K=16



(c)K=32

Figure 1: Feature visualization comparison results

III. D. Detailed analysis

Taking the Re-TACRED dataset as an example, this section will further analyze the effectiveness of the knowledge graph relationship extraction method in this paper. Firstly, various types of relationships existing in the dataset are compared and analyzed, secondly, specific cases are compared and analyzed, and finally, similar relationships are visualized and analyzed. The effectiveness of the method is verified through multiple perspectives.

III. D. 1) Comparative analysis of various types of relationships

In this paper, a detailed comparison and analysis is made with the strong baseline model KnowPrompt on all kinds of relationships, and the specific experimental results are shown in Fig. 2, where 1~37 of the horizontal coordinates correspond to the R1~R37 relationships, respectively, and the vertical coordinates represent the accuracy rate. From the experimental results, it can be seen that among the 37 types of relations existing in the dataset Re-TACRED, the accuracy of this method is higher than or equal to the baseline model KnowPrompt for 30 types of relations, which indicates that this method is effective in predicting most of the relations.

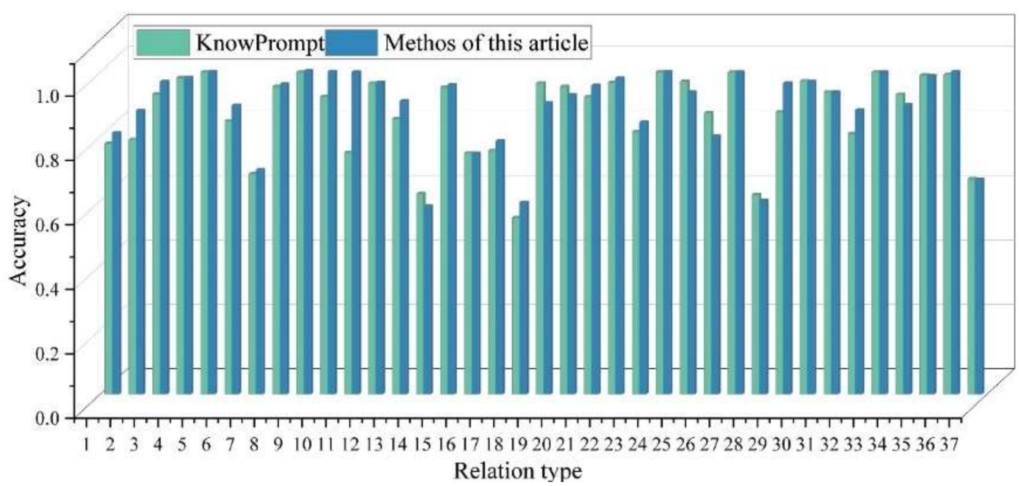
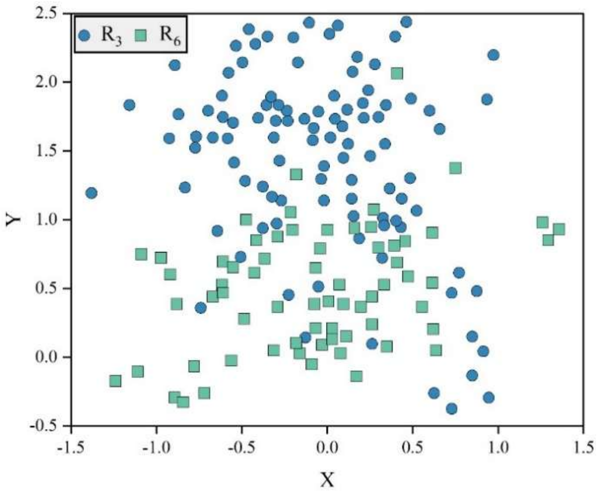


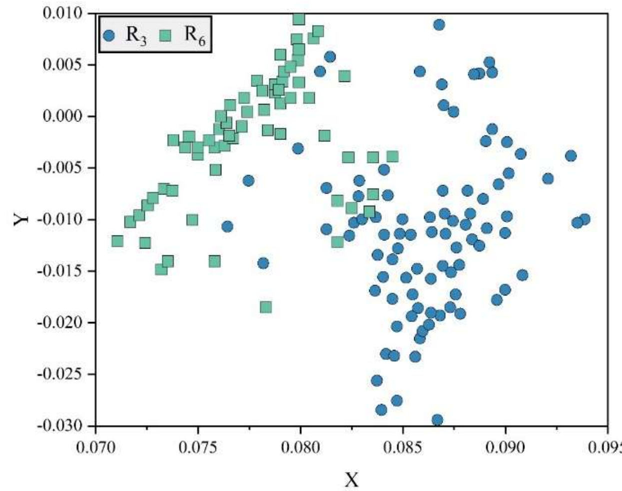
Figure 2: Various relationships

III. D. 2) Visual Analysis of Similarity Relationships

In this paper, it is argued that one of the main reasons for the failure of classification prediction is the existence of some relationship classes with high similarity. Therefore, in this section, two similar relations R3 and R6 are selected from the dataset Re-TACRED to be carried out, and a number of instances are randomly extracted from the paper from the two relations, and the features of the similar relations are visualized using t-SNE. The specific visualization results are shown in Fig. 3, Fig. (a) shows the feature visualization results before introducing this paper's knowledge graph relationship extraction method, and Fig. (b) shows the feature visualization results after introducing this method. From the visualization results, it can be seen that the feature embeddings of similar relations are relatively separated after the introduction of this method. This makes it easier to categorize similar relationships. This experiment can prove that the present model can produce better discriminative features, especially for the challenging task of knowledge graph relationship extraction.



(a) Before introducing the method of relation extraction in this paper



(b) After introducing the relationship extraction method in this paper

Figure 3: The comparison results of feature visualization

IV. Construction of a knowledge map for the dissemination of innovation in the art of ji opera

In this chapter, the knowledge graph relationship extraction method based on graph neural network proposed above will be used to construct a knowledge graph for the innovative communication of Ji Opera art, so as to provide academic support for the inheritance and development of Ji Opera.

IV. A. Knowledge Graph Ontology Model

This section uses the top-down knowledge graph construction process [23]. In the top-down construction of knowledge graph, it is necessary to define the ontology model and data schema first. Ontology, as a standardized description of knowledge in a specific domain, defines the class set, relationship set, attribute set, etc. of the domain knowledge graph in a figurative way, and manages the schema layer of the knowledge graph. Through the construction of ontology model, it can formally express all kinds of concepts and their relationships in the domain, provide users with a common understanding of the domain knowledge, and constrain the specification of entities, relationships and entity attributes, etc., which can serve as a guide for subsequent knowledge extraction and organization.

The Protégé tool was used to construct the ontology model of the knowledge graph of Jiqu art innovation and communication, as shown in Figure 4. The ontology includes 4 event entity categories: "Art Creation Event", "Stage Presentation Event", "Communication Promotion Event", and "Inheritance Education Event", as well as 9 event element entity categories of "Time", "Place", "People", "Institution", "Conference", "Journal", "Paper", "Patent" and "Project".

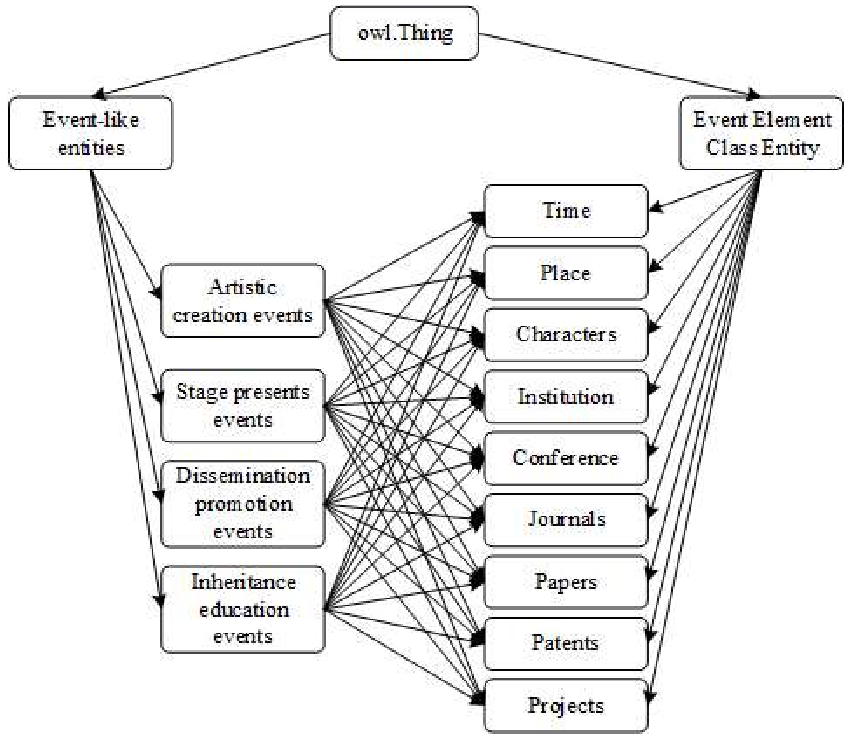


Figure 4: Knowledge map of Jiju Opera art innovation communication

IV. B. Access to knowledge

Knowledge graph consists of one piece of knowledge, whether the knowledge is correct and its coverage is the key to the successful realization of knowledge graph, so how to correctly obtain the required knowledge is the basis of knowledge graph construction. Real-world data are mainly divided into three categories: structured data, semi-structured data and unstructured data, and the knowledge in the field of discipline construction is mainly contained in text-based unstructured data and web-based semi-structured data.

After practical analysis and effect evaluation, this paper takes the network resources in the Internet as the main data source, and crawls the text data containing relatively rich knowledge from the university website for the extraction of innovative communication events of JI Opera, and then takes “Baidu Encyclopedia” as the data source of entity attributes, and crawls the semi-structured data therein to complete the knowledge The model extracts the event elements from the model.

In this paper, we use Baidu Encyclopedia as the data source, and then use Requests library to crawl the relevant attribute information of the extracted entities from the encyclopedia page to supplement the knowledge.

1) Locate the target page URL. Through observation, we find that the URLs of Baidu encyclopedia pages have a certain regularity, and splice the URLs with the names of target entities to form the target page URLs to be crawled.

2) Initiate the request and get the page data. After getting the URL of the target page, use the get method of Requests library to initiate a request and get the page data in response.

3) Attribute information extraction. From the obtained page data, basic information data and illustrative atlas links are parsed out. For the basic information data, after removing blank characters and other preprocessing operations, various types of attribute information of the entity are formed. If the page contains a link to an illustration gallery, the page is crawled according to the new URL to obtain the entity's image information. Through the above steps, the process of extracting attribute information of the target entity is finally completed.

IV. C. Knowledge integration

Although the authenticity of the data is guaranteed there may still be cases where the same entity has different names. This is when knowledge fusion is needed. The overall task of knowledge fusion is to calculate the similarity between entities, the similarity of entities within a certain threshold to be classified as the same entity, this paper's approach is to connect the sameAs relationship between the different representations of the same entity, in the case of a user query on an entity, but also on the entity that has a sameAs relationship to do the same query. The entity similarity calculation method used in this paper is described below.

For node pairs in the knowledge graph, the similarity can be calculated based on their mapping relationship (parent-child/brother relationship) with the nearby entities, which is known as structure-level similarity. There are 3 types of similarity calculation methods as follows:

$$sim_S(C_1,C_2)=\mu_P sim_{string}(SC_1,SC_2) \tag{32}$$

$$sim_B(C_1,C_2)=\mu_B sim_B(BC_1,BC_2) \tag{33}$$

$$sim_R(C_1,C_2)=\mu_R sim_R(RC_1,RC_2) \tag{34}$$

Eqs. (32) to (34) are the parent, child and brother similarity calculations, respectively. For nodes C_1 and C_2, their parent class nodes are SC_1 and SC_2, subclass nodes are BC_1 and BC_2, and brother nodes are RC_1, RC_2, μ_P, μ_B, and μ_R are the similarity attenuation coefficients in the parent class rule, subclass rule, and brother rule, respectively. After calculating the above 3 similarities, the fusion is carried out by weighted average, and the final similarity between the nodes is obtained as:

$$sim_{structure}(C_1,C_2)=\frac{\alpha sim_S(C_1,C_2)+\beta sim_B(C_1,C_2)+\gamma sim_R(C_1,C_2)}{\alpha+\beta+\gamma} \tag{35}$$

where, α, β, γ are the weighted average coefficients, and there are usually $\alpha>\beta>\gamma$ due to the different impacts of various types of rules on nodes.

In order to test the effect of knowledge fusion, in this paper, 1000 fused entity pairs are randomly selected, and their semantic similarity is evaluated by calculating their semantic similarity based on their shared attributes and relationships, and the formula for semantic similarity is:

$$sim_W(C_1,C_2)=\sum_{\rho(\omega C_1,\omega C_2)\in S(C_1,C_2)} Wordsim(\omega C_1,\omega C_2)\times\max\left(idf(\omega C_1),idf(\omega C_2)\right) \tag{36}$$

where $Wordsim(\omega C_1,\omega C_2)$ represents the word similarity of the common attributes of nodes C_1 and C_2, and $idf(\omega C_1)$ is the inverse text frequency index of ωC_1. It was tested and found that the task is better when taking the maximum value compared to taking the average or minimum value of $idf(\omega C_1)$ and $idf(\omega C_2)$. The distribution of semantic similarity measured by the experiment is shown in Fig. 5, and the experiment shows that the number of entities with similarity of 0.8 or more accounts for 72.5% of the total number. The experiment proves that the method of knowledge fusion by calculating structure-level similarity works well.

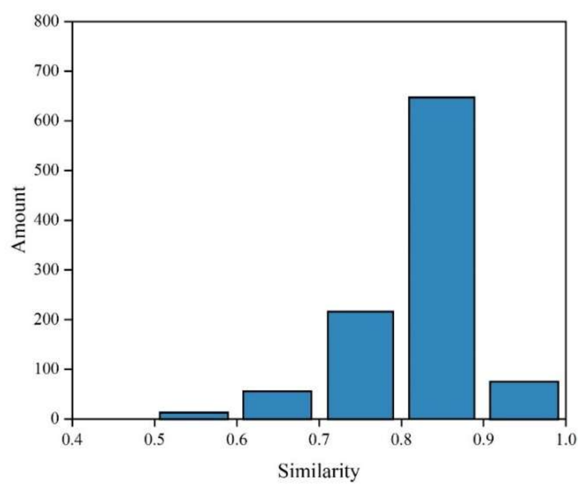


Figure 5: Semantic similarity distribution

IV. D. Knowledge storage and visualization

Neo4j is a Java implementation of the open source NoSQL graph database, the use of free adjacency characteristics of the graph storage structure, to provide faster transaction processing and data relationship processing capabilities. In this paper, we use Echarts to achieve knowledge graph visualization, Neo4j only as a graph database to use. Echarts is based on JavaScript open source visualization library, which comes with the type of relationship graph is a common choice in the front-end implementation of knowledge graph visualization , and can also be used with

JavaScript to achieve the force-oriented graph , show dependencies, display attributes and other functions. functions. Based on Echarts, the knowledge map visualization of Jiyu opera art innovation communication is shown in Figure 6.

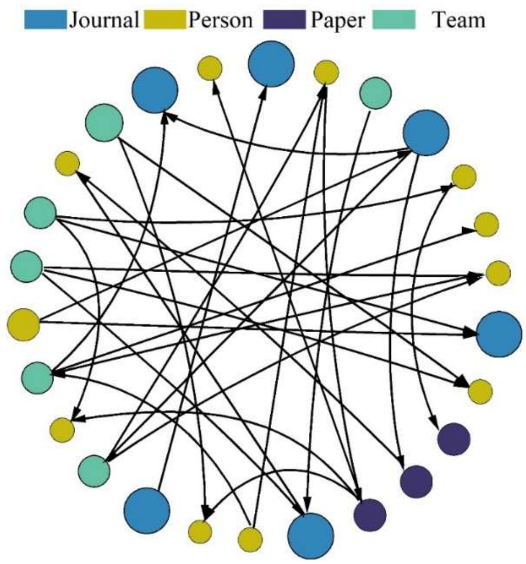


Figure 6: Knowledge graph visualization

V. Analysis of hotspots for research on the innovative dissemination of Ji opera art

Combined with the knowledge map of innovation communication of Ji opera art constructed above, this chapter will analyze the research hotspots and evolution trends of the knowledge of innovation communication of Ji opera art in terms of keyword co-occurrence, clustering and convexity.

V. A. Keyword co-occurrence analysis

The results of keyword co-occurrence analysis are shown in Figure 7. It can be seen that the knowledge map of artistic innovation dissemination of Ji opera takes “dissemination” as the core element and combines the artistic innovation dissemination of Ji opera with new media, higher education and college students. The keyword co-occurrence shows that the research on the knowledge management of artistic innovation communication of Ji opera is in line with the milestones achieved in the context of the new era of technological support, Internet development, life care, and the guidance of correct values in social media.

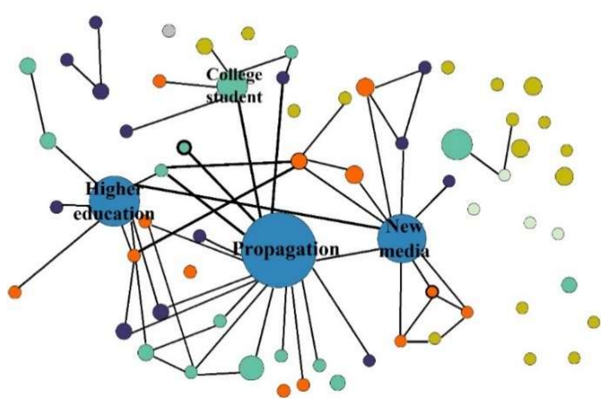


Figure 7: Keyword co-occurrence analysis

V. B. Keyword Cluster Analysis

By comprehensively analyzing the literature from the Web of Science and the China Knowledge Network (CNN), we aim to explore the key areas and research hotspots of the innovative communication of Ji opera art. Through the cluster analysis method, the keywords are divided into 10 main categories, as shown in Figure 8, which reveals the main research directions and academic focuses in the field of innovative communication of Jiyu Opera art.The

10 main categories are repertoire and scripts, performance program, music system, stage art, script literature, inheritance and education, digital technology, media communication, audience research, and policies and regulations.

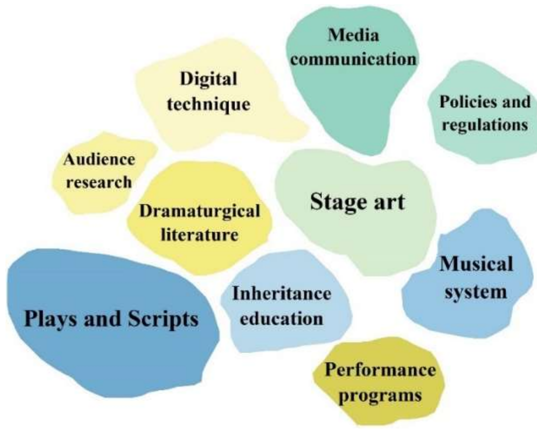


Figure 8: Keyword clustering knowledge map

V. C. Keyword Convexity Analysis

From 1995 to 2024, the results of the analysis of the keywords' prominence in the field of communication of innovation in the art of ji opera, sourced from the Web of Science and the China Knowledge Network, are shown specifically in Table 3, which is designed to reveal the changes in the focus and trends of academic research during this period. The intensity reflects the rate of increase in the degree of academic attention or citation frequency of the keywords within a specific time period. The higher the value, the more attention the keyword receives in the research field, and its related research results may have a greater impact in academia or practice. The emergence period indicates the time range of keyword emergence, that is, the time period from the beginning of the keyword receiving widespread attention to the beginning of the decline in attention. During this period, the emergence and development of related research is the most active, reflecting the concentration of academic interest in a certain topic.

The intensities of digital inheritance and cross-border integration have increased significantly in recent years, reaching 2.45 and 2.23, respectively, indicating that these two topics have become hot spots for research in the innovative communication of ji opera art. In particular, the prominence of public opinion between 2015 and 2021 reflects the far-reaching impact of social media and Internet technology development on the innovative communication of Ji opera art.

Concerns about youthful expression and immersive performances have increased rapidly in a short period of time. In terms of time span, the research interests of policy support and international dissemination lasted for a longer period of time, from 2009 to 2016, and a single year bump in 2022, respectively, indicating that the policies under different periods of time for the support and protection of traditional drama, and the internationalization of the dissemination of traditional drama culture are the continuous concerns of the research on the communication of Jiyu Opera art innovation.

The emergence of IP development and short-video marketing from 2021 to 2024 reflects researchers' continued attention to the public's interest in short-video platforms and theater derivation in recent years.

Through the above analysis, it can be seen that the hotspots of research and their evolution within the field of innovative communication of Ji opera art not only reflect the dynamic changes in the protection, inheritance and dissemination of traditional theatrical culture, but also provide important insights and references for future research directions and practical applications.

Table 3: key keywords in Jiju opera art innovation communication

Keywords	strength	Beginning year	End year	Prominent period
Popularization of education	1.57	2000	2003	1995-2024
Policy support	1.94	2009	2016	1995-2024
Digital inheritance	2.23	2012	2017	1995-2024
Cross-border integration	2.45	2015	2021	1995-2024
Younger expression	1.8	2015	2016	1995-2024

Immersive performance	1.86	2021	2021	1995-2024
IP development	1.76	2021	2024	1995-2024
Short video marketing	1.71	2021	2024	1995-2024
International communication	2.01	2022	2022	1995-2024
Cultural tourism linkage	1.84	2022	2022	1995-2024
Live performance	2.36	2018	2018	2018-2024
Community operation	1.25	2019	2019	2018-2024
Theme innovation	1.19	2019	2020	2018-2024
Intangible cultural heritage protection	1.05	2019	2019	2018-2024
Theater innovation	1.14	2020	2020	2018-2024
Interactive narrative	1.89	2021	2021	2018-2024
Dialect protection	1.55	2021	2021	2018-2024
AI composition	1.55	2021	2021	2018-2024
Holographic projection	1.03	2021	2021	2018-2024
Meta-universe	1.03	2021	2021	2018-2024

VI. Conclusion

This paper proposes a knowledge graph relationship extraction method based on graph neural network to construct a knowledge graph for the innovative communication of Ji opera art. Under the sample size K=8, K=16, K=32, the method in this paper has better performance on different datasets of SemEva, TACRED, TACREV and Re-TACRED, and outperforms the comparative Graph Neural Network (GNN), Prototype Network (Proto) model and KnowPrompt model. Further comparative analysis of feature visualization and relationship visualization with KnowPrompt model shows that this method outperforms KnowPrompt for feature aggregation in the case of insufficient K=8 and K=16 samples, and both perform better in the case of sufficient K=32 samples. Among the 37 types of relations present in the dataset Re-TACRED, the accuracy of this method is higher than KnowPrompt for 30 types of relations, and the classification performance in feature visualization of similar relations is also better.

The ontology includes 4 event entity categories: "Artistic Creation Event", "Stage Presentation Event", "Communication and Promotion Event", and "Inheritance Education Event", as well as 9 event element entity categories of "Time", "Place", "People", "Institution", "Conference", "Journal", "Paper", "Patent" and "Project". The knowledge fusion method used in the construction of the knowledge graph in this paper is tested, and the number of entities with semantic similarity of more than 0.8 measured by the knowledge fusion method in this paper accounts for 72.5% of the total number, and the knowledge fusion effect is good. Finally, Neo4j is only a graph database, and Echarts is used to realize the visualization of the knowledge graph of Jiju art innovation and communication.

From the three aspects of keyword co-occurrence, clustering and convexity, the research hotspots and evolution trends of the knowledge of innovative communication of Ji opera art are analyzed in combination with the knowledge map of innovative communication of Ji opera art constructed in this paper. In the results of keyword co-occurrence analysis, “communication” is taken as the core element, and it is combined with new media, higher education and college students. Through the cluster analysis method, the keywords are divided into 10 major categories: repertoire and script, performance program, music system, stage art, script literature, inheritance education, digital technology, media communication, audience research, policies and regulations. The keywords within the field of innovation and communication of Ji opera art are analyzed in terms of convexity, in which the intensity of digital inheritance and cross-border integration reaches 2.45 and 2.23 respectively, the intensity of which has increased significantly in recent years and become a research hotspot. Public opinion is convex between 2015 and 2021, youthful expression, immersive performance in the short term attention increases rapidly, policy support and international dissemination of the time span and the duration of the research interest is longer, respectively, from 2009 to 2016, and a single year of convex in 2022, support and protection, the international dissemination of traditional theatrical culture is the continuous focus of the research. ip development, short video marketing came to the fore between 2021 and 2024, a research point that has gained sustained attention in recent years.

On the whole, the knowledge map of the innovative communication of Ji opera art established by utilizing the knowledge map relationship extraction method proposed in this paper can provide academic support for the inheritance development and innovative communication of Ji opera in a better way, and provide important insights for the future research direction and practical application.

Funding

This work was supported by Department of Education of Jilin Province of Scientific research projects (Project number: JJKH20210474SK).

References

[1] Chen, M. (2019, April). Analysis on Industrialization Development Path of Intangible Cultural Heritages of Jilin Province. In 3rd International Conference on Culture, Education and Economic Development of Modern Society (ICCESE 2019) (pp. 500-504). Atlantis Press.
[2] Wu, J., Jiang, K., & Yuan, C. (2019). Determinants of demand for traditional Chinese opera. Empirical Economics, 57, 2129-2148.
[3] Cai, Z., Cai, K., Huang, T., Zhang, G., & Chen, R. (2024). Spatial distribution characteristics and sustainable inheritance strategies of national traditional fine arts intangible cultural heritage in China. Sustainability, 16(11), 4488.
[4] Liu, S., & Abdullah, N. Q. J. B. (2023). Digital Transformation in Chinese Theatre Opportunities and Risks. Studies in Art and Architecture, 2(3), 52-56.
[5] Li, F., & Song, L. (2023). Video game music and cultural dissemination: a study of honour of kings as a MOBA game. Galactica Media: Journal of Media Studies, 5(3), 170-191.
[6] Jiang, Y. P., Su, C., & Li, X. C. (2025). Virtual reality technology for the digital dissemination of traditional Chinese opera culture. International Journal of Human–Computer Interaction, 41(4), 2600-2614.
[7] Hong, N. I. (2022). New Ideas for Inheriting Traditional Opera Arts in the New Media Era——Taking the Cantonese Opera Film The Tale of the White Serpent-Passions for Example. The journal of xinyang normal university (philosophy and social science edition), 42(5), 100-105.
[8] Lan, L. (2021). Analysis on the development strategy of traditional Chinese opera based on digital media technology. Arts Studies and Criticism, 2(4), 51-58.
[9] Su, B. (2022). HOW TO DISSEMINATE THE CHARM AND SPIRIT OF CHINESE OPERA WITH THE HELP OF SHORT VIDEO. Psychiatria Danubina, 34(suppl 4), 675-675.
[10] Shimray, S. R. (2019). Understanding Social Media Structure and Dissemination of Cultural Heritage Knowledge. International Journal of Innovative Knowledge Concepts, 7(4).
[11] Chen, Y., Xue, K., & Dai, M. (2020). The academics of Intangible Cultural Heritage-knowledge map analysis based on CiteSpace (2003-2019). International Journal of Intangible Heritage, (15), 181-198.
[12] Hu, W., Li, M., Chi, X., Wang, X., & Khan, A. U. (2024). Intangible cultural heritage research in China from the perspective of intellectual property rights based on bibliometrics and knowledge mapping. Humanities and Social Sciences Communications, 11(1), 1-11.
[13] Ge, X., Wang, Y. C., Wang, B., & Kuo, C. C. J. (2024). Knowledge graph embedding: An overview. APSIPA Transactions on Signal and Information Processing, 13(1).
[14] Zhu, Y., Wang, X., Chen, J., Qiao, S., Ou, Y., Yao, Y., ... & Zhang, N. (2024). Llms for knowledge graph construction and reasoning: Recent capabilities and future opportunities. World Wide Web, 27(5), 58.
[15] Wang, X., Chen, L., Ban, T., Usman, M., Guan, Y., Liu, S., ... & Chen, H. (2021). Knowledge graph quality control: A survey. Fundamental Research, 1(5), 607-626.
[16] Cabeça, S. M. (2018). Cultural mapping: A sustainable methodology for intangible cultural heritage. Memoriamedia Review, 3(5), 1-9.
[17] Jiaxin, Z., Zur, R., & Yun, M. (2024). Visual analysis of intangible cultural heritage research hotspots based on knowledge graph. Built Environment Journal, 21, 208-218.
[18] Dou, J., Qin, J., Jin, Z., & Li, Z. (2018). Knowledge graph based on domain ontology and natural language processing technology for Chinese intangible cultural heritage. Journal of Visual Languages & Computing, 48, 19-28.
[19] Fan, T., & Wang, H. (2022). Research of Chinese intangible cultural heritage knowledge graph construction and attribute value extraction with graph attention network. Information Processing & Management, 59(1), 102753.
[20] Hamid Reza Daneshpajouh & Frédéric Meunier. (2025). Box complexes: At the crossroad of graph theory and topology. Discrete Mathematics,348(6),114422-114422.
[21] Duc Thach Son Vu,Tan M. Nguyen & Weiqing Ren. (2025). Learning and predicting dynamics of compositional multiphase mixtures using Graph Neural Networks. Journal of Computational Physics,529,113851-113851.
[22] Shao Hao & Wang Shunfang. (2023). Deep Classification with Linearity-Enhanced Logits to Softmax Function. Entropy (Basel, Switzerland),25(5).
[23] Lukas Bahr,Christoph Wehner,Judith Wewerka,José Bittencourt,Ute Schmid & Rüdiger Daub. (2025). Knowledge graph enhanced retrieval-augmented generation for failure mode and effects analysis. Journal of Industrial Information Integration,45,100807-100807.