

Research Article

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Multi-source auxiliary information tourist attraction and route recommendation algorithm based on graph attention network

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Abstract: In the field of tourism recommendation systems, accurately recommending scenic spots and routes for users is one of the hot research directions. In order to better consider the complex interaction between user preferences and attraction features, as well as the potential connections between different information sources, this study constructed a graph attention network model using knowledge graphs for tourist attraction and route recommendations, and extracted features from visual images using visual geometry group-16. The results indicate that, in Xian, when the learning rate is 0.01, the area under the curve value is 0.916. The area under the curve of New York is 0.909, and the learning rate is 0.001. The area under the curve value of the Tokyo dataset is 0.895. When the learning rate is moderate, the model quickly stabilizes in the first 16 rounds and reaches its optimal state in 26–30 rounds. When the propagation depth is 2, the accuracy is 0.920, 0.905, and 0.895, respectively. After introducing visual features, the accuracy, recall, and *F1* score improved by 10 to 15.7%. The multi-layer perceptron further increased the effect by 4–6%. These experimental data fully demonstrate the effectiveness and accuracy of the recommendation algorithm. This study provides a powerful tool for tourism recommendation systems, which helps to further improve user experience.

Keywords: graph attention network, tourist attractions, route recommendation, multi-source auxiliary information, multi-layer perceptron

1 Introduction

The explosive growth of tourism-related information on the Internet has provided tourists with unprecedented diversity of choices. However, the massive growth of this information also brings about the problem of “information overload.” Tourists often face the challenge of massive amounts of information when making travel decisions, making it difficult to filter out truly interesting tourist attractions and routes. This information overload not only increases the choice pressure on tourists, but also reduces the quality of the tourism experience. In this context, developing a recommendation system that can provide accurate, efficient, and personalized recommendations for tourists has become extremely important [1,2]. However, traditional recommendation systems face many challenges when dealing with such vast and diverse data. Especially in the tourism field, due to the reliance of many recommendation systems on user historical behavior data, the sparsity of historical data becomes a major obstacle for first-time or infrequent tourists. This data sparsity problem makes it difficult for traditional recommendation systems to accurately capture the true interests and needs of these tourists, thereby affecting the effectiveness and quality of recommendations [3]. When processing input data, graph attention network (GAT) fully considers the relationships between data, enabling it to

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more accurately capture the correlations between data when processing graph structured data. It has the ability to automatically learn the relationships between nodes without the need for manual presetting [4]. To this end, a multi-source auxiliary information tourist attraction and route recommendation algorithm on the ground of GAT was proposed in the study. This method first deeply integrates multi-source data through a combination of GAT and knowledge graphs. Then, visual geometry group (VGG)-16 is used to extract attraction features from visual images. The social relationships of tourists are integrated through the GAT to achieve interest propagation, and a multi-layer perceptron is applied to complete the recommendation algorithm. The research aims to provide users with more personalized and accurate recommendations for tourist attractions and routes and to enhance user satisfaction and travel experience to a greater extent. This study innovatively combines GAT and knowledge graph embedding (KGE), deeply analyzes multi-source auxiliary information, and provides a novel solution for the field of tourism recommendation systems, which is helpful for the development of the tourism industry and the improvement of tourism experience. The overall structure of the research includes four parts: the first part summarizes the research achievements and shortcomings of deep learning and recommendation algorithms at home and abroad. In the second part, a tourist attraction and route recommendation algorithm was designed on the ground of GAT. The third part is to compare and analyze the proposed recommendation algorithm through research experiments. The fourth part summarizes the experimental results, points out the shortcomings of the research, and proposes future research directions.

2 Related works

Deep learning is an advanced machine learning method. When combined with recommendation algorithms, especially when dealing with multi-source auxiliary information, it opens up new possibilities to overcome the data sparsity problem in traditional recommendation systems and improve recommendation accuracy [5]. To gain a deeper understanding of the potential and impact of this technology combination, the following will introduce some relevant research by scientists and scholars. Sheng et al. constructed MOOC multi-source heterogeneous information to capture heterogeneity between entities and proposed a personalized recommendation model on the ground of attention collaborative extended matrix factorization. It utilizes a graph convolutional network on the ground of meta-path node sampling to learn the structure and semantics of the network, and generates joint representation embeddings through attention mechanisms. Experimental results have shown the robustness and superiority of the model on two real datasets [6]. Chen et al. introduced an attention flow network and modeled user purchase records by describing the process of change in purchase intention through attention flow. On the ground of this, a personalized recommendation algorithm is proposed. This algorithm integrates purchase sequences into a weighted attention flow network, recommends products on the ground of user attention decay and network transition probability, and is effective in linear time. The efficient performance of the method has been validated through testing on multiple real datasets [7]. Liu et al. proposed a collaborative filtering algorithm that integrates temporal context information and user context, focusing on expanding and discovering user interests. It integrates the model into collaborative filtering and utilizes a popularity penalty function to weight recommendation similarity. When generating recommendations, it considers user context and weights candidate short videos. It generates Top-K recommendation lists in diverse ways. The example analysis demonstrates the accuracy and diversity of the method [8]. Zhao et al. proposed an adaptive context embedding hypergraph convolutional network on the ground of session recommendation. It integrates contextual information from the project and its neighborhood in its convolution, and it uses adaptive transformation functions to eliminate the influence of irrelevant terms. It also adopts a soft attention mechanism to obtain user interests and recommendations. The experimental results show that the model has significant improvements compared to existing methods [9]. Cepeda-Pacheco and Domingo developed a multi-label deep learning classifier to enhance the happiness of tourists in tourism and implemented tourism search and planning activities. They obtained information through internet of things devices, and the results showed that the accuracy of this method reached 99.9% [10]. An and Moon

designed an intelligent tourism recommendation system that combines long short-term memory and convolutional neural network (CNN) based on emotional analysis of tourism evaluation, and the results showed that the system is effective [11].

Zhang and Chen optimized the social tag recommendation system by using a time attention model to sort tags and remove junk tags, and combined with a time decay model to pay attention to the temporal changes of tags. On the ground of this, a social tag optimization recommendation algorithm on the ground of a complete three-part graph network is proposed, which combines user and item preference information and uses collaborative filtering to generate recommendation items. The experiment shows that the recommendation prediction of this algorithm is more accurate [12]. Ye et al. proposed a new sequential recommendation method that learns project trend information from implicit user interaction history and integrates it into project recommendations. It introduces self-attention mechanism for representation and evaluates the use of variant models of gated graph neural networks to enhance representation. The results show that this method improves performance by up to 18.2% and effectively learns project trends at low computational complexity. The results demonstrate the criticality of project trends in recommendation systems [13]. Yang et al. proposed a multi-source knowledge transfer method that helps classify unlabeled nodes in the target network through graph patterns in multi-source networks. It selects the most transferable source network to learn common subgraph patterns and uses these patterns to construct structural features for the target network. This experiment has shown that this method surpasses advanced technology in social recommendation and citation networks [14]. Yu et al. proposed the neural pairwise sorting decomposition machine NPRFM for project recommendation, which integrates multi-layer perceptual neural networks into the pairwise sorting decomposition machine. By stacking the second-order interactions of encoding features in a neural network with dual interaction layers, it simultaneously uses a paired sorting model to learn user relative preferences. To compensate for the lack of consideration of feature interaction importance in NPRFM, a new variant is proposed to introduce attention mechanism. The experimental results show that NPRFM surpasses traditional decomposition machine models [15]. Liu and other scholars proposed an intelligent tourism recommendation system with self-attention aggregators and graph transformation networks to predict user interests and preferences, which satisfies the dynamic timeliness of interest points. The results show that this method performs well [16]. Forouzandeh et al. proposed travel recommendations for tourists and analyzed the decision-making process of tourists by combining fuzzy TOPSIS and artificial bee colony algorithm. The results showed the feasibility of this method [17].

In summary, previous researchers have made great efforts to improve the accuracy of recommendations. However, in the field of tourism, research on recommendation systems that combine multi-source heterogeneous data is still relatively rare. For this purpose, the study adopted the GAT model, combined with knowledge graphs and VGG-16 networks, and finally introduced multi-layer perceptrons to construct a comprehensive recommendation model. This model aims to more accurately capture user interests and provide new research directions and methods for the future development of tourism recommendation systems.

3 A multi-source auxiliary information tourist attraction and route recommendation algorithm on the ground of GAT

The study first proposed the GAT model. On this basis, a knowledge graph was further combined to extract features from visual images through the VGG-16 network and integrate them with the attribute information of tourists. Next, it utilizes GAT to integrate the social relationships of passengers and spread their interests. Finally, a multi-layer perceptron model was proposed to implement tourist attraction and route recommendation algorithms.

3.1 Location-based social networks and ripple net model construction

In recommendation systems, GAT can effectively handle the relationship between user and target requirements, thereby improving the accuracy of recommendations. By integrating the rich semantic information of knowledge graphs into recommendation systems, KGE can help solve the cold start problem. At the same time, it can also enhance the interpretability of recommendations and support more complex recommendation scenarios. Therefore, to address the failure of recommendation systems to accurately shape multi-source auxiliary information, this study first proposed the GAT model. Then, it integrates the KGE to construct a three-layer location-based social network graph, where visitors are connected through social connections and carry attribute information. The independent abstraction of tourist attractions forms KGE, expanding the implicit preferences of tourists. Passengers and destinations are connected through check-in activities. When learning passenger features, encode their basic, label, and image information, and extract the images using VGG-16. The encoded vector is input into GAT to aggregate passenger social relationships. It then obtains implicit interests along the knowledge graph and considers geographical distance. Finally, it combines social and interest characteristics to obtain passenger interest representations. The proposed model has demonstrated its ability to process multi-source data by integrating visual features and knowledge graphs using VGG-16. This indicates that the proposed model can effectively integrate different types of data, such as text, images, and other structured data, in order to adapt to diverse inputs. The key to GAT is the graph attention layer, which inputs the feature matrix and adjacency matrix. GAT is a flexible neural network structure that can dynamically adjust the attention intensity to different nodes. This flexibility allows the proposed model to adapt to datasets of different scales and complex social relationship graphs. In GAT, after the node features change, the attention mechanism is used to calculate the coefficients of the two nodes, as shown in the following equation [18]:

$$e_{ij} = \text{Leaky Re LU}(a^T \cdot \text{Concat}(W\vec{x}_i, W\vec{x}_j)), \quad (1)$$

where $\text{Leaky Re LU}(\cdot)$ represents the activation function, T represents the flipping, and $\text{Count}(\cdot)$ represents the joining. The attention value output by this algorithm indicates the criticality of node j 's traits to node i . In social networks, the tracking behavior of passengers is often unilateral, so a masking attention mechanism strategy is implemented to only calculate the attention values from node j to node i in the social network friend cluster N_i of node i . Next, Softmax is adopted to normalize the attention values, as shown in the following equation:

$$a_{ij} = \text{softmax}_j(e_{ij}) = \frac{\exp(e_{ij})}{\sum_{k \in N_i} \exp(e_{ik})}. \quad (2)$$

It adopts a crowdsourced attention mechanism in GAT to ensure the educational process of its own attention, as shown in Figure 1.

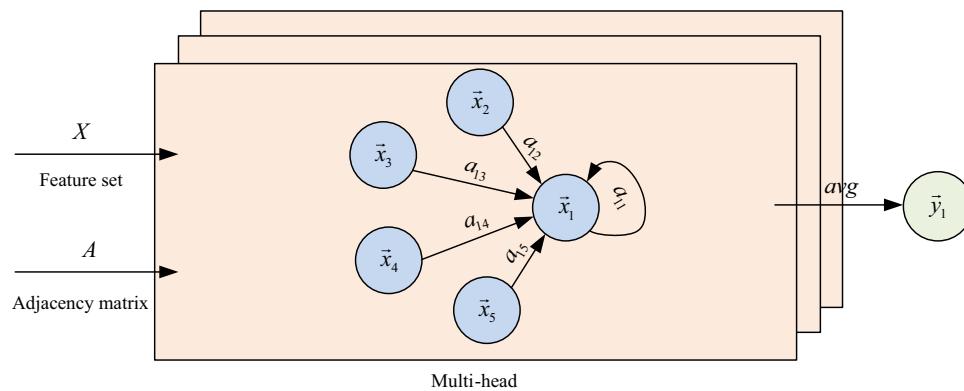


Figure 1: Multi-end attention mechanism model structure diagram.

As shown in Figure 1, it achieves the ultimate result by stacking multiple layers of GAT. As shown in equation (3), the system presents a collection of presentation traits generated by k monomer attention mechanisms:

$$\vec{y}_i' = \text{ELU} \left(\frac{1}{k} \sum_{k=1}^k \sum_{j \in N_i} a_{ij} W_k \vec{x}_j \right), \quad (3)$$

where ELU represents the linear activation function, k is the number of sets of output features of the monomer attention mechanism, and W_k is a shared linear variation parameter matrix. There are numerous visual attributes in the images captured by passengers, and finding suitable ways to extract these visual attributes has become the key to improving recommendation accuracy. Tourists may be attracted by the visual charm of the attraction. It considers two scenic spots i and j , and by refining the visual attributes of the scenic spot images, it obtains the visual matching degree $\text{sim}(i, j)$ of the scenic spot, which helps to select tourists. The current refining methods include color maps, feature transformation, and CNNs. CNNs automatically recognize advanced attributes and incorporate them into recommendation systems to increase accuracy. VGG-16 is a leading CNN design, widely used for extracting image attributes due to its efficient classification and convenient adjustment, as shown in Figure 2.

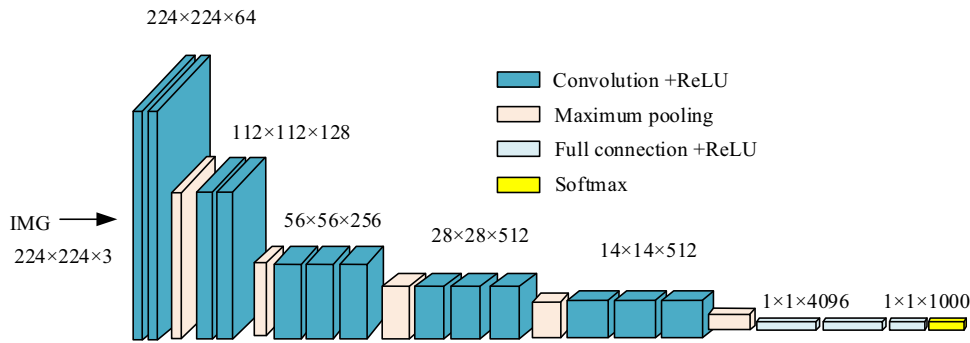


Figure 2: Structure diagram of VGG-16.

Next, research will be conducted to construct recommendations for tourist destinations and routes. Location-based social network (LBSN) and common social platforms such as WeChat, Weibo, Facebook, and Ins have accumulated numerous passenger generated information. This information can be used to represent location-based social network graphs. The standard location-based social network graph covers both travelers and attractions, as shown in the traditional LBSN graph in Figure 3. A community network is constructed

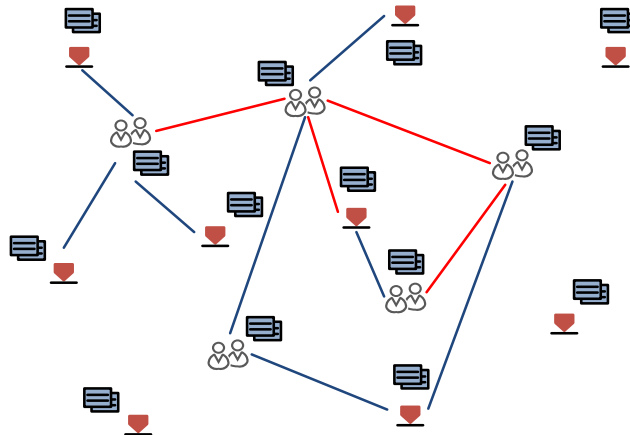


Figure 3: Diagram of a typical LBSN.

between different travelers, and a signing network is established between travelers and attractions. However, the standard LBSN diagram omits the interaction between scenic spots. If this composition is used, the skill of exploring scenic spot interaction will naturally be lost. Therefore, it is necessary to revise the standard LBSN diagram, stratify the location-based social network diagram, and separate the scenic spots into KGE. It utilizes the background information and real connections within the diagram to bridge the scenic spots. Finally, it extracts the potential hobbies of passengers [19,20].

This study developed a model on the ground of the optimized LBSN map, and the ultimate goal of the scenic spot recommendation model is to master a target method. When providing the community connection, signature form, knowledge graph, and corresponding assistant information of the passenger, it is possible to estimate the preference score of passenger u_i for alternative attraction v_j . Then, on the ground of this score, it generates a directory of tourist attractions to recommend to users, as shown in the following equation:

$$s_{u_i, v_j} = F(u_i, v_j | S, C, G, Q), \quad (4)$$

where s_{u_i, v_j} implies the tourist's preference rating for the attraction, S represents the social contact, C represents the signing the form, G represents the KGE, and Q represents the multi-source auxiliary information. Knowledge graphs often contain practical truths and connections between entities, as shown in Figure 4. The scenic spot Da Ci En Temple is linked to faith and history, while faith and ancient history are directly connected to the scenic spot Caotang Temple. Because they all belong to Zen Buddhism. To explore the implicit preferences of tourists, the study introduces the KGE to attraction suggestion model.

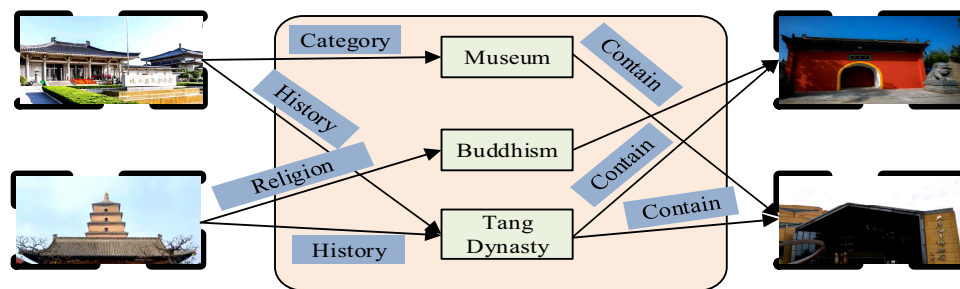


Figure 4: KGE attractions diagram (The scenic spot pictures are sourced from <https://www.chnmuseum.cn/>).

Using KGE as a multi-source auxiliary information to study recommendation mechanisms, KGE has demonstrated excellent performance. It converts elements and relationships into embedded arrays, automatically recognizing contextual information in the knowledge graph. However, knowledge graphs are often used for link prediction and require a full graph architecture. In tourist attraction recommendations, attraction updates are rapid and it is difficult to construct a complete knowledge map. Therefore, the study introduces Ripple Net into the scenic knowledge graph model. The relevant equation of Ripple Net is defined in the following equation:

$$\varepsilon_u^k = \{t | (h, r, t) \in G \text{ and } h \in \varepsilon_u^{k-1}\}, \quad k = 1, 2, \dots, H, \quad (5)$$

where (h, r, t) represents a triplet of knowledge graph G ; h, r, t represents entities, attributes, and attribute values, respectively; ε_u^k represents the tourist attractions that the passenger has visited, and represents the departure point that the passenger likes. The k -level ripple group of passenger u is presented in the following equation:

$$s_u^k = \{(h, r, t) | (h, r, t) \in G \text{ and } h \in \varepsilon_u^{k-1}\}, \quad k = 1, 2, \dots, H. \quad (6)$$

3.2 Construction of a multi-source auxiliary information tourist attraction and route recommendation algorithm on the ground of GAT

The tourism data environment includes various types such as urban tourism, rural tourism, and seaside tourism, and the characteristics of each type of scenic spot and route may vary significantly. The proposed model's graph attention mechanism can optimize the relevance and accuracy of recommendation systems by learning data with different characteristics. The combination of KGE and GAT in the proposed model helps to quickly identify emerging tourism trends and adjust recommendation strategies, thereby better responding to market changes. This study further proposes a tourist attraction and route recommendation model on the ground of GAT, as shown in Figure 5. This structure consists of two main parts: tourists and attractions. The passenger section takes into account social network characteristics and potential hobbies comprehensively. First, it extracts features from passenger images, merges them with other information, and then integrates them using the GAT layer. It utilizes Ripple-Net to explore implicit preferences of passengers. In terms of tourist attractions, due to the complexity of passenger modeling, only multiple information of tourist attractions is merged and learned using a single-layer neural network. The modeling of tourist attractions is actually the synthesis of static information such as location, type, and historical rating. The static information is rich, but the structure is relatively simple and does not change much. Therefore, in order to reduce the complexity of the overall model and consider the effective utilization of computing resources, a single-layer neural network is studied to achieve the fusion of scenic spot information. This ensures the effectiveness of the model while avoiding unnecessary computational burden. At the same time, ensure the efficiency of the model and flexibly adapt to the modeling needs of different parts. Finally, the features of tourists and attractions are predicted by a multi-layer perceptron to provide personalized attraction recommendations for tourists [21].

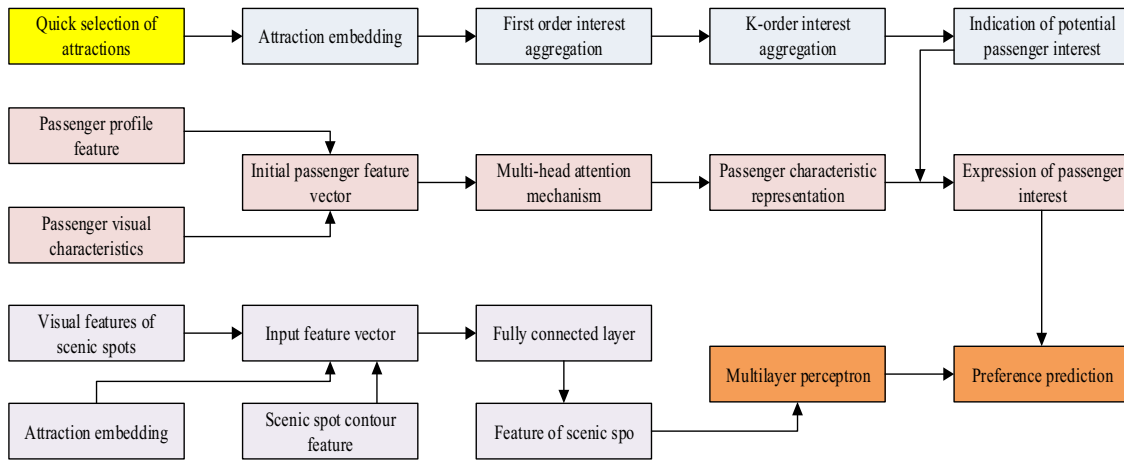


Figure 5: Tourist attraction and route recommendation model.

To incorporate graphic visual attributes into the tourism recommendation model, key visual attributes are first identified from photos of tourists or attractions. Recently, CNN technology has been widely used in the field of graphic attribute identification due to its ability to recognize advanced image attributes. Due to the fact that there is more than one image of a tourist or attraction, to obtain a representative visual attribute array, a weight synthesis strategy is adopted to integrate the visual attributes of multiple images and generate a visual attribute array for the tourist or attraction [22]. It assumes that the image set of tourists or attractions represents $P = \{p_1, p_2, \dots, p_N\}$, and the visual attribute array of tourists or attractions is shown in the following equation:

$$\vec{p} = \omega_1 \vec{p}_1 + \omega_2 \vec{p}_2 + \dots + \omega_N \vec{p}_N, \quad (7)$$

where ω_i represents the weights of each image, and \vec{p} represents the visual properties of the i th image. All images in the attraction and tourist photo sets have equal weights. The advantage of GAT is its ability to dynamically adjust nodes and edges. When new user data, attraction information, or user interactions are introduced, it can adjust weights in real time and reflect these changes in real time. The previous section mentioned that passenger preferences are influenced by social partners, so integrating the social chain into the suggestion system is crucial. In unique social chains, travelers have varying perceptions of their friends. Therefore, in integrating adjacent points of passengers, it is necessary to weigh the diverse impacts among friends. For example, if two passengers are friends but have completely different preferences, using equal weight integration may introduce attributes that passengers do not like. To achieve precise fusion, a GAT is used to determine the weights of each social partner and then integrate the social chain into passenger nodes. The passenger profile attribute vector is shown in the following equation:

$$I^u = \{\vec{I}_1^u, \vec{I}_2^u, \dots, \vec{I}_N^u\}, \vec{I}_i^u \in \mathbb{R}^{U1}, \quad (8)$$

where \vec{I}_i^u represents the profile attribute and $U1$ represents the relevant information of the passenger profile attribute vector, such as features, gender, and work. Research the use of single-value encoding strategies to transcode these general attributes, to obtain clear attribute vectors for passengers. The vector of passenger preference labels is shown in the following equation:

$$L^u = \{\vec{L}_1^u, \vec{L}_2^u, \dots, \vec{L}_N^u\}, \vec{L}_i^u \in \mathbb{R}^{U2}, \quad (9)$$

where $U2$ represents the size of the passenger preference label vector. The visual attribute vector of passengers is shown in the following equation:

$$V^u = \{\vec{V}_1^u, \vec{V}_2^u, \dots, \vec{V}_N^u\}, \vec{V}_i^u \in \mathbb{R}^{U3}, \quad (10)$$

where V^u represents the visual attribute vector of the passenger, and $U3$ represents the dimension of passenger visual attribute vector. Specifically, the study selects a group of attribute descriptions of passenger nodes as input parameters for the model, as shown in the following equation:

$$\begin{cases} u = I \oplus L \oplus V \\ \vec{u}_i = \vec{I}_i \oplus \vec{L}_i \oplus \vec{V}_i. \end{cases} \quad (11)$$

After obtaining the initial attribute description of the passenger, the input GAT model integrates the passenger's community information. The attribute description of passenger u_i combined with community data is the mean output of multiple GAT layers, as shown in the following equation:

$$\vec{u}_i = \text{ELU} \left(\frac{1}{k} \sum_{k=1}^k \text{GAT}_k(u) \right), \quad (12)$$

where $\text{GAT}_k(u)$ represents the processing flow of the GAT model. A knowledge graph has multiple entities and their connections, containing rich information and semantic connections. To explore the implicit concerns of travelers, the Ripple-Net framework was adopted in the study, treating the previous tourist attractions as the initial set of the knowledge graph. Next, it calculates the semantic connections between candidate attractions and initial attractions, and it spreads passenger preferences on the knowledge graph on the ground of these connections. The proposed model integrates the social relationships of tourists to achieve interest dissemination, captures the evolution of user preferences, and enables real-time updates of user preferences through user interaction and changes in the network. This is to explore the potential attention of tourists to new attractions, as shown in Figure 6(a).

Ripple-Net assumes that passengers who are interested in the subject may also be interested in the related subsubjects. The preferences of tourists for potential attractions will be extended to the secondary body through β_i on the path of the knowledge graph, as shown in Figure 6(b). Include seasonal factors such as seasons, specific holidays, or holidays as attributes of graph nodes in the model to consider the impact of seasonal changes. The implicit preference u_i^{-KG-1} of passengers on the primary correlation set can be calculated on the ground of the weighted sum of the sub body t_i , as shown in the following equation:

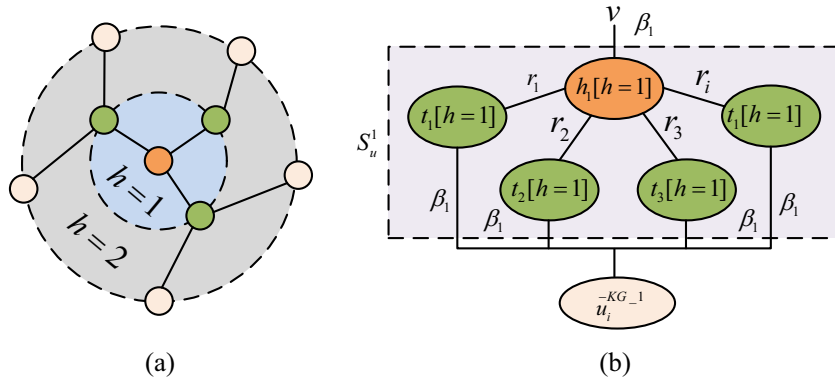


Figure 6: Hobby propagation diagram: (a) set of ripples and (b) first-order interest calculation.

$$u_i^{-KG-1} = \sum_{(h,r,t) \in S_u^1} \beta_i t_i. \quad (13)$$

Finally, the next step is to calculate the passenger's preference attributes, as shown in the following equation:

$$\vec{u}_i^f = \vec{u}_i^S \oplus \vec{u}_i^{KG}, \quad (14)$$

where \vec{u}_i^f represents the passenger's preference attribute. As mentioned earlier, the study utilizes a multilayer perceptron (MP) to grasp the deep interaction between tourists and attractions. Next, it links the attribute descriptions of tourists and attractions and puts them into MP processing. The use of MP enables the model to learn and predict the specific preferences of individual users, and it can dynamically adjust recommendations based on the latest user behavior and feedback, improving the accuracy of personalized recommendations. Through the transformation of several fully connected layers, the evaluation of tourists' interests in attractions is obtained, as shown in the following equation:

$$\begin{cases} \vec{d}_1 = \vec{u}_i^f \oplus \vec{v}_i^f \\ \vec{d}_2 = \sigma(W^{(2)}\vec{d}_1 + b_1) \\ \dots, \\ \vec{d}_{l-1} = \sigma(W^{(l-1)}\vec{d}_{l-2} + b_{l-1}) \\ \hat{y}_{u_i, v_j} = W^T \vec{d}_{l-1} + b. \end{cases} \quad (15)$$

where l represents the number of levels, while u_i represents the passenger's preference rating for potential attraction v_j . Due to the relative ranking of attractions rather than absolute ratings, this study needs to consider noninteracting attractions as negative samples, with the goal of ensuring that the recommended ranking of interacting attractions is higher than that of noninteracting ones. On the ground of this idea, Bayesian personalized ranking (BPR) is adopted as the calculation method, as shown in the following equation:

$$\arg \min \text{Loss} = \arg \min \sum_{(u_i, v_j, v_m) \in S} -\ln \sigma(\hat{y}_{u_i, v_j} - \hat{y}_{u_i, v_m}) + \lambda \|\theta\|_2^2. \quad (16)$$

4 Analysis of tourist attraction and route recommendation results on the ground of GAT with multi-source auxiliary information

The study first outlined the dataset involved and validated the learning rate and AUC parameter settings of the model. Next, the experiment investigates the impact of the interest propagation layer on the effectiveness of recommending tourist attractions and routes. Finally, the effects of negative sample selection, visual attributes, and ratings obtained using MP on tourist attraction and route recommendations were examined.

4.1 Analysis of learning rate and AUC value results for three datasets

This research experiment utilized three datasets, namely, Xian, New York, and Tokyo. Among them, the Xian dataset comes from the Mafengwo website, which uses specialized techniques to obtain and filter representative photos of scenic spots. The datasets of New York and Tokyo are filtered on the ground of specific latitude and longitude ranges, with longitude ranges of [40.98, 40.55] and [35.86, 35.51], respectively, and dimension ranges of $[-73.68139.91]$. In the constructed recommendation model, the selection of hyperparameters is particularly important, especially when applying GAT and interest propagation layers. This model uses area under the curve (AUC) for training to evaluate its effectiveness. The choice of learning rate is directly related to the convergence speed of the model. As shown in Figure 7(a), when the learning rate is 0.0001, the model converges slowly, while when the learning rate is 0.05, the model does not converge. At this point, the performance of the model is affected and there is instability. According to Figure 7(b), when the learning rate is 0.01, the model has the highest AUC value on the Xian dataset. This indicates that the model has good classification performance. Therefore, the optimal learning rate is chosen as 0.01.

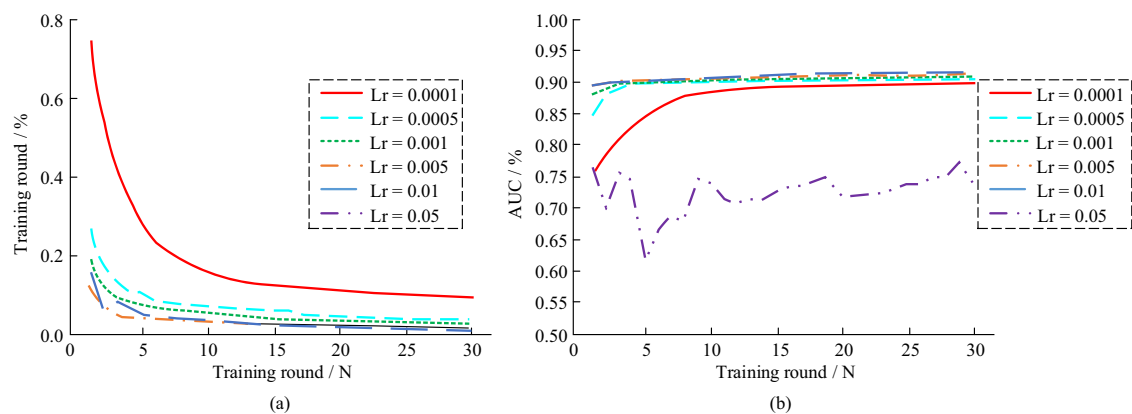


Figure 7: Learning rate and AUC results in Xian data: (a) model loss and (b) model AUC.

For the New York dataset, Figure 8(a) shows the convergence of the model under different learning rates. Clearly, with learning rates of 0.005 and 0.01, the model converges rapidly in the initial 11 rounds and remains stable in the following 21 rounds. The learning rate of 0.001 is somewhat slow in the early 11 rounds, but can reach a lower loss value in the later stages. It is worth noting that a learning rate of 0.05 leads to the problem of gradient explosion. Figure 8(b) shows that the area value under the subject working characteristic curve of the model is the highest at a learning rate of 0.001. Therefore, for the New York dataset, the recommended learning rate is 0.001.

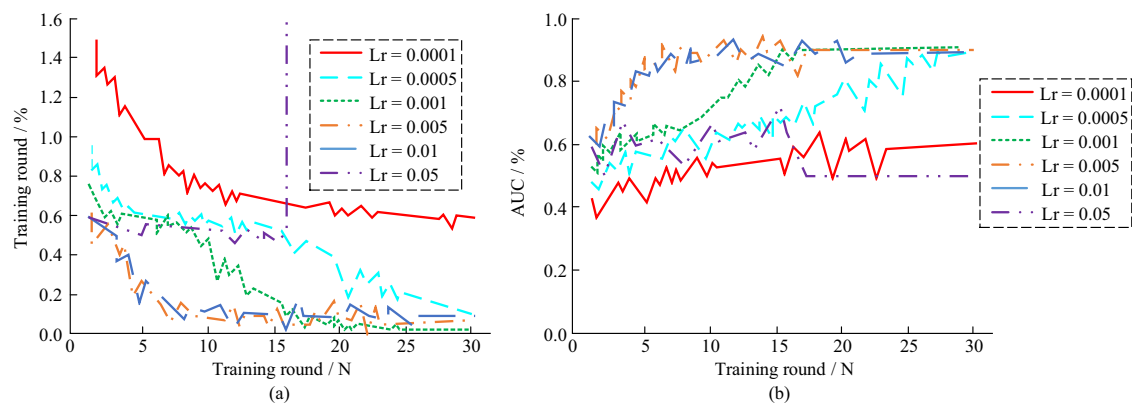


Figure 8: Learning rate and AUC results in New York data: (a) model loss and (b) model AUC.

For the Tokyo dataset, according to Figure 9(a), using a learning rate of 0.005, the loss value of the model decreases the fastest. But when the learning rate is 0.001, although the initial convergence speed of the model is slightly slower, the final loss value can reach its lowest point. Furthermore, Figure 9(b) shows the maximization of the area value under the subject operating characteristic curve of the model at a learning rate of 0.001. Therefore, it is recommended to choose 0.001 as the learning rate of the model on Tokyo.

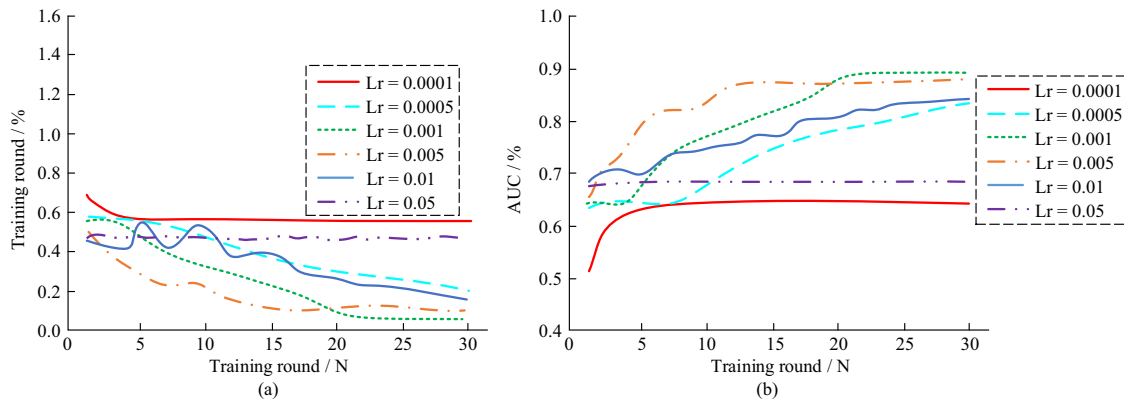


Figure 9: Learning rate and AUC results in Tokyo data: (a) model loss and (b) model AUC.

Through experiments on the Xian, New York, and Tokyo datasets, it can be clearly seen from Figures 7–9 that after selecting an appropriate learning rate, the model quickly stabilizes in the first 16 rounds and reaches a stable state between 26 and 30 rounds. At an appropriate learning rate, the ranking performance of the model is also quite stable, and the area value under the curve remains stable in the range of 0.88 to 0.92. This means that in recommendation, the ranking probability of positive samples is 88–92% before negative samples. This further confirms the crucial role of the initially set learning rate in the effectiveness of the model.

4.2 Impact of interest propagation layer on the effectiveness of recommending tourist attractions and routes

The study adopted a Ripple Net interest propagation model on the ground of KGE as the recommendation system. In the experiment, the main focus was on exploring the impact of the dimensionality and number of

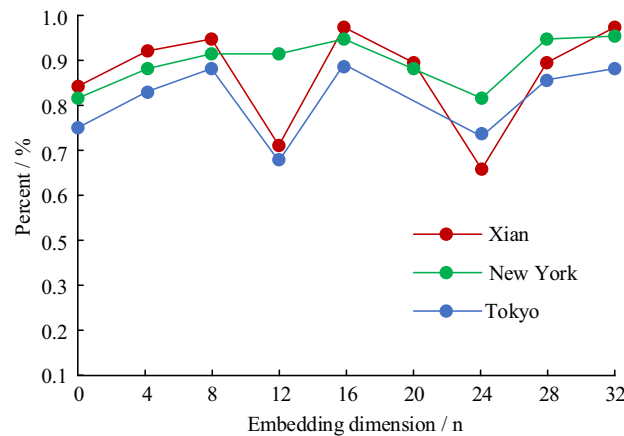


Figure 10: AUC values for different vector space dimensions.

hops of the vector space on recommendation performance, as shown in Figure 10. This indicates that as the dimension of the vector space increases, the sorting performance steadily improves, indicating that higher dimensions of the vector space can better encode information. The experimental results show that when the dimension of the vector space is 16, Xian, New York, and Tokyo are 0.916, 0.909, and 0.895, respectively, indicating that the model performs the best. Therefore, 16 dimensions are chosen as the optimal vector space dimension for the interest propagation layer.

Next, this study discusses the mechanism by which passenger interests are transmitted through entity relationships in the interest propagation model of KGE. This study focuses on exploring the impact of communication depth on mining deep-level interests of passengers, and the relevant data are shown in Table 1. This indicates that different propagation depths have a significant impact on model performance. When the propagation depth is 2, Xian, New York, and Tokyo are 0.920, 0.910, and 0.897, respectively, achieving the best performance of the model. A depth that is too small may make it difficult to delve deeper into interests, while a depth that is too large may introduce unnecessary noise and reduce recommendation quality.

Table 1: AUC values at different propagation depths

| Propagation depth | 1 | 2 | 3 | 4 |
|-------------------|-------|-------|-------|-------|
| Xian data | 0.916 | 0.920 | 0.920 | 0.919 |
| New York data | 0.905 | 0.910 | 0.904 | 0.908 |
| Tokyo | 0.895 | 0.897 | 0.895 | 0.895 |

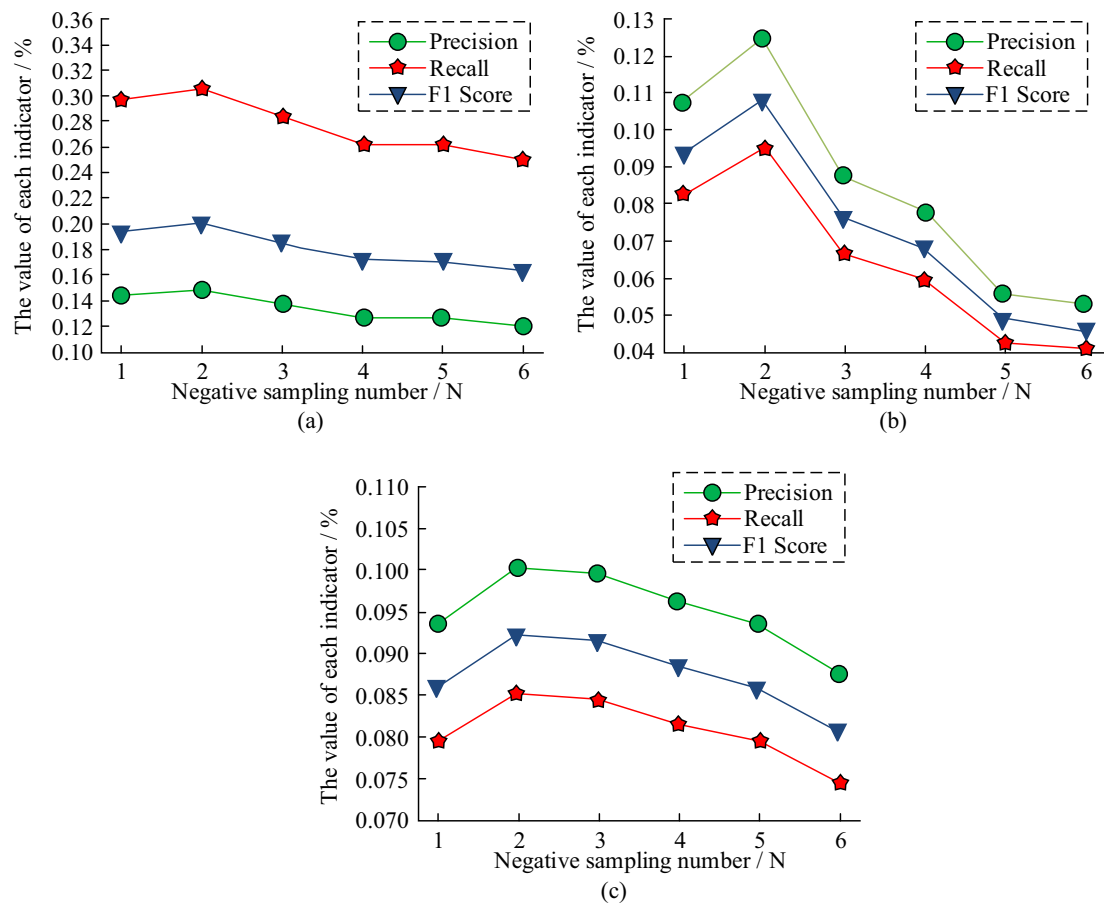


Figure 11: Influence of negative sample sampling on recommendation quality: (a) Xi'an dataset, (b) New York dataset, and (c) Tokyo dataset.

4.3 Results and analysis of three methods for recommending tourist attractions and routes

The study aims to validate the proposed scenic spot recommendation model through experiments, which integrates the effects of negative sample selection, visual attributes, and MP on recommendation performance. The model is trained within 25–31 rounds with a regularization coefficient of 0.00005 to reduce the risk of overfitting, and the random inactivation rate is set to 0.6. Using BPR to calculate sorting loss, the experiment explored the impact of different negative sample selection numbers on the effectiveness. Each tourist attraction interaction corresponds to N previously visited attractions, forming a triplet for training. Figure 11 shows the variation of negative sample selection quantity N from 1 to 6. This indicates that as the quantity increases, the accuracy, recall, and $F1$ value of the model also improve. But after reaching a certain point, these indicators begin to decline. This reflects that too many negative samples may cause data skewness, thereby affecting model performance. Therefore, when selecting a quantity of 2, the model performs best.

To explore the role of attributes in tourist attraction and route recommendation, the study compared the original model with its version without visual features, called NV. The performance of two methods was observed in the top 10 to 20 scenarios, as shown in Figure 12, indicating that the proposed model outperformed the NV version in all evaluation criteria. The accuracy, recall rate, and $F1$ value have all improved by 10 to 15.7%. This further confirms the value of visual attributes in the recommendation process, demonstrating that integrating image features can effectively enhance the accuracy of tourist attraction and route recommendations.

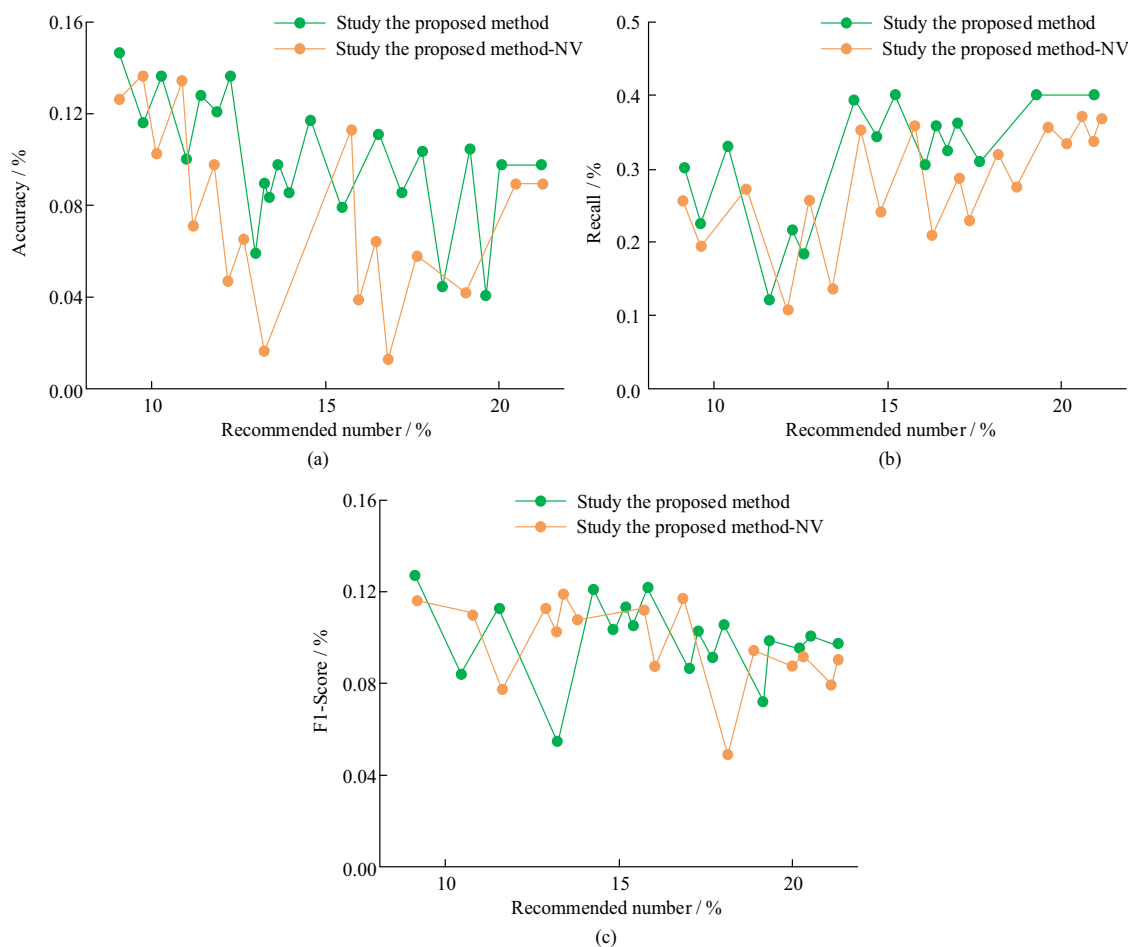


Figure 12: Effects of visual attributes: (a) accuracy, (b) recall, and (c) $F1$ -score.

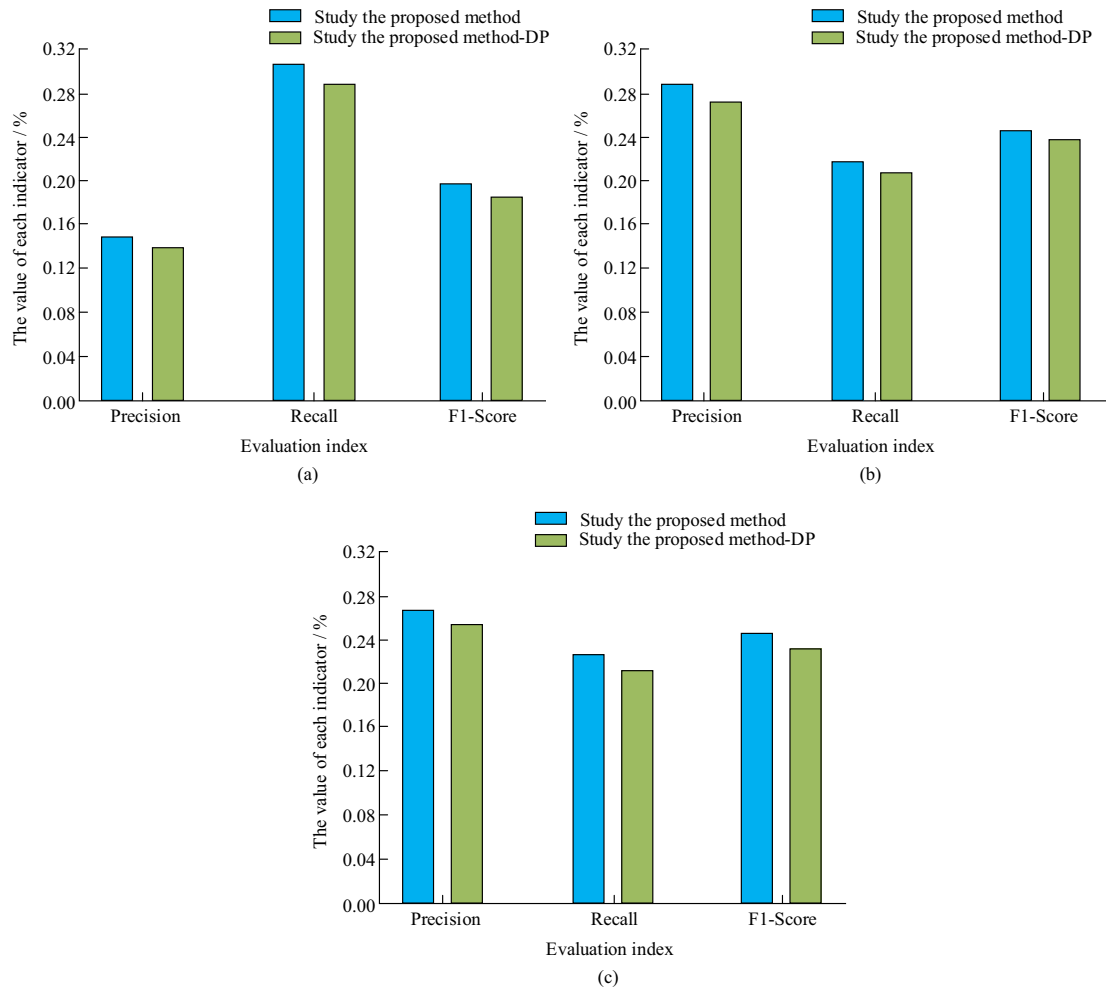


Figure 13: Influence of multilayer perceptrons: (a) Xi'an dataset, (b) New York dataset, and (c) Tokyo dataset.

In the scoring prediction stage of the research experiment, the addition of MP has brought non-linear advantages to the model. To gain a deeper understanding of the differences between MP and traditional inner product strategies, detailed comparative experiments were conducted on three datasets. Figure 13 shows a comparison of the effects of ten recommended tourist attractions for travelers. This indicates an improvement

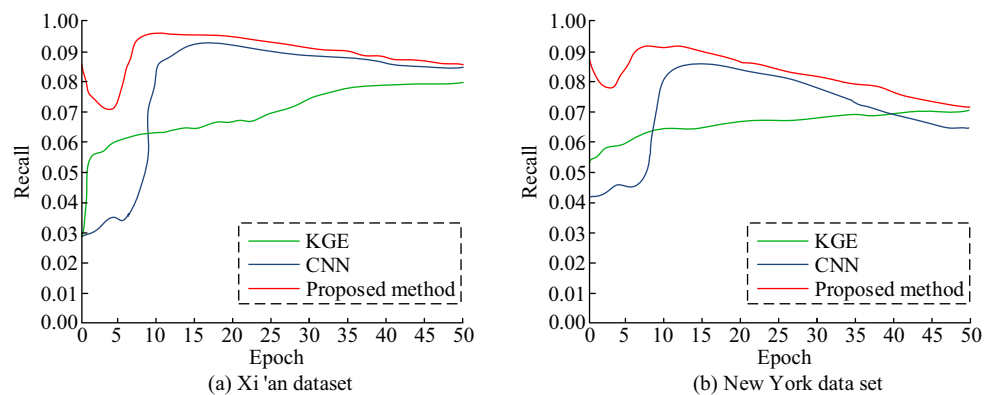


Figure 14: Comparison of different methods: (a) Xi'an dataset and (b) New York dataset.

of 4–6% in accuracy, recall, and $F1$ value on all three datasets. This further proves that the introduction of multi-layer perceptrons has brought performance improvements to the proposed model compared to a simple inner product strategy.

To verify the robustness of the proposed method, Figure 14 shows a comparison between the method and two recommendation models, KGE and CNN, and their recall results on the Xi'an and New York datasets. The recall rate of the proposed method is higher than that of KGE and CNN in both datasets, indicating that the proposed method can more comprehensively capture the items that users may be interested in. This method can still maintain high performance and good robustness in different environments and conditions.

5 Conclusion

This study utilized GAT to design a multi-source auxiliary information algorithm for recommending tourist attractions and routes, in order to solve the problem of rapid expansion of tourism related information. The results indicate that the effectiveness of the algorithm was demonstrated through experiments using three datasets: Xian, New York, and Tokyo. On the Xian dataset, when the learning rate is set to 0.01, the AUC value of the model reaches 0.916. On the New York dataset, the AUC of the model at a learning rate of 0.001 is 0.909. For the Tokyo dataset, under the same learning rate, the AUC reaches 0.895. This indicates that algorithms with moderate learning rates have higher accuracy in different datasets. In terms of vector space dimension, when the dimension is set to 16, the accuracy of the model on three datasets is 0.916, 0.909, and 0.895, respectively, demonstrating excellent performance. When the propagation depth is set to 2, the accuracy on the Xian, New York, and Tokyo datasets is 0.920, 0.905, and 0.895, respectively, which is better than other depths. After adding visual features, the model significantly improved on all evaluation criteria. Compared with the version without visual features, the accuracy, recall, and $F1$ value improved by 10 to 15.7%, which proves the importance of visual features. In addition, after introducing multi-layer perceptrons, the accuracy, recall, and $F1$ values on these three datasets improved by 4 to 6%. Therefore, the model is effective in recommending tourist attractions and routes. But there are still shortcomings, such as data sparsity and noise. Future research directions can consider combining more auxiliary information and deep learning techniques to further improve the accuracy and effectiveness of recommendations.

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Data availability statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

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