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Study on the Transformation Path of Cultural Communication Mode of Chinese Film Industry in the Era of Artificial Intelligence

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SUMMARY: *Nowadays, the vigorous development of artificial intelligence technology and connotation not only injects new vitality into Chinese movies, but also promotes the exploration and development of new paths of cultural dissemination of Chinese movies. In this paper, based on graph convolutional neural network and heterogeneous network, M-DGCN, a model of cultural communication of Chinese movie industry, is established. it utilizes Motif structure to obtain the higher-order spatial information of the network data of cultural communication of Chinese movie industry and combines with the two-channel graph stochastic convolutional network to highlight the more valuable information in the process of cultural communication of Chinese movies. The qualitative comparative analysis method is then introduced to explore the factors affecting the development of cultural communication power of Chinese film industry, using IMDB database as the source of research data. The study shows that the MAE error of the M-DGCN model tends to decrease with the increase of the number of nearest-neighbor layers considered, and the consistency indices of the conditional groupings in the QCA results exceed the threshold value of 0.85, which indicates the stronger explanatory power of the path combinations for the samples. Therefore, the optimization of the cultural communication mode of Chinese film industry in the intelligent era needs to be based on the dimensions of content, marketing and experience in order to better promote Chinese films to the world.*

KEYWORDS: *graph convolutional network; heterogeneous network; Motif structure; M-DGCN; qualitative comparative analysis; Chinese film industry; cultural communication*

1 Introduction

Driven by the wave of digitization, Artificial Intelligence (AI) technology has penetrated into all aspects of the film industry, from the pre-script creation to the late special effects rendering, the intervention of AI not only greatly improves the production efficiency, but also provides brand new possibilities for the innovation of the cultural dissemination mode of China's film industry [1-4]. In today's era of rapid development of science and technology, people's pace of life has become faster and faster, and digital media consumption has become the mainstream, which also provides certain innate conditions for the cultural dissemination of China's movie industry [5, 6]. Film and television works themselves appear on the basis of the development of science and technology, so film and television works have the advantages of fast dissemination speed, wide dissemination range, etc., and the use of film and television works can achieve better cultural dissemination effects [7-9]. And AI can personalize the recommendation of the film and television works that the audience is interested in through big data algorithms, providing more effective and convenient communication channels for film and

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television works, so that the cultural significance of the film and television industry can be played to the maximum [10-12]. However, the transformation of the cultural communication mode of China's film industry cannot be realized by technology alone, and requires the multi-dimensional support of technology, talents, facilities and policies.

In the field of technology, it is necessary to increase the investment in research and development of intelligent technology, and never stop introducing and innovating advanced intelligent technology to meet the needs of film production and projection [13, 14]. In the field of talents, it is necessary to strengthen the cultivation of talents in intelligent technology, cultivate a group of professionals who are proficient in the advanced technology of the film industry, and at the same time introduce international first-class talents in film and television production technology [15, 16]. In addition, the transformation of the cultural communication mode of China's film industry also needs to have perfect infrastructure construction and policy support supervision. Through the construction of intelligent theaters and related facilities, strengthen the cooperation with theaters to promote the full implementation of the transformation of the cultural communication mode [17, 18]; formulate relevant policies to support and regulate the development of the intelligent transformation, and at the same time, strengthen the supervision to maintain the healthy development of the cultural communication of the film industry [19, 20].

Aiming at the limitations of the existing methods, this paper proposes a cultural communication network model of Chinese movie industry based on graph convolutional network and heterogeneous directed graph. The model fully considers the relevance of the Chinese movie communication network and utilizes the Motif structure to automatically capture the higher-order information in the process of Chinese movie cultural communication. It also combines the random convolution of two-channel graph to highlight the cultural information, which significantly enhances the explanation of the cultural communication of Chinese movies. Qualitative comparative analysis is also used to study the relevant factors affecting the cultural communication power of the Chinese film industry, aiming at the optimization of the cultural communication model of the Chinese film industry in the era of artificial intelligence.

2 Graph Convolution-Based Model for Cultural Communication in Movies

The development of film has formed a trend of co-progress with technology under the impetus of technological development. Throughout the history of cinema, every film revolution is closely related to technological progress, and film, as an important carrier of cultural dissemination, is also promoting the globalization of multiculturalism. Driven by technology, future movies will change in terms of production technology, movie content, dissemination methods and viewing modes. Therefore, it is crucial to actively explore the transformation trend of the cultural communication mode of China's movie industry in the era of artificial intelligence.

2.1 Heterogeneous Networks and Graph Convolutional Networks

2.1.1 Representation of Heterogeneous Networks

A graph is a graph consisting of vertices and edges, where the vertices can represent any thing and the edges represent the relations that the vertices have to each other. In graph theory, a simple undirected graph is an ordered pair $G=(V,E)$, where V is the set of points and

$E \subseteq \{\{x, y\} : (x, y) \in V^2, x \neq y\}$ is the set of edges, which represents the relationships between all pairs of vertices. For an edge $\{x, y\}$, the vertices x, y are the endpoints of the edge, and the edge connects two vertices.

More generally, an undirected graph is defined as the ordered triple $G = (V, E, \varnothing)$, where V is the set of points; and E is the set of edges, at which point E is no longer bounded to be a subset of that set. where $\varnothing : E \to \{\{x, y\} : (x, y) \in V^2\}$ maps each edge to an unordered vertex pair, and so edges connect vertex pairs. In this definition, self-loops and heavy edges are allowed, where a self-loop is an edge with the same vertices at both ends, and a heavy edge is two or more edges connecting the same endpoints.

On the basis of an undirected graph, a graph in which the edges connecting two vertices have a direction is called a directed graph. Define the binary group $G = (V, E)$ as a simple directed graph, where V is the set of nodes and $E \subseteq \{(x, y) \mid (x, y) \in V^2 \wedge x \neq y\}$ is an edge, also called a directed edge. The elements in them are ordered pairs of nodes, and when $E \subseteq \{(x, y) \mid (x, y) \in V^2\}$, the graph is called a simple directed graph that permits self-loops. On an edge (x, y) from x to y, the nodes x and y are called the vertices of this edge, where x is the start or tail and y is called the end or head. A node in a directed graph can belong to no edge, and the edge (x, y) is the inverse edge of (y, x). The number of edges that end at a node is called the in-degree of the node, and the opposite is called the out-degree of the node.

When the adjacency matrix stores the graph, the storage for the nodes is divided into homomorphic and heteromorphic graphs, homomorphic nodes are stored using a one-dimensional array, while heteromorphic graphs are saved using a two-dimensional array of $n \times 2$, where the second column indicates the node type. Neighborhoods between nodes are stored using a two-dimensional array, which is called the adjacency matrix. Given a graph G containing n nodes, its adjacency matrix is a $n \times n$ square matrix defined as:

$$arc[i][j] = \begin{cases} 1, & if \ (v_i, v_j) \in E \ or \ < v_i, v_j > \in E \\ 0, & otherwise \end{cases} \tag{1}$$

When $arc[i][j] = 1$ it means there is a relationship between vertices i, j, and 0 means there is no relationship. When G is an undirected graph, $a[i][j] = a[j][i] (0 \leq i, j \leq n)$, and the adjacency matrix is a symmetric matrix; when G is a directed graph, $a[i][j]$ is not necessarily equal to $a[j][i]$. When the edges of G are weighted edges, its adjacency matrix is expressed as:

$$arc[i][j] = \begin{cases} w_{(i,j)}, & if \ (v_i, v_j) \in E \ or \ < v_i, v_j > \in E \\ \infty, & otherwise \end{cases} \tag{2}$$

2.1.2 Graph Convolutional Neural Networks

The core idea of Graph Neural Networks (GNN) is to enhance the representation of the model through message propagation mechanism and to optimize the node representation through downstream tasks, which are formally described as follows:

$$\begin{cases} h_v = f\left(x_v, x_{co}[v], h_{ne}[v], x_{ne}[v]\right) \\ o_v = g\left(h_v, x_v\right) \end{cases} \tag{3}$$

where f is the local transformation function, g is the local output function, and $x_v, x_{co}[v], h_{ne}[v], x_{ne}[v]$ denote the node features, edge features, neighbor node states, and neighbor node features, respectively.

Convolutional neural network (CNN) can aggregate the neighbor features in Euclidean space through convolution operator. The Euclidean space has good translation invariance, i.e., the internal structure of the space is independent of the position. But in non-Euclidean graph data the relationship between nodes is complex and the number of neighbor nodes is not fixed, i.e., it does not have the translation invariant property of Euclidean grid data. Therefore, the traditional CNN model cannot be directly applied to graph data structures. In order to generalize the convolution operation to non-Euclidean space, a large number of researchers have carried out research in the two directions of spectral domain and spatial domain, respectively. The core idea of the spectral domain method is to apply the convolution theorem to transfer the spatial graph signal to the spectral domain, and then transform back to the spatial domain after completing the convolution operation. However, the computation based on Laplace matrix will affect the model efficiency, thus, Chebyshev polynomials are adopted to replace the convolution kernel in the spectral domain, and the computational process is as follows:

$$ChebNet(x) = \sum_{k=0}^{K-1} \theta_k T_k(\tilde{L})x \tag{4}$$

where $T_K(x) = 2xT_{k-1}(x) - T_{k-2}(x)$ denotes the recursive form of the Chebyshev polynomials. $x \in R^N$ denotes the graph signal matrix with N nodes. $\tilde{L} = 2L/\lambda_{\max} - I_N$ denotes the normalized Laplace matrix, $L = I_N - D^{-1/2}AD^{-1/2}$ denotes the Laplace matrix of the undirected graph, and $\lambda_{\max}$ is the maximum of the undirected graph Laplace matrix L. eigenvalues, D denotes the diagonal array consisting of node degrees, I_N denotes the unit array, and θ denotes the model parameters to be learned.

The researchers further simplified the convolution process in ChebNet and proposed a spatial graph convolution neural network (GCN) model that can effectively extract features of graph data, proving that spectral graph convolution is equivalent to spatial convolution when the spectral convolution function is polynomial or first-order. Therefore, the GCN formalization is defined as follows:

$$GCN\left(X\right) = f\left(\bar{A}XW\right) \tag{5}$$

where $f\left(\cdot\right)$ denotes the nonlinear activation function, W denotes the convolution kernel parameter, $\bar{A} = \tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2}$, and considering the self-connections, $\tilde{A} = A + I_N$, and $\tilde{D}$ denotes the node degree matrix.

The GCN model directly extracts the neighbor information based on the predefined spatial topological relations, and maps the topological structure and attribute features into vector information for preservation. Therefore, the GCN method is able to learn the topological relationships of graph structures directly, whereas in traditional neural network models, the topological relationships between nodes can only be used as features of nodes.

2.2 Model Design of Chinese Movie Cultural Communication

2.2.1 Models of Cultural Communication in Cinema

For the cultural dissemination of Chinese movie industry, diversified audiences are an effective path to enhance the Chinese movie industry. Based on this, this paper proposes a directed heterogeneous graph neural network algorithm based on Motif structure for Chinese movie cultural communication, and establishes the M-DGCN model architecture as shown in Fig. 1, in order to learn the audience characteristics of different nodes in the cultural communication of Chinese movie industry. First, the original directed heterogeneous input graph is passed through a multilayer graph convolutional network to learn the important Motif structures and mine the higher-order hidden relationships among nodes. Next, the information is propagated over the original graph topology and the learned Motif structures through two channels to capture the information aggregated from different directions. Finally, the information learned from the two channels is stitched together to obtain the final output node representation.

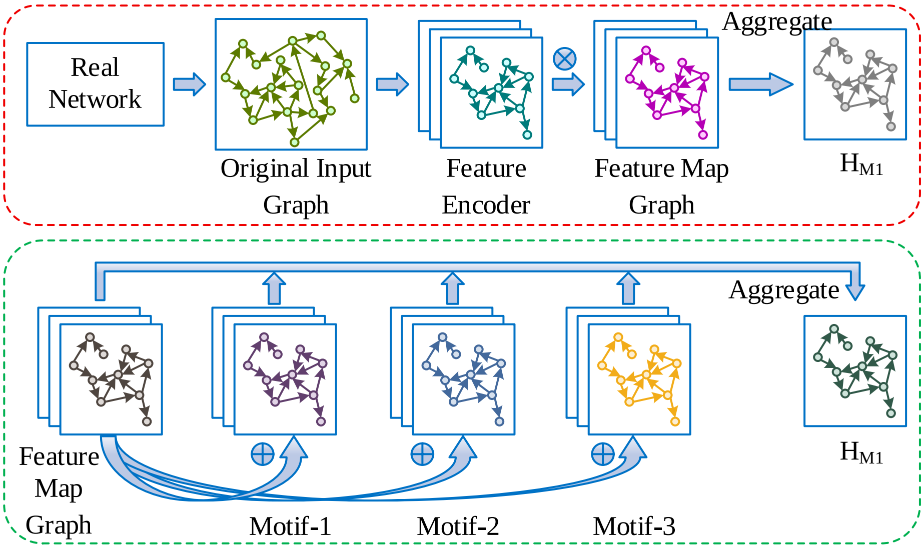


Figure 1: M-DGCN model architecture

In addition, previous heterogeneous graph neural network models only consider pairwise relationships between nodes and ignore higher-order relationships between multiple nodes. For example, in the cultural communication network of China's movie industry, there is a co-viewing relationship among users, friends, and movies; if a user watches a movie, then his friends may also receive the recommendation information of this movie, and thus watch this movie. This may result in losing some hidden and important information in the network. Therefore, in this paper, we utilize the automatic capture of Motif structure to mine the higher order information between the nodes.

2.2.2 Automatic Capture of Motif Structures

In this section, based on the spectral domain graph convolution framework in graph neural network, combined with the constructed Motif adjacency matrix, the Motif graph convolution module is constructed for extracting the higher-order spatial information of the cultural communication network data of Chinese film industry. Spectral domain graph convolution defines graph convolution in the spectral domain through the convolution theorem, using the convolution theorem to do multiplication on the signal in the spectral space, and then using the

Fourier inverse transform to transform the signal to the original space to realize graph convolution, thus solving the problem of the difficulty in defining the convolution caused by the fact that the graph data do not satisfy the translation invariance. The Fourier transform on the graph depends on the Laplace matrix of the graph, so the symmetrically normalized Laplace matrix is used to define the graph structure. To wit:

$$D_{ii} = \sum_{j=1}^{n} A_{ij} \tag{6}$$

$$L = I - D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \tag{7}$$

where D denotes the degree matrix of the graph structure, which is a diagonal matrix. I denotes the unit matrix of dimension n and A denotes the adjacency matrix. L denotes the symmetric normalized Laplace matrix, which is semipositive since L is a real symmetric matrix. Then L can be eigen-decomposed. To wit:

$$L = U \Lambda U^T \tag{8}$$

where Λ is a diagonal matrix where each diagonal element has its corresponding eigenvector. All the eigenvectors then form the eigenvector matrix U.

We can define the Fourier transform on the graph by the eigenvector matrix U as:

$$Va = U^T Va \tag{9}$$

Va is the original signal of the nodal feature on the graph, and Va denotes the representation of the nodal feature signal in the spectral domain. Similarly, the Fourier inverse transform on the graph is denoted:

$$Va = UVa \tag{10}$$

Based on the Fourier transform on the graph we can define the convolution formula on the graph as:

$$Va(Conv)\, y = U\left(U^T Va \odot U^T y\right) \tag{11}$$

where $(Conv)$ denotes the graph convolution operation and $\odot$ denotes the matrix doing the Hadamard multiplication. We can replace $U^T y$ with a diagonal matrix, then Eq. (11) can be rewritten as:

$$Va(Conv)\, y = Ug(\theta) U^T Va \tag{12}$$

where $g(\theta)$ is the diagonal matrix representing $U^T y$, which can be viewed as the convolution kernel for graph convolution.

However, the computational complexity of computing the convolution kernel is high at this point. Therefore Chebyshev polynomials are chosen to act as convolution kernel to reduce the computational complexity. The new convolution kernel is shown below:

$$\begin{gathered} T_i(\varphi) = 2\varphi T_{i-1}(\varphi) - T_{i-2}(\varphi) \\ T_0(\varphi) = 1 \\ T_1(\varphi) = \varphi \end{gathered} \tag{13}$$

At this point the convolution kernel $g(\theta)$ can be expressed as:

$$g(\theta) = \sum_{i=0}^{k} \theta_i T_i(\Lambda) \tag{14}$$

$$\Lambda = \frac{\Lambda}{\lambda_{\max}} - I \tag{15}$$

where θ_i is the Chebyshev polynomial coefficients and $\lambda_{\max}$ is the maximum eigenvalue of the Laplace matrix. In turn, the convolution formula can be simplified as:

$$Va(Conv)y = \left(\sum_{i=0}^{k} \theta_i T_i(\tilde{L}) \right) Va \tag{16}$$

$$\tilde{L} = \frac{2L}{\lambda_{\max}} - I_n \tag{17}$$

The Motif adjacency matrix is obtained based on the statistical significance of each higher-order connectivity relation, which expresses the effect of higher-order connectivity relations on spatial information. The adjacency matrix in the spectral domain map convolution is replaced with Motif adjacency matrix and the new convolution kernel is calculated as:

$$\begin{cases} M = I_n - D_M^{-1/2} A_M D_M^{-1/2} \\ \tilde{M} = 2M / \lambda'_{\max} - I_n \end{cases} \tag{18}$$

where A_M is the Motif adjacency matrix, M is the Laplace matrix of the normalized Motif adjacency matrix, D_M is the degree matrix of A_M, and $\lambda'_{\max}$ is the maximal eigenvalue of the Laplace matrix of the Motif adjacency matrix, and the final expression for the computation of the convolution of the Motif map is:

$$Va(Conv)y = \left(\sum_{i=0}^{k} \theta_i T_i(\tilde{M}) \right) Va \tag{19}$$

2.2.3 Random convolution of two-channel graphs

The two-channel graph stochastic convolutional network consists of three parts, i.e., topological map, feature map, and hierarchical attention. Firstly, H augmented feature matrices $\tilde{X}^{(1)}, \cdots, \tilde{X}^{(H)}$ are inputted to the topological and feature maps, respectively. For the feature map GCN, the input map is $G_f = (A_f, X)$. The h th augmented feature matrix $\tilde{X}^{(h)}$, the output at the l th layer of the feature map can be expressed as:

$$Z_f^{(h)(l)} = \mathrm{Re}LU\left(\tilde{D}_f^{-\frac{1}{2}}\tilde{A}_f\tilde{D}_f^{-\frac{1}{2}}\tilde{Z}^{(h)(l-1)}W_f^{(l)}\right) \tag{20}$$

where ReLU is the activation function, $\tilde{A}_f = A_f + I_f$, I_f is the unitary matrix, $\tilde{D}_f$ is the degree matrix of $\tilde{A}_f$, and $W_f^{(l)}$ is the weight matrix of the l th layer of the feature graph, and $\tilde{Z}^{(h)(l-1)}$ is the representation of the nodes obtained after a hierarchical attention update. In order to share information, each node feature representation at each layer of the feature graph shares the same weight matrix $W_f^{(l)}$.

For the topological graph, the input graph is $G_t = (A_t, X)$, where $A_t = A$ is the original topological graph. Similarly, the h th augmented feature matrix $\tilde{X}^{(h)}$, the output of which is represented at the l th layer of the topological map as $Z_t^{(h)(l)}$. As with the feature graph, the feature representation of each node in each layer of the topological graph shares the same weight matrix $W_t^{(l)}$.

With the above approach, multiple node representations can be learned on the feature space and topological space, respectively. In order to combine these representations and highlight more valuable information, this paper devises a method to adaptively combine the corresponding node representations in the hidden layers of the topological and feature graphs to obtain a more efficient node representation as:

$$\tilde{Z}^{(h)(l)} = \tilde{\alpha}_t^{(h)(l)}Z_t^{(h)(l)} + \tilde{\alpha}_f^{(h)(l)}Z_f^{(h)(l)} \tag{21}$$

where $\tilde{\alpha}_t^{(h)(l)}$ and $\tilde{\alpha}_f^{(h)(l)}$ are the diagonal matrices of attention weights obtained by the attention mechanism.

In order to compute the hierarchical attention, the importance of the corresponding node representation is first learned using the attention mechanism, i.e:

$$\left(\alpha_t^{(h)(l)}, \alpha_f^{(h)(l)}\right) = att\left(Z_t^{(h)(l)}, Z_f^{(h)(l)}\right) \tag{22}$$

where $\alpha_t^{(h)(l)}, \alpha_f^{(h)(l)} \in \mathbb{R}^{n\times 1}$ denote the n nodes of $Z_t^{(h)(l)}$ and $Z_f^{(h)(l)}$, respectively, for the Attention value.

Attention is paid to node v_i, which is represented in $Z_f^{(h)(l)}$ as $\mathbf{z}_{fi} \in \mathbb{R}^{1\times m}$. The attention value w_{fi} is first obtained as:

$$w_{fi} = v^T \cdot \tanh\left(W_1 \cdot \left(z_{fi}\right)^T + b_1\right) \tag{23}$$

where $W_1 \in \mathbb{R}^{m\times m'}$ is a weight matrix, $b_1 \in \mathbb{R}^{m'\times 1}$ is a bias vector, and $v \in \mathbb{R}^{m'\times 1}$ is a shared attention vector. Similarly, z_{ti} has an attention value of w_{ti}. Then, the $soft\max$ function is used to normalize w_{fi} and w_{ti} to obtain the final weights as:

$$\alpha_{fi} = soft\max\left(w_{fi}\right) \tag{24}$$

where a larger value of α_{fi} indicates that the corresponding node representation is more important. Similarly, $\alpha_{ti} = soft\max\left(w_{ti}\right)$. For all n nodes of the h th augmented feature matrix in the l th layer, one obtains $\alpha_t^{(h)(l)} = \left[\alpha_{t1}, \cdots, \alpha_{tn}\right]$ and $\alpha_f^{(h)(l)} = \left[\alpha_{f1}, \cdots, \alpha_{fn}\right]$. Finally, the attention weight diagonal matrix is:

$$\tilde{\alpha}_t^{(h)(l)} = diag\left(\alpha_t^{(h)(l)}\right) \tag{25}$$

$$\tilde{\alpha}_f^{(h)(l)} = diag\left(\alpha_f^{(h)(l)}\right) \tag{26}$$

where $\tilde{\alpha}_t^{(h)(l)}, \tilde{\alpha}_f^{(h)(l)} \in \mathbb{R}^{n\times n}$.

The H augmented node feature matrices $\tilde{X}^{(1)}, \cdots, \tilde{X}^{(H)}$ are subjected to graph convolution operations with the two input graphs G_t and G_f, respectively, and the outputs of the topological and feature graphs are obtained as $2H$ A node representation $Z_t^{(1)}, \cdots, Z_t^{(H)}, Z_f^{(1)}, \cdots, Z_f^{(H)}$.

2.3 Validation of the Movie Cultural Communication Model

2.3.1 Comparison of model performance

The initial purpose of establishing a cultural communication network model for the Chinese movie industry is to better promote the cultural communication effect of Chinese movies as a way to help different users recommend movies that better meet their needs, thus contributing to the high-quality development of the Chinese movie industry. As a result, this paper uses two public datasets, MovieLens 100K and Yelp2018, to verify the effect of the M-DGCN model designed in this paper. The programming language used in this experiment is Python language, and PyTorch is used as the deep learning framework, as well as the RecBole recommender system framework, and the running environment is Windows 10 flagship edition.

The hidden vector dimension of the two datasets is fixed to 150, and the batch size is set to 120. All parameters are initialized using a Gaussian distribution with a mean of 0. The learning rate is set to 0.005, and the regularization coefficient is set to 0.0001. The Adam algorithm, which is computationally efficient and automatically adjusts the learning rate, is used to optimize the model parameters. For the benchmark model, this paper refers to the optimal parameter settings reported in the corresponding original paper and reports its experimental results directly, since the same dataset and evaluation settings are used in this paper. For model performance, this paper chooses the accuracy P@K and the average inverse rank MRR@K. P@K is a measure of prediction accuracy and indicates the proportion of correctly predicted items among the top K. MRR@K denotes the average of the inverse rank of correctly recommended items, where the larger the value is, the higher the position of the target item in the recommendation list. Figures 2 and 3 show the performance comparison results of different models on MovieLens 100K and Yelp 2018 datasets, respectively.

From the experimental results in the figures, traditional algorithms such as POP and Item-KNN, as they only recommend based on the similarity of the items without considering the structural information embedded in the item sequences within the session.The performance of the models such as GRU4Rec, NARM, STAMP, etc. is greatly improved compared to the traditional methods, which suggests that the deep learning methods are able to efficiently extract the sequence relationships and more accurately extract the user interests. In addition, the high performance of the NARM and STAMP models suggests that the use of the attention mechanism to learn the importance of different items during session representation can better capture user preferences. From the experimental results, it can be found that all the graph-based models outperform the RNN-based methods, SR-GNN and FGNN model each session sequence as a subgraph and apply graph neural networks to item coding, showing the effectiveness of graph neural networks in session-based recommendation, which can fully exploit and utilize the many-to-many relationships among items by convolving the item-item graph structure. In addition S-DHCN utilizes the hypergraph to model different levels of session embeddings in a session and obtains good performance, testing the effectiveness of hypergraph modeling as well as self-supervised learning.

The M-DGCN model proposed in this paper achieves the best performance on both metrics (K=5 and 15) for both datasets. The main reason for this is that, compared to the existing graph structure-based session recommendation algorithms SR-GNN, FGNN and S-DHCN, this paper further introduces a graph convolutional network based on Motif structure on top of the structures such as item local and global graphs, which provides a more complete modeling of the complex relationships between items and items, items and sessions, and sessions and sessions, and more comprehensively captures the users' interest preferences. Therefore, the M-DGCN model designed in this paper can better graphically represent the correlations between users and users, users and movies, and movies and communication in the cultural communication network of the Chinese movie industry, and then enhance the influence of cultural communication in the Chinese movie industry.

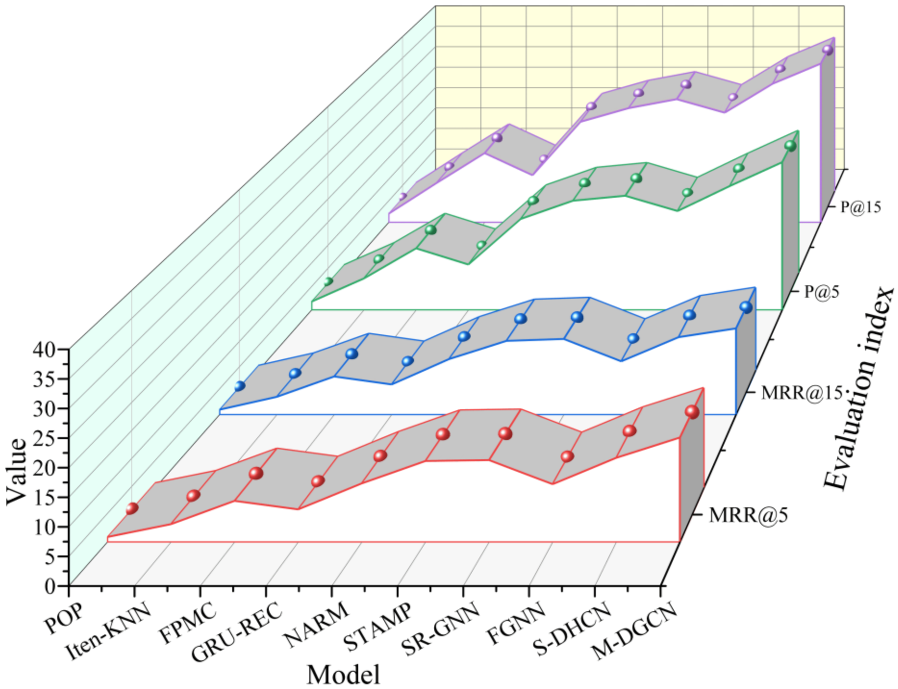


Figure 2: The performance of the model on the MovieLens-100K dataset

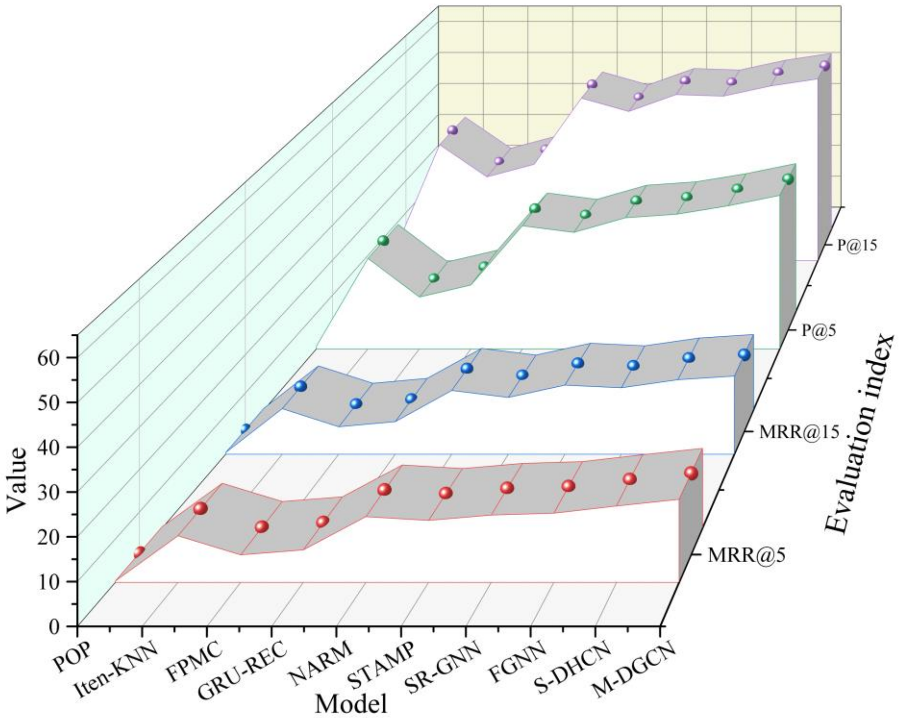


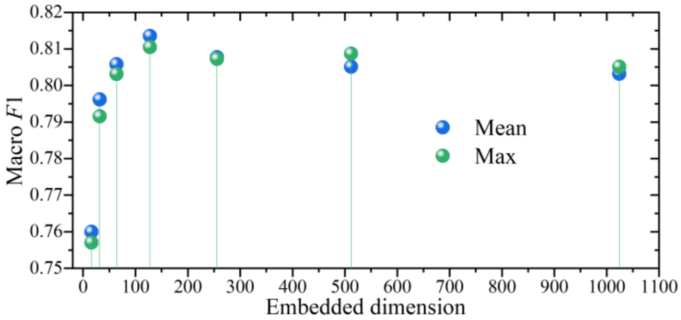
Figure 3: The performance of the model on the Yelp2018 dataset

2.3.2 Parameter sensitivity analysis

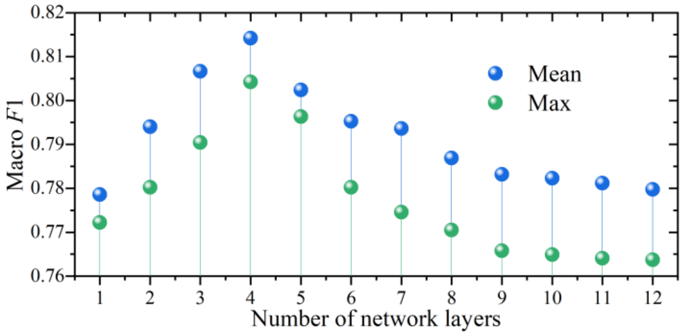
In order to investigate the effect of changing parameters on the model, this section performs a parameter sensitivity analysis on the MovieLens-100K dataset. Taking the node classification task as an example, the effects of different embedding dimensions and different network layers on the model performance are analyzed. The Macro F1 value is used as an evaluation index to analyze the trend of the maximum and mean values of the model under different parameters. Fig. 4 shows the comparison results of parameter sensitivity, where Fig. 4(a)~(b) shows the comparison results of embedding dimension and number of network layers, respectively.

(1) Embedding dimension. The fixed network level is 4 layers. From Fig. 4(a), it can be seen that the node embedding effect keeps improving with the increase of embedding dimension, indicating that the more information can be retained by the node vectors. The peak is reached at 128 dimensions. If the embedding dimension continues to increase the embedding performance decreases, indicating that too high a dimension may incorporate more noisy information, which is not conducive to the model representation performance.

(2) Network level. In the network hierarchy experiment in Fig. 4(b), the fixed embedding dimension is 128 V. GCN performs optimally when the network hierarchy is two layers, and over-smoothing occurs when it exceeds two layers. As GCN continuously aggregates the neighbor node features, the global node features after multi-layer network aggregation tend to be similar, while weakening the node's own features, resulting in the oversmoothing phenomenon. The M-DGCN model performs optimally when the network level reaches four layers. This is due to the fact that the M-DGCN model retains the features of all network levels, so that the final node representation not only contains its own feature information, but also integrates higher-order semantic information. As the network hierarchy increases, the model has relatively more parameters, overfitting occurs, and the performance decreases.



(a) Embedded dimension



(b) Number of network layers

Figure 4: Comparison of parameter sensitivity

2.3.3 Impact of network depth

For the application of the M-DGCN model in the cultural communication network of the Chinese movie industry, this section takes the user's rating of a movie as an example, and there are various possible reasons for recommending a movie to a user. The model determines that the user has a high fit with this movie, possibly because the user likes the director of the movie or one of the actors. The model believes that a user may like a director because the user has seen and given high ratings to a number of works directed by the director in the past, and that liking these works may come from the recommendations of other related users, who are related to the user because they have seen some of the same movies, and so on.

When judging a user's preference for a movie, it is important to focus not only on the characteristics of the movie itself, but also on the characteristics of the nodes connected to the movie, which are the first-order nearest neighbors of the movie node. When considering the user's relationship with the nearest-neighbor nodes again, it is again necessary to consider their neighboring nodes, which is the second-order nearest neighbor, and so on. Since a user fits with each movie for different reasons, it is important to interact the user's vector with the movie's first-order nearest neighbors, second-order nearest neighbors, and even multi-order nearest neighbors at the same time, which can better mine the complex information between the user and the movie.

The choice of the number of nearest neighbors is a hyperparameter of the model, and this section explores the choice of the number of nearest neighbors, using the MovieLens-100K dataset, to understand how the number of nearest neighbors affects the model results. In order to make the comparison results independent of the randomness of the training set splits, this section uses a ten-fold cross-validation method, where the entire dataset is split into 10 equal parts, and seven of them are used for model training at a time, while the remaining three are used for prediction. Once all the models are trained, there is a prediction result for the entire dataset, and this result is used for the comparison of different parameters.The results of MAE and RMSE with increasing number of nearest neighbors are shown in Fig. 5.

It can be seen that as the number of nearest neighbor layers considered by the model increases, there is a decreasing trend in the MAE error, while the RMSE error exhibits a certain increasing trend. This indicates that considering higher-order nearest neighbors will make the model focus more on the samples with smaller prediction errors, and the weight of the samples with larger prediction errors in the model is relatively reduced, then the model can be more robust to outliers. The samples with larger prediction errors are often those new users, or cold movies without much interaction data, and users or movies with more interaction data will have smaller prediction errors, and multilayer nearest neighbors can more fully exploit this rich information. However, if the model is needed to solve the cold-start problem better, a smaller number of nearest neighbor layers should be selected so that cold movies can be better disseminated and recommended.

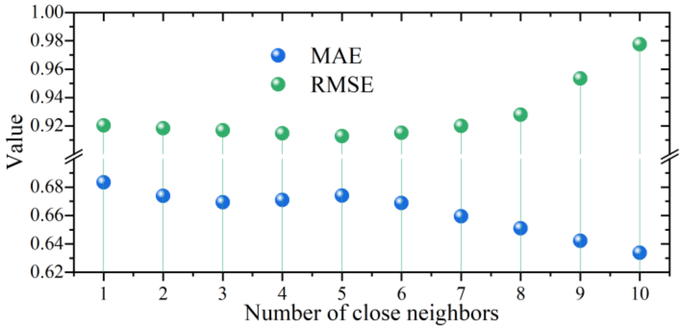


Figure 5: The impact of the increase in the number of close neighbors

3 Influential Factors of Chinese Movie Cultural Communication

Nowadays, Chinese movies have entered a stage of high-quality development. Against this background, it has become increasingly urgent to raise the question of how to “go out” in Chinese movie cultural communication and to think about it. On the basis of clarifying the network performance of cultural communication in the Chinese movie industry, we further discuss the influencing factors of cultural communication in the Chinese movie industry, aiming to better satisfy the needs of diversified audiences, occupy more market shares, and promote Chinese culture to go out.

3.1 Qualitative Comparative Analysis and Sample Selection

3.1.1 Qualitative comparative analysis

Qualitative Comparative Analysis (QCA) is a research method based on set theory and Boolean logic.The logic of the QCA method is to get the universal characterization of the case, i.e., the universal relationship between the condition combinations and the resultant phenomena of the resultant factors, through the use of Boolean algebra and based on the Boolean algebra to explore the effect of the condition combinations on the affiliation.

First, the introduction of Boolean algebra. Boolean logic is the cornerstone of the QCA method and its underlying theory is utilized throughout the research process. This includes the conventions of Boolean algebra and Boolean minimization in QCA methods. In this paper, we assume that there are four conditional variables (X , Y , Z , and P) and one outcome variable (R), which is listed as a Boolean expression:

$$X* \sim Y + A* B \rightarrow R \tag{27}$$

Operators are categorized into, "*" (multiplication sign) indicates logical "AND" (and), "+" (plus sign) indicates logical "OR" (or), "~" indicates a logical not (does not occur, does not exist), "→" (arrow character) is used to indicate the connection between the condition and the result. Then the above Boolean expression can be read as a combination of X exists and Y does not exist, or A exists and B exists, which can lead to the result R . Boolean minimization can be understood from the following operation:

Suppose the combinations that lead to the existence of the result R are the following:

(1) $X *Y* \sim A* \sim B \rightarrow R$.

(2) $X *Y* \sim A* B \rightarrow R$.

(3) $X* \sim Y* \sim A* \sim B \rightarrow R$.

(4) $X* \sim Y* \sim A* B \rightarrow R$.

Following Boolean minimization one can simplify (1) and (2) as:

$$\begin{aligned} X *Y* \sim A* \sim B \ + \ X *Y* \sim A* B \ &= \ X *Y* \sim A(\sim B + B) \\ &= X *Y* \sim A \rightarrow R \end{aligned} \tag{28}$$

That is, no matter which value (0 or 1) is used for the condition "B", the result "R" has the same value, which means that in linguistic reasoning, the condition "B" is redundant, and it can be removed from the This means that in linguistic reasoning, the condition "B" is redundant and can be removed from the initial expression, thus leaving us with a shorter, more simplified expression.

Similarly (3) and (4) can be simplified as follows:

$$X* \sim Y* \sim A(\sim B + B) = X* \sim Y* \sim A \rightarrow R \tag{29}$$

Simplifying Eqs. (28) and (29) again, we obtain:

$$X* \sim A \rightarrow R \tag{30}$$

Second, the degree of affiliation of combinations of conditional variables.QCA describes the relationship between combinations of conditional variables and the outcome variable in terms of consistency and coverage to indicate the degree of affiliation. In particular, consistency indicates the degree of affiliation of a combination of conditional variables to the outcome variable, and its value ranges from 0 to 1. Coverage indicates the degree of affiliation of the unique path of the outcome produced by the combination of condition variables, which also takes values between 0 and 1. When coverage reaches 1, it indicates that its corresponding path of the combination of condition variables leads to the unique path of the outcome produced. Therefore, consistency and coverage are important criteria to be utilized in the QCA approach.

3.1.2 Sample and variable selection

IMDB is the largest film and television database in the world, and its data quality is generally recognized by the film and television industry. The huge amount of information gathered at high speed makes it an important participant in writing the history of world cinema in the Internet era. In this study, the IMDB database is screened in detail as follows:

(1) Only films are examined, with no restrictions on film length, color, sound format, etc.

(2) Only films whose origins include mainland China are examined, including mainland Chinese productions, Chinese-foreign co-productions, and cross-strait co-productions.

(3) No restriction on language type.

(4) Only films released in mainland China are examined in the database to ensure that the sample consists of films officially released in mainland China.

(5) The year of the films is between January 1, 2012 and December 31, 2024.

According to the above search principles, a total of 4,682 Chinese movies were obtained within the screening scale. Through the IMDB platform, data mining was carried out on the 4,682 Chinese movies within the screening scale, including ratings, number of people who scored the movies, the weekly performance of each movie in terms of heat value between January 2012 and December 2024 (the performance of heat value within 1 year of the movie's release should be excluded, so as to minimize the impact of the immediate influence on the research), the number of awards (the sum of the awards and nominations, and the total of the awards on the IMDB platform), and the number of awards and nominations (the sum of the awards and nominations on the IMDB platform). The top 30 Chinese films were selected from the list of awards (the sum of the number of awards and the number of nominations, including Oscars listed on IMDB). From these data, the top 30 Chinese films were selected for the QCA analysis later.

On the basis of analyzing the performance of the cultural communication network model of the Chinese film industry, this paper further introduces QCA to explore the relevant factors affecting the cultural communication power of the Chinese film industry. Synthesizing the requirements of QCA research method, this paper selects eight conditional variables, mainly including the number of genres, genre elements, director-actor influence, creative body, film and television adaptation, distribution companies, cultural discounts and realism. And the quality of Chinese movie works, audience breadth and heat performance are comprehensively examined, and the cultural communication power index is calculated with a weight of 4:2:4 to ensure the comprehensiveness and scientificity of the design of the resultant variables. Table 1 shows the results of variable design and assignment of cultural communication power of Chinese movie industry.

Table 1: Variable design and assignment results

Type	Name	Data	Value
Production and broadcasting attributes	Distribution company	Yes	1
		No	0
	Film adaptation	Yes	1
		No	0
	Creative subject	Co-produced by China and foreign countries	1
		It was produced in Chinese mainland	0
	Direction-actor influence	Have won more than 60 awards	1
		The number of winners is below 50	0
	Number of types	The number of types>1	1
		The number of types=1	0
Content attributes	Type element	Drama film	1
		Non-feature film	0
	Realism	Yes	1
		No	0
	Cultural discount	Cultural premium	1
		Cultural discount	0
Result variable	Cultural dissemination power	Index>24.78	1
		Index≤24.78	0

3.2 Factors affecting the dissemination of film culture

3.2.1 Constructing the truth table

Before obtaining the truth table, two operations need to be performed, the first is to determine the appropriate case frequency threshold, the conditional grouping states with the number of cases less than the threshold are considered as logical residuals. The second is to determine the appropriate raw consistency threshold, the antecedent group states with raw consistency scores greater than or equal to the threshold are considered to be a subset of the set of results, and their results will be assigned a value of 1 by the fsQCA software, and vice versa.

According to the dichotomous assignment criteria above, the raw data of the collected samples are coded, and the coded data are imported into the fsQCA software and run, and the eight conditional variables of number of genres (NT), genre elements (TE), director-actor influence (DA), creative subject (CS), film and television adaptation (FA), distribution company (DC), cultural discount (CD), and realism (RE) are selected and the cultural Dissemination power (CDP) outcome variable, construct the truth table, and delete the field with zero number of cases (fsQCA software selects "Delete current row to last low"). According to the suggestions of QCA experts and the sample size of this paper, the frequency threshold of cases is set to 1 and the consistency threshold is set to 0.75, and the truth table of the attributes of cultural diffusion power of China's movie industry is finally obtained as shown in Table 2.

Table 2: Truth Table of Culture Communication of Chinese Movies

No.	CD	NT	TE	DA	FA	CS	DC	RE	CDP
1	1	0	1	0	0	0	1	0	0
2	1	0	1	1	1	1	0	0	1
3	1	1	1	1	0	0	0	0	1
4	1	0	1	0	0	0	0	0	1
5	0	0	1	0	0	1	0	0	1
6	1	1	1	0	1	1	0	0	0
7	0	1	1	0	1	1	0	1	0
8	0	1	0	0	1	0	0	1	0
9	0	0	0	0	1	0	0	0	0
10	0	1	0	0	1	0	1	0	0
11	0	0	1	0	0	1	1	0	0
12	0	0	1	1	0	1	1	0	0
13	0	0	1	0	1	1	0	0	0
14	0	1	1	1	0	1	0	1	1
15	0	1	1	0	0	1	0	1	1
16	0	1	1	0	1	0	0	1	1
17	0	1	1	0	0	1	1	0	1
18	0	1	0	1	0	0	0	0	1
19	0	0	1	0	0	1	0	0	1
20	0	1	1	0	0	0	0	0	1
21	0	0	0	0	0	0	0	0	0
22	0	0	1	0	1	0	1	0	0
23	0	0	0	0	0	0	0	1	1
24	1	1	1	0	1	1	0	1	0
25	0	1	0	0	0	1	0	1	1
26	0	1	1	0	0	1	1	0	0
27	1	0	1	0	0	0	1	0	1
28	0	0	1	0	0	0	0	0	1
29	0	0	1	0	1	0	0	0	1
30	0	1	0	0	0	0	0	0	0

3.2.2 Univariate necessity detection

Univariate necessity testing, i.e., analyzing the effect of each condition variable on the outcome variable individually, i.e., testing whether it is a necessary condition for the existence of the outcome, is a necessary step before constructing the QCA truth table. Among them, the consistency index and coverage index are the core indexes for judging whether a variable is a necessary condition. It is generally believed that when the consistency indicator is greater than 0.75, it can be considered that the conditional variable (X) is a sufficient condition for the outcome variable (Y), i.e., the conditions corresponding to the variable can lead to the occurrence of the outcome. When the consistency indicator is greater than 0.85, it can be considered that the conditional variable (X) is a necessary condition for the outcome variable (Y), and it can even be assumed that the outcome could not be produced without the condition. The coverage indicator is generally considered to indicate the explanatory power of the condition variable for the outcome. When the coverage indicator is 0.85, it means that the condition variable explains 85% of the cases.

In this study, we imported the data in Table 2 into the fsQCA software, selected the “Necessity Detection” function, and set the condition variable and its opposite condition (denoted by “~”) to "Conditional “, set the result variable to ”result", and get the output results of univariate necessity detection as shown in Table 3.

As can be seen from the table, among all the conditional variables, none of the conditional variables' consistency index reaches the high level of 0.85, which indicates that within the scope of this paper, there is no single condition that can be used as a necessity for the cultural dissemination power of China's movie industry. It should be noted that the consistency index (0.8168) of cultural discount (DC) exceeds the threshold of 0.75, while none of the other conditional variables' consistency indexes exceeds 0.75. This suggests that the cultural discount makes it a sufficient condition for the cultural communicative power of the Chinese film industry to gain a greater impact, while none of the other conditional variables on their own are sufficient to adequately explain the occurrence of the results. This suggests that for the cultural communication power of the Chinese film industry, in addition to the influence of cultural discounts, there are other factors that compare, influence, and combine with each other, which need to be carried out later in further conditional group state analysis.

Table 3: Output results of univariate necessity detection

Code	Consistency	Coverage
Cultural discount	0.0892	0.2985
~Cultural discount	0.6843	0.5879
Number of types	0.5568	0.5142
~Number of types	0.4832	0.5798
Type element	0.6637	0.4852
~Type element	0.3358	0.6676
Direction-actor influence	0.0816	0.1918
~Direction-actor influence	0.7103	0.6575
Film adaptation	0.5437	0.6194
~Film adaptation	0.4563	0.4586
Creative subject	0.2516	0.3758
~Creative subject	0.6943	0.6237
Distribution company	0.0836	0.2676
~Distribution company	0.8168	0.6045
Realism	0.7034	0.5486
~Realism	0.3019	0.5143

3.2.3 Analysis of Conditional Configuration Results

Running the truth table in the fsQCA software results in three solutions, namely the complex solution, the simple solution and the intermediate solution. The complex solution considers all possible combinations of conditions, while the simple solution considers only individual conditions. The intermediate solution lies in between these two; it considers some of the combinations of conditions but does not cover all possibilities. The intermediate solution occupies an important place in QCA analysis, as it helps the researcher to understand more fully the effects of different condition groupings on the results, and helps the researcher to identify combinations of conditions that are neither individually necessary nor sufficient, and which may have an effect on the results in a given situation. The intermediate solution allows researchers to gain a more comprehensive understanding of the complex relationship between conditional groupings of states and outcomes, and reveals the combinations of conditions that may be at work in different contexts, as well as the core and edge conditions of the combinations. The intermediate solution is therefore considered the preferred solution for qualitative comparative analysis reporting, and this research tradition of reporting the intermediate solution is also adopted in this paper.

In order to present the final grouping results more clearly and intuitively, this study follows the requirements of the fsQCA research methodology and adopts a specific form of results presentation. The detailed presentation of the results is shown in Table 4, which visualizes the effects of different condition groupings on the results. The table uses X to indicate the presence of the core condition, Y to indicate the absence of the core condition, a to indicate the presence of the edge condition, b to indicate the absence of the edge condition, and “-” to indicate that the presence or absence of the condition is irrelevant.

The data results show that the consistency index of all combinations exceeds the threshold of 0.85, which fully demonstrates the strong explanatory power of the path combinations for the sample. Looking further at the seven cause combinations, six of them are particularly typical due to their higher coverage, which explains the results particularly strongly. Based on the results of the conditional grouping analysis, the following grouping paths are derived:

(1) Cultural Premium*Multi-Genre*Drama*High Award Count*Chinese-Western Co-Productions & Cross-Strait Co-Productions*North America's Top 6 Distribution Companies*Non-Realism.

(2) Multi-genre*Drama*Multi-award winning*Film and TV adaptations*Chinese-foreign co-productions and cross-strait co-productions*Six major North American distribution companies*Non-realism

(3) Cultural Premium*Multi-genre*Drama*Low number of awards*Non-film and television adaptations*Chinese-foreign co-productions vs. cross-strait co-productions*Non-North American top six distribution companies*Non-realistic

(4) Cultural Discount*Multi-genre*Non-Drama*Low Award Count*Non-Film and Television Adaptation*Chinese and Foreign Co-Productions and Cross-Strait Co-Productions*Non-North American Top 6 Distributors*Non-Realism.

(5) Cultural Discounts*Multi-Genre*Drama*Multi-Award Winner*Non-Film & TV Adaptation*Mainland China Pitch*Non-North American Top 6 Distributors*Realism.

(6) Cultural Discount * Single Genre * Drama * Fewer Awards * Film and TV Adaptation * Sino-Foreign and Cross-Strait Co-Production * Non-North American Top 6 Distributors * Realism.

(7) Cultural Premium*Multi-genre*Drama*High number of awards*Non-film and television adaptations*Chinese-foreign co-productions and cross-strait co-productions*Non-North American six major distribution companies*Realism.

Table 4: China film industry culture propagation force configuration

Variable	Configuration path						
	1	2	3	4	5	6	7
Distribution company	a	a	b	a	b	Y	b
Film adaptation	-	a	b	b	Y	X	Y
Creative subject	X	X	X	a	b	X	a
Direction-actor influence	a	a	b	a	X	Y	X
Number of types	a	a	a	a	a	Y	a
Type element	X	X	X	b	a	X	a
Realism	Y	Y	Y	b	a	a	a
Cultural discount	a	-	a	b	b	b	a
Consistency	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Original Coverage	0.1431	0.0958	0.0475	0.0483	0.0956	0.0475	0.0475
Net Coverage	0.0953	0.0476	0.0475	0.0483	0.0956	0.0475	0.0475
Overall Consistency	1.000						
Overall Coverage	0.5129						

The Boolean minimization principle, as a rigorous logical analysis method, aims to reveal the intrinsic connection and influence mechanism between things by simplifying and optimizing logical expressions. According to the Boolean minimization principle, the six path combinations can be merged into three types, i.e., co-production drama type, original award-winning type and adaptation reality type.

In the co-production drama type, Chinese movies with high cultural communication power = multi-genre * drama * Chinese-foreign co-production and cross-strait co-production * non-realism. In this path, the leading role is played by Chinese-foreign co-productions or co-productions with three places across the Taiwan Strait in non-realistic dramas.

In the original award-winning category, Chinese films with high cultural diffusion = multi-genre * drama * high number of awards * non-film and TV adaptation * non-North American top six distribution companies * realism. In this path, the core conditions in groupings (5) and (7) are high number of awards and non-film adaptations.

In the adaptation-reality type, Chinese films with high cultural diffusion = cultural discounts * single genre * drama * low number of awards * film and television adaptation * Chinese-foreign co-productions and cross-strait co-productions * non-North American six major distribution companies * realism. The central role in this path is film and television adaptation.

3.3 Cultural Communication Strategies for the Movie Industry

3.3.1 Compact film content

Essentially, as an important part of creative industry, movie culture, on the basis of inheriting and carrying forward the excellent traditional Chinese culture, should be continuously integrated with the latest cultural creativity, so as to ensure the high quality and high efficiency of the dissemination of movie culture. Generally speaking, an excellent and classic movie often incorporates national sentiment and national elements, combining movie content creation with national culture, and constructing the foundation of the movie with profound cultural connotation. Various information access channels in the era of artificial intelligence provide an extremely convenient and rich database of national elements for movie creation. Through WeChat, Weibo, websites, forums, APPs, etc., we can quickly search for Chinese folk culture, red culture, opera culture, Confucian culture, etc., which are needed for movie creation, laying a solid foundation for creating a movie culture with national characteristics.

With the propaganda advantage of film culture itself, and the wide range of new media, cross-time and space technology features, creative films can be made into a gold medal "business card" of cultural communication, and vigorously promote the mainstream culture of harmony and democracy, morality and the rule of law, and stimulate the value of cultural communication of films to the maximum extent. At the same time, it is also necessary to strengthen the conceptual guidance of the movie, actively integrate the socialist core values into the creative content, and promote positive social energy as the main theme, so as to gradually guide the audience to correctly perceive the society and life, establish the correct "three views", and contribute to the society to the best of its ability.

3.3.2 Integrated cross-border marketing

Under the environment of artificial intelligence, cross-border integrated marketing is an effective communication strategy for movie culture. The continuous development and gradual popularization of intelligent technology makes the audience acquire information through more diversified channels, and if each platform is allowed to fight on its own, it is likely to form a scattered situation. The focus of cross-platform integrated marketing strategy is to maximize the spread of movie word-of-mouth by integrating the advantages of different media platforms, so as to maximize the benefits of movie communication. Specifically, cross-platform integrated marketing can be used to increase the exposure of a movie by releasing promotional advertisements on multiple platforms.

Cross-platform integrated marketing can also improve audience entertainment and participation through multimedia forms and creative means. For example, movie producers can carry out cross-border cooperation with games, music, variety shows and other related platforms, so as to carry out unique promotional activities to attract the attention of more viewers and get them involved. In cross-platform integrated marketing, movie producers can also make use of Internet live broadcasting, virtual reality and other technologies to create a unique interactive experience during the promotional process, thus enhancing audience stickiness and participation and promoting word-of-mouth dissemination of the movie.

3.3.3 Provision of personalized services

In order to attract more viewers and maintain their loyalty, studios need to adopt some new strategies to meet the needs and expectations of their viewers, and one of the key strategies is to provide more personalized services by building a close relationship with their viewers. Movie studios can engage with audiences through social networking platforms and other digital channels. These platforms can help studios understand the needs and interests of their audiences so that they can better design content for them. For example, when producing a new movie, studios can post trailers or behind-the-scenes videos on social media to give audiences a preview of what the movie will be about.

In addition, studios can use big data analytics to understand audience behavioral patterns and preferences for movie genres and styles. Based on this data, studios can develop more precise content plans to better meet audience needs. Movie studios can also increase audience engagement and loyalty by providing richer experiences. For example, they can set up virtual reality devices or 3D projectors in theaters to allow audiences to experience scenes from the film in an immersive way. At the same time, studios can also offer customized viewing packages or membership programs to encourage viewers to stay tuned to their productions.

4 Conclusion

As an art form closely related to technology, movies are deeply affected by the era of artificial intelligence. The article first establishes a network model of Chinese movie cultural communication based on graph neural network and analyzes its feasibility in movie recommendation. Then, combined with qualitative comparative analysis, it explores the relevant factors affecting the cultural communication power of Chinese movies and gives the optimization strategy of cultural communication in Chinese movie industry. The study shows that relying on algorithms can better help the Chinese film industry to realize the network communication of culture, and there are a variety of conditions that have a high impact on the cultural communication power of the Chinese film industry. Therefore, in the era of artificial intelligence, the optimization of the cultural communication mode of the Chinese film industry needs to further consolidate the film content, integrate cross-border marketing, and provide personalized services from the user's perspective, in order to contribute to the deep development of the cultural communication of the Chinese film industry.

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