Research Article

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Interactive recommendation of social network communication between cities based on GNN and user preferences

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Abstract: To further enhance the effectiveness of interactive recommendation for intercity social network communication, the study proposes a novel interactive recommendation model for intercity social network communication. This model focuses on point-of-interest preference migration and recommendation modeling by integrating the self-attention mechanism, cross-attention mechanism, and graph neural network. The method effectively solves the problem of cross-city users' interest point preference change and constructs a recommendation framework based on interest point heat. The experimental results showed that the recommendation accuracy of the new model was up to 93.52%. Compared with the existing more advanced recommendation methods, the recommendation coverage of Chengdu–Chongqing dining and food points of interest could be up to 96.72%. The recommendation coverage of Shanghai–Beijing business and residential and science, education, and culture points of interest could be up to 95.17%, and the maximum time reduction was 2.07 s. The contribution of this study is the introduction of a novel graph attention mechanism, which improves the accuracy and stability of recommendations. This provides an effective technical solution for intercity social network communication recommendations.

Keywords: points of interest, user preference, social networks, GAT, CA, SA

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1 Introduction

Users from different cities share information and exchange opinions through social networking platforms. This cross-regional interaction not only affects individuals' lifestyles but also has a profound impact on the economic and cultural development of cities [1]. However, due to the diversity of user needs and the complexity of social relationships, how to effectively promote interactive recommendations through social networks between cities has become a hot research topic. Point of interest (POI) recommendation, as an important means to enhance user experience and social interaction, has gradually attracted the attention of researchers [2]. Jin *et al.* proposed a learning framework based on context-aware region similarity to measure POI similarity between regions in different spatial and application contexts. This framework could significantly enhance the popularity of social communication between cities [3]. Liu *et al.* proposed a cross-city disease-dependent POI recommendation model to enhance the effectiveness of residents' health POI communication. The recommendation accuracy of this model could reach up to 92.73%, and it was very popular [4]. Liu *et al.* found that it is difficult for people to effectively find the best route from one place to another through public transportation systems. To this end, the team proposed a traffic POI recommendation model that balances time and distance costs. The recommendation recall rate of this model could reach 91.23%, which far exceeded the performance of traditional models [5]. Dai *et al.* proposed a scientific social POI recommendation system to promote the development of intercity scientific, social networks by combining data from intercity knowledge network platforms and deep learning algorithms. The average accuracy of the system in POI recommendation tests for knowledge networks between eight cities, including Chengdu and Chongqing, Guiyang, and Hunan, was close to 92.38%, and the data stability was strong [6]. Heydariyan *et al.* proposed a hybrid optimization method combining the Sticky Mushroom Algorithm and the sine cosine algorithm (SCA) for the problem of overlapping community detection in social networks. The algorithm significantly improved the accuracy and convergence speed of community detection by combining the advantages of both methods and especially showed high effectiveness when dealing with complex social network structures [7]. Sheykhzadeh *et al.* proposed a node-ranking-based local community detection method, which achieves community detection without global network information by ranking nodes in terms of their local importance. The method demonstrated high efficiency and scalability when dealing with large-scale social networks and was suitable for scenarios that require fast community localization [8]. Aghdam *et al.* proposed a new opinion leader selection method by combining the African vulture optimization algorithm with the Hunger Games search algorithm. This hybrid algorithm showed higher accuracy and computational efficiency in the task of influencer identification in social networks and was suitable for areas such as marketing and information dissemination [9].

Graph neural network (GNN), an advanced algorithm capable of processing unstructured data, especially social network graph structures, has gradually become a research focus [10]. Liu *et al.* proposed an interactive tourism POI recommendation model in combination with GNN to improve the accuracy of cross-city tourism user preference recommendations. Compared to traditional models, this model could output more effective recommendation results [11]. Wang *et al.* believed that most existing models only focused on exploring local spatiotemporal relationships between POIs based on the current user's trajectory sequence. Therefore, after combining the GNN algorithm, a user-intelligent POI recommendation model with global perspective capture was proposed. The POI recommendation task completion rate of this model on real datasets could approach 95% [12]. Liu *et al.* believed that existing research has overlooked the high-order

Table 1: Results of the comparison of methods across the literature

Literature	Method	Advantages	Disadvantages
Jin *et al.* [3]	Context-aware region similarity learning framework	Improved intercity social propagation and POI similarity	Lacks optimization for cross-city user interest migration
Liu *et al.* [4]	Cross-city disease-dependent POI recommendation model	Enhanced recommendation accuracy and effectiveness in health POI communication	Limited to a specific domain (health), lacks broad applicability
Liu *et al.* [5]	POI recommendation model based on time and distance costs	Significantly optimized route recommendations in public transport	Does not account for personalized user needs, lacks dynamic recommendations
Dai *et al.* [6]	Deep learning-based scientific, social POI recommendation system	Improved accuracy in knowledge network social POI recommendations	Primarily focused on academic domains, limited applicability to other areas
Heydariyan *et al.* [7]	Hybrid slime mold algorithm and SCA for community detection	Enhanced precision and convergence speed in social network community detection	Efficiency may drop in large-scale, complex networks
Sheykhzadeh *et al.* [8]	Local community detection based on node ranking	Does not require global network information, suitable for large-scale networks	Limited detection capability in complex network structures
Aghdam *et al.* [9]	African Vultures Optimization and Hunger Games Search algorithm hybrid for opinion leader selection	Improved accuracy and computational efficiency in identifying opinion leaders	Mainly used for opinion leader selection, limited application scenarios
Liu *et al.* [11]	GNN-based interactive POI recommendation model for tourism	More accurate recommendations suited for cross-city tourism users	Lacks consideration of dynamic changes in user interests
Wang *et al.* [12]	Global perspective user POI recommendation model	Captured global spatiotemporal relationships, improved recommendation accuracy	High model complexity requires significant computational resources
Liu *et al.* [13]	GNN-integrated personalized POI recommendation model	Enhanced high-level user-POI collaboration effects, improved personalized recommendation accuracy	Lacks handling of cross-city user interest migration
Qin *et al.* [14]	GNN with the geographic constraint sampling strategy	Improved geographic information completeness in POI recommendation	Needs further optimization for adaptability in highly dynamic environments

collaborative effects between users and POIs, resulting in unsatisfactory recommendation results. To this end, they integrated GNN into POI recommendation and ultimately proposed a personalized POI recommendation model. The recommendation accuracy, recall rate, and normalized cumulative gain of this model were superior to existing models [13]. Qin *et al.* believed that there was still a problem of incomplete geographic information in POI recommendations in the existing social network interaction recommendations between cities. To this end, a novel recommendation model was proposed by integrating GNN and geographically constrained sampling strategies. The recall rate of this model has increased by 3.92%, and the hit rate has increased by 2.53% compared to advanced models [14]. A comparison of these various literature methods is shown in Table 1.

In summary, although existing research has made some progress, such as improving user experience and social interaction effects through POI recommendation technology, these studies still face issues such as low recommendation accuracy and significant environmental interference when dealing with user POI preference migration and social relationships between different cities. To this end, this study innovatively integrates the self-attention (SA) mechanism, cross-attention (CA) mechanism, and a special graph attention network (GAT) from GNN, proposing a novel recommendation model. The contribution of the research lies in the introduction of SA and CA mechanisms to solve the problem of cross-city user preference migration for POI. Then, a GAT-based POI heat modeling method is proposed to improve the accuracy and stability of the recommendation. This modeling provides a new technical idea for intercity social network dissemination recommendations. It aims to effectively improve the technical level of existing POI recommendations and provide a new approach for future social network dissemination and interactive recommendations.

2 Materials and methods

To improve the efficiency of social network communication and interactive recommendations between cities, this study focuses on user POI as the main direction. First, by introducing CA and SA mechanisms separately to characterize the POI feature vectors of users in the source city and target city, a POI migration method is proposed through fusion, concatenation, and dimensionality reduction. Then, based on this migration method, this study considers the issue of the popularity of the target POI and combines the feature aggregation method of GAT in GNN to screen out the recommendation results with the highest popularity and influence and high similarity to the interests of the source city. Finally, a new type of interactive POI recommendation model for intercity user social network dissemination is proposed.

2.1 Cross-city POI migration modeling considering user preferences

POI refers to places or locations that users may be interested in within a specific geographic location, such as restaurants, attractions, and shopping centers. In practical

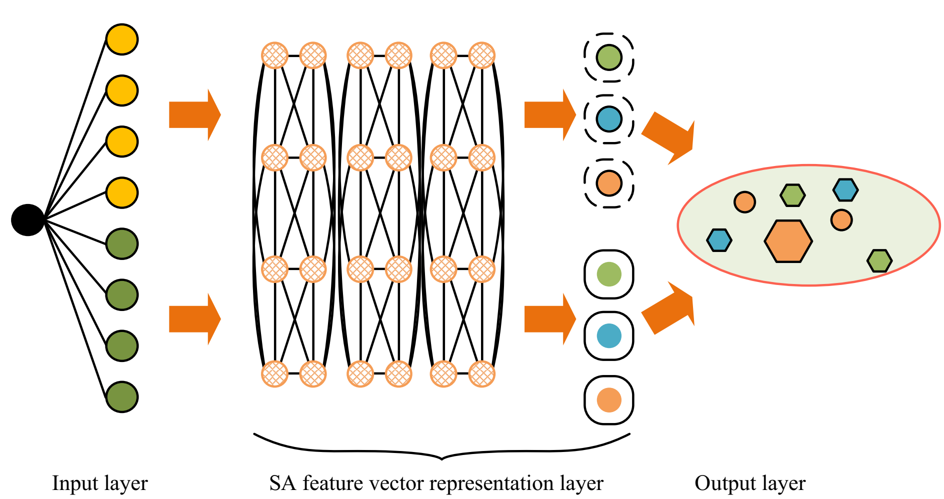

Figure 1: SA mechanism calculation for POI within a user's city.

urban applications, users usually have stable POI preferences, but when they move between different cities, these POIs may undergo significant changes, known as the POI migration phenomenon. This dynamic change makes it difficult for traditional recommendation models to maintain the accuracy and relevance of recommendations [15,16]. To obtain the importance of each POI, the SA mechanism is introduced for weight allocation. Compared to other methods, the SA mechanism can reduce reliance on external information, thereby enhancing the capture of internal correlations in data [17]. The SA mechanism calculation of POIs within the user's city is shown in Figure 1.

In Figure 1, first, the user's historical behavior and geographic location data are input into the input layer. Second, in the SA mechanism layer, the model processes the input data through the SA mechanism, identifies users' potential preferences for different POIs, and calculates relevant weights. Then, this information is transformed into feature vectors in the feature vector representation layer, representing the user's level of interest in different POIs within the current city and, finally, the output. The feature vector representation of the new POI, the weight coefficients of the SA mechanism, and the fused feature representation of multiple POIs are shown in the following equation:

$$\begin{cases} Q = W^q \times R^s \\ K = W^k \times R^s \\ V = W^v \times R^s \\ A = \text{soft max}(K \times Q^T) \\ R^{s'} = A \times V, \end{cases} \tag{1}$$

where Q, K, and V are the query vector, key vector, and value vector, respectively, W^v, W^k, and W^q represent weighted matrices, R^s is the input feature vector, soft max is the function normalization, and *soft* max and V are attention weights and value vectors, respectively. The feature vector of the new POI is linearly reduced to obtain the true user features, and the calculation formula is shown in the following equation:

$$u_s' = \sigma(W_1(R_1^{s'} \| R_2^{s'} \cdots \| R_n^{s'}) + b_1), \tag{2}$$

where u_s' is the user's new POI feature after dimensionality reduction, b_1 is the dimensionality reduction bias vector, and σ is the activation function. Similarly, this method can also calculate the POI preference feature weights of users in other cities. However, how to ultimately make the two converge remains a thorny issue. Therefore, this study introduces the CA mechanism to conduct global feature interaction on the dissemination of interest preferences among users on social networks between cities, aiming to achieve the goal of transferring POI preferences among end-users. Compared to other methods, the CA mechanism can quickly learn the representation of problems and answers and then adjust the weights appropriately, thereby improving the correlation and interactivity between problems and answers within and between cities [18,19]. A schematic diagram of the calculation of the CA mechanism for POI between user cities is shown in Figure 2.

In Figure 2, first, the POI data feature vector of the user in the source city is normalized together with the similar POI data feature vector of the user in the target city as input. The interest preference matching degree is generated by calculating the CA mechanism, and the POI migration trend of users in the target city is captured by adjusting the weighting coefficients. Finally, by summing and pooling multiple POI information, a more comprehensive recommendation feature vector is generated. The POI similarity normalization between the source city and the target city for users is shown in the following equation:

$$\beta_r = \text{soft}(R_r^T W_s u_s'), \tag{3}$$

where R_r^T is the POI similarity calculation value of the user in the target city, W_s is the dimension change matrix after

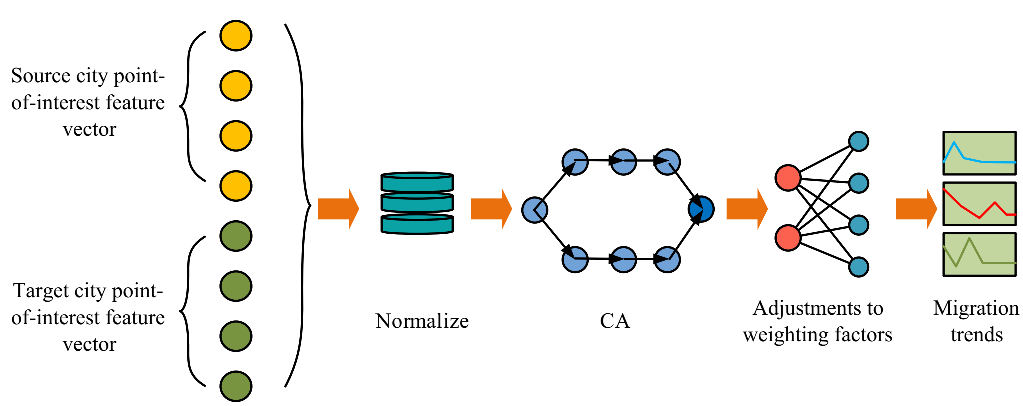

Figure 2: Calculation of the CA mechanism for the user's intercity POI.

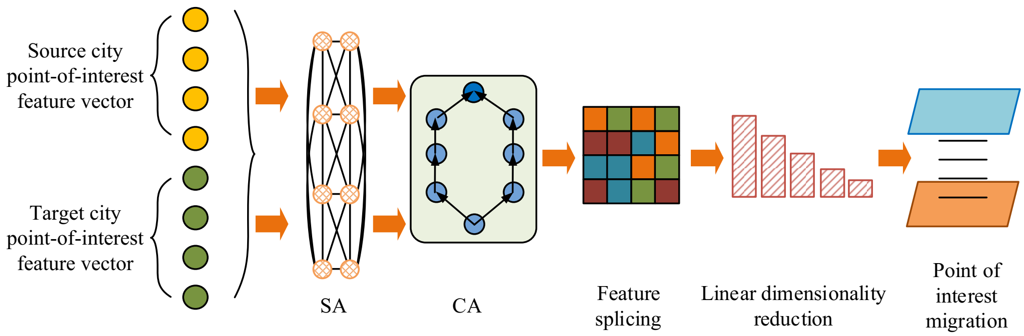

Figure 3: The migration process of user preference POI.

CA mechanism feature vector learning, and β_r is the normalized user POI similarity calculation coefficient. After weighting, the true POI migration feature vector of the user's target city is obtained, as shown in the following equation:

$$u_T' = \sum_{r=1}^{M} \beta_r R_r^T, \tag{4}$$

where u_T' is the weighted POI migration feature vector of the user's target city, M is the M-th similarity coefficient, and r is the r-th POI. Based on the capture of POI feature vectors for users inside and outside the city, this study combines the two to obtain cross-city POI migration results. The process is shown in Figure 3.

In Figure 3, the entire migration fusion process is divided into two channels. First, users input POI information data in both the source and target cities. Second, the SA mechanism is used to perform dimensionality reduction and embedding representation on the POI data of users in the source and target cities, and the feature vectors of POIs are obtained separately. Afterward, the CA mechanism fuses the two types of feature vectors to obtain the final cross-city POI vector, as shown in the following equation:

$$U = \sigma(W_2[u_S' \| u_T' + b_2]), \tag{5}$$

where W_2 and b_2 are the weight matrix and bias vector of the hidden layer, respectively. The transfer loss function, Transfer Loss, is used to constrain the similarity calculation of feature vectors, as shown in the following equation:

$$\tau_T = \frac{u_S' \cdot u_T'}{\|u_S'\| \cdot \|u_T'\|}, \tag{6}$$

where τ_T is the cosine similarity.

2.2 Construction of an interactive POI recommendation model between cities based on GNN

After constructing the inter-city user POI preference migration model, it was found that if POI, such as tourism, medical treatment, employment, and education, are used as the main targets, these users often tend to prefer locations with higher popularity [20]. Traditional methods rely solely on the strength of the POI correlation between two locations for recommendation, which cannot meet user needs with high standards. Therefore, this study uses popularity

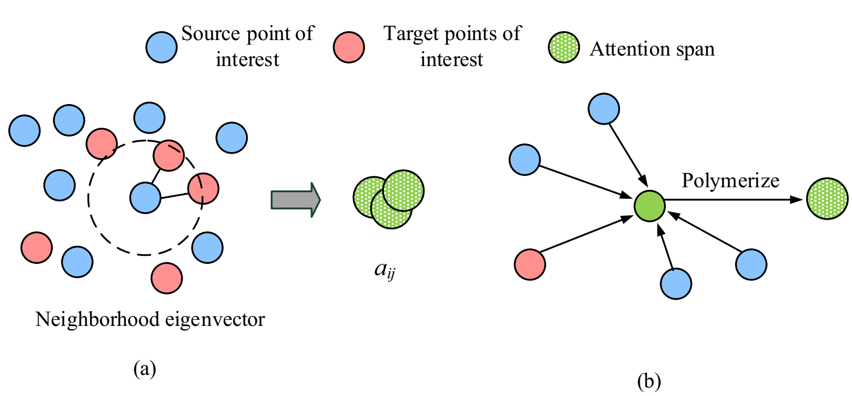

Figure 4: Schematic diagram of the GAT structure.

as a POI selection label and introduces GNN to model the network topology of POI popularity features and geographic locations in the target city. GAT, as a specific model in GNN, introduces an attention mechanism to optimize spatially based GNN [21,22]. GAT overcomes some limitations of traditional GNN, enabling the model to better understand and process node relationships in graph data. The GAT structure diagram is shown in Figure 4 [23].

Figure 4(a) shows the calculation process of the attention coefficient, and Figure 4(b) shows the node state update process. By weighting the feature vector h_j of neighboring nodes and applying an activation function, the attention weight α_{ij} can be obtained and then aggregated to generate the target node h_i. In Figure 4(b), the state of the target node h_i is updated by combining the features of all neighboring nodes and their corresponding attention coefficients. The formula for the attention coefficient is

$$e_{ij} = \mathrm{LeakyReLU}(\alpha[Wh_i \| Wh_j]), \tag{7}$$

where j is the attention score between node i and node e_{ij}, α is a learnable attention weight vector, W is a learnable weighted matrix, and LeakyReLU is the activation function. The calculation of attention weights is shown in the following equation:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k\in N_i}\exp(e_{ik})}, \tag{8}$$

where e_{ik} is the attention score between node i and node k, and N_i is the set of neighboring nodes of node i. The update of node features is shown in the following equation:

$$h_i' = \sigma\left(\sum_{j\in N_i}\alpha_{ij}Wh_j\right), \tag{9}$$

where h_i' is the updated feature representation of the node i. This study uses GAT to extract the most popular user POIs in the target city and constructs a POI popularity topology framework based on this, as shown in Figure 5.

In Figure 5, first, in the embedding layer, the attribute data of POI are embedded as feature vectors. Next, these feature vectors represent the relationship structure between POIs by constructing a POI map. The graph attention layer uses GAT to process nodes in the POI graph and obtain aggregated information about neighboring nodes. Finally, in the POI graph aggregation layer, the processed POI graph is aggregated to form the final POI heat topology structure. The heat aggregation feature representation of POI by GAT is shown in the following equation:

$$h_i^{(l)} = \sigma(\mathrm{Agg}(h_i^{(0)}, \{h_j^{(l-1)}, \forall V_j \in N(V_j)\})), \tag{10}$$

where $h_i^{(0)}$ is the initial feature vector for embedding the target POI, $N(V_j)$ is the set of domain nodes for the target POI V_j, and Agg is an aggregation function. This study combines the above calculation methods and incorporates the attention mechanism into the aggregation function so that the feature vector of a single POI V_j can be jointly determined by its connected edge weights, thereby avoiding the problem of incomplete consideration of global information. At this point, the attention coefficient determined by the weights between neighboring points is calculated as shown in the following equation:

$$\begin{aligned}\alpha_{ij}^* &= f(h_i^{(0)},\ h_j^{(l)},\ e_{ij})\\ &= \mathrm{LeakyReLU}(\alpha(e_{ij}\cdot[W_1h_i^{(0)}\|W_2h_i^{(l)}])),\end{aligned} \tag{11}$$

where α_{ij}^* is the attention coefficient value determined based on the weights of neighboring points. The POI similarity between two cities is transformed into a weight matrix, and weight fusion is performed through concatenation and vector multiplication. Then, high-dimensional feature mapping is applied to output the optimal attention coefficient value. Finally, the influence coefficient between two POIs can be obtained by normalizing with the softmax function, as shown in the following equation:

$$\mathrm{att}_{ij} = \mathrm{soft\ max}(\alpha_{ij}) = \frac{\exp(\alpha_{ij})}{\sum_{k\in N(V_i)}\exp(\alpha_{ik})}, \tag{12}$$

where att_{ij} is the coefficient of influence. By substituting the influence coefficient into Eq. (9), the information aggregation update of adjacent solution nodes, namely POIs, is obtained, as shown in the following equation:

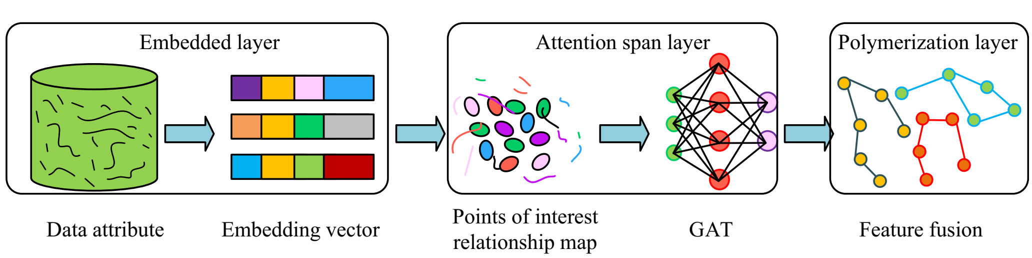

Figure 5: The topological framework of the heat level of the POI in the target city.

$$h_i^* = \sigma\left(\sum_{j\in N(V_i)} \mathrm{att}_{ij} W_t h_i^{(l-1)}\right), \tag{13}$$

where W_t is the POI shared transformation matrix. After multiple aggregation updates, a single POI feature matrix representation of the user in the target city can be obtained, as shown in the following equation:

$$V_T = \{v_1^T,\ v_2^T,\ v_3^T,\ \ldots\ v_M^T\}, \tag{14}$$

where V_T is a single POI feature matrix. This study uses matrix decomposition to obtain the probability of users accessing POI V_j in the target city, as shown in the following equation:

$$y_{\text{score}} = u_i \times (V_j)^T \tag{15}$$

In summary, this study proposes a novel intercity social network communication interactive POI recommendation model by combining user preference POI migration and user target city POI popularity aggregation. The structure of the model is shown in Figure 6.

In Figure 6, the model can be divided into three main modules: user preference transfer module, recommendation prediction module, and data filtering module. First, user characteristics are input and processed by the SA mechanism to generate a spatiotemporal feature representation of the user in the source city. Then, the CA mechanism is used to capture the cross-city migration of user characteristics by combining their activity data in different cities. Second, these data are fused and concatenated, and the dimensionality is reduced to construct a POI matrix for the user's target city. Then, the target POI matrix with the greatest influence is selected through the calculation of POI popularity and feature aggregation in the target city. Finally, the best POI recommendation is obtained by matching based on the similarity of POIs with the source city.

3 Results

This study established a suitable experimental environment, set experimental parameters and datasets, tested the optimal values of the loss function and attention weight coefficients of the new model, and compared the preference transfer and recommendation accuracy of similar models. In addition, the comparison of recommendation coverage, recommendation classification, and recommendation time was conducted using seven POIs from two real cities to verify the true effectiveness of the research model.

3.1 Performance testing of urban POI interactive recommendation model

The experimental setup has an Intel Core 2.5 Hz dual-core CPU and 16 GB of memory. The GPU is NVIDIA GeForce RTX 1660, the programming language is Python 3.7.15, and the deep learning framework is Python 1.3.2. The size of the model embedding layer is 128. The optimizer uses the classic Adam algorithm with a learning rate set to 0.001. The Yelp dataset contains information on user reviews and ratings of local merchants (*e.g.*, restaurants and stores).

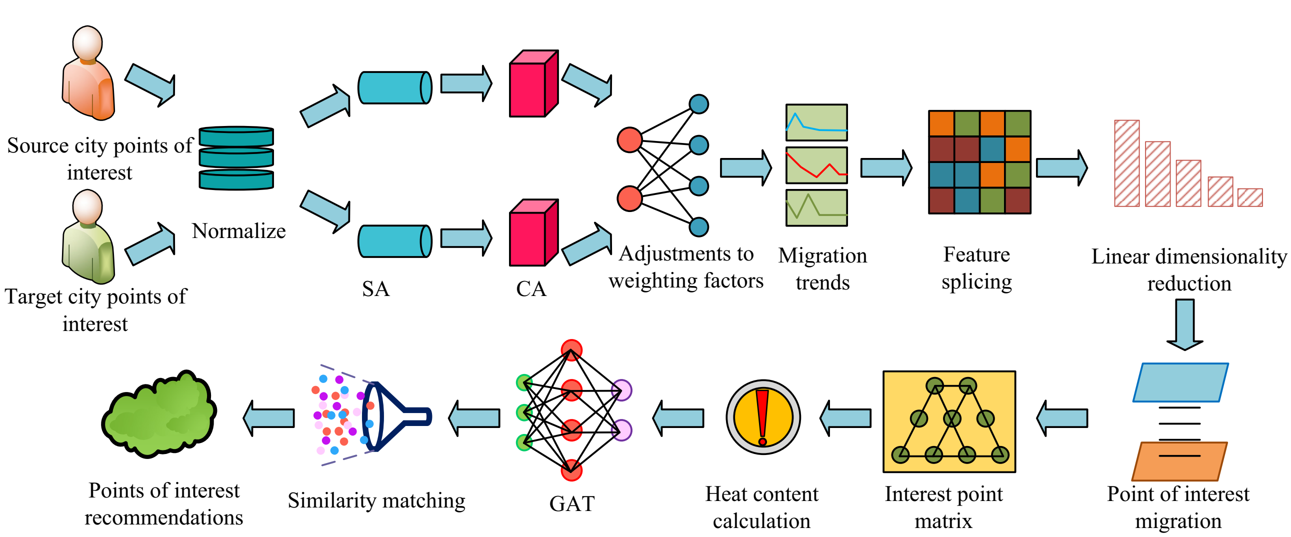

Figure 6: Novel intercity social network communication interaction POI recommendation model structure.

This dataset is suitable for testing POI recommender systems based on user feedback. The dataset covers a wide range of types of merchants and their user ratings. The Brightkite dataset is user check-in data from the Brightkite social network. It records the time, geographic coordinates, and location names of users checking in at different geographical locations. This dataset is mainly used for evaluating cross-city POI recommendations and is particularly suitable for analyzing users' behavioral patterns across different cities. This study first attempts to determine the transfer loss function in POI preference transfer and the values of attention weight coefficients in the recommendation model to maintain the efficient state of the subsequent model for testing. The result is shown in Figure 7.

Figure 7(a) and (b) shows the test results of the transfer loss function values and attention weight coefficients. In Figure 7(a), although the recommendation accuracy is the highest when transfer loss is 1.0, there is a slight decrease in model performance in the later stage. When the transfer loss value is 0.6, the model's recommendation accuracy data are more stable, with a maximum recommendation accuracy of 89.91% and 170 iterations. In Figure 7(b), when the attention weight coefficient is set to 1.0, the highest recommendation accuracy of the model is 88.24% after 250 iterations. Therefore, the transfer loss parameter is found to take the value of 0.6 after many experiments to achieve the best balance between recommendation accuracy and stability. This value can achieve a better balance between keeping the model's high accuracy and stability. Meanwhile, the attention weight coefficient is set to 1.0 to ensure the optimal performance of the model in capturing user interest points and feature fusion. These parameters are chosen not only to improve the recommendation accuracy of the model but also to ensure the model's adaptability in different datasets and environments. Deviation from these optimal values can lead to a significant decrease in recommendation accuracy, especially in terms of recommendation coverage and convergence speed. Therefore, the impact of these parameters on the algorithm performance has important sensitivities, and reasonable parameter settings are the key to improving model performance. This study compares advanced recommendation models of the same type as GNN, such as heterogeneous GNN (HetGNN), relational graph convolutional network (RGCN), and attention-based GNN (AGNN) that integrate attention mechanisms. The test results are shown in Figure 8.

Figure 8(a) and (b) shows preference transfer test data for four models on the Yelp and Brightkite datasets. In the Yelp dataset of Figure 8(a), the preference migration rate of the proposed model shows the highest stability and accuracy in both datasets. In the Brightkite dataset, the preference migration rate reaches 93.7% with an error of only 2.1%. This indicates that the proposed model is able to effectively capture users' POI preference migration across cities, especially in the recommendation task with different geographic locations. Compared to the other models, the HetGNN and RGCN models have lower preference migration rates because they do not possess sufficiently strong cross-city preference learning capabilities. AGNN, despite being able to capture a certain amount of user preferences, has a high model complexity and is prone to unstable convergence. These results show that the proposed model has a significant advantage in intercity interest point migration, especially in coping with diverse user needs with high adaptability. Tests are conducted using precision, recall, *F*1 value, and average recommendation time as indicators, as shown in Table 2.

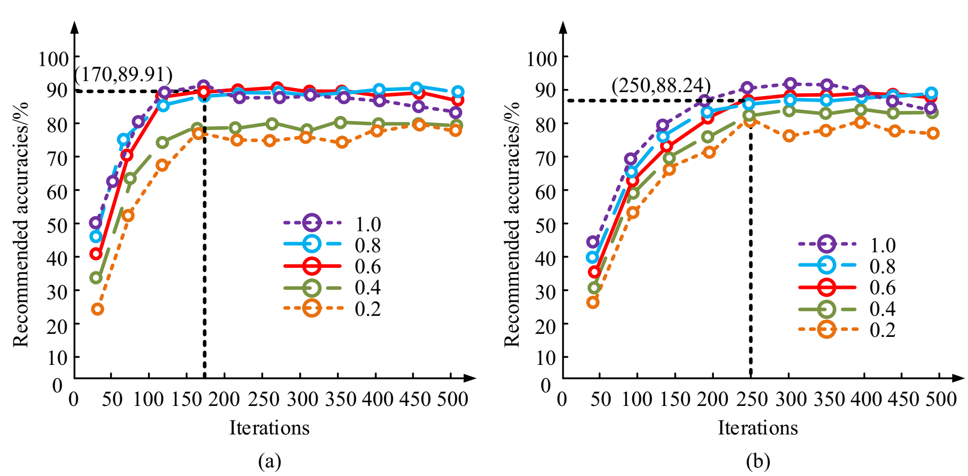

Figure 7: Transfer Loss function and attention weighting coefficient test results. (a) Transfer loss function and (b) attention weighting coefficient.

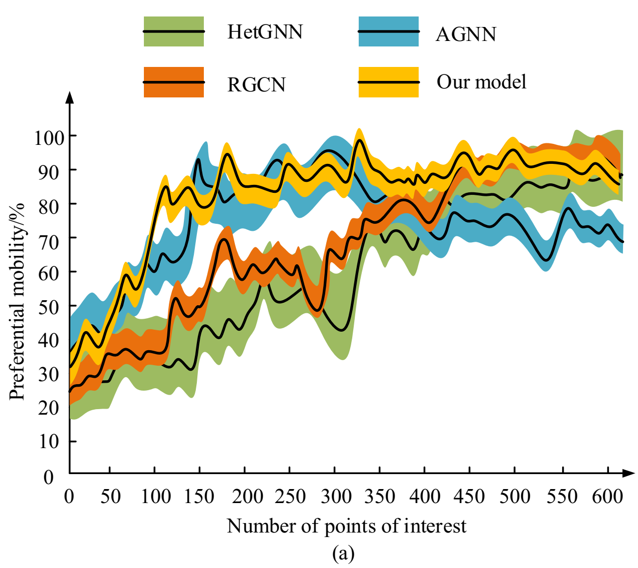

Figure 8: Preference migration rate test results for different models. (a) Yelp and (b) Birghtkite.

In Table 2, in Yelp, the highest *P*, *R*, and *F*1 values for the research model are 93.52, 91.24, and 92.38%, respectively, with an average recommendation time of 2.19 s. Compared to HetGNN, RGCN, and AGCN, the research model has significant advantages in recommendation accuracy, stability, and recommendation rate. This reflects the high accuracy and consistency of the proposed model in capturing user POI preferences and generating recommendation results. In Brightkite, the performance of each indicator of the research model is the best, with the highest *P*, *R*, and *F*1 values of 93.36, 91.89, and 92.63%, respectively, and an average recommendation time of 2.23 s. This result further shows that the proposed model not only has advantages in recommendation accuracy but also can effectively improve recommendation efficiency, which is suitable for large-scale real-time application scenarios.

Table 2: Metrics test results for the recommended model

Data set	Model	*P* (%)	*R* (%)	*F*1 (%)	Average recommendation time (%)
Yelp	HetGNN	88.24	89.64	88.94	6.41
	RGCN	85.13	87.66	86.39	6.33
	AGNN	90.76	90.58	90.67	4.27
	Research model	93.52	91.24	92.38	2.19
Brightkite	HetGNN	89.69	84.19	86.94	5.18
	RGCN	88.54	86.59	87.57	4.18
	AGNN	91.27	89.44	90.36	4.02
	Research model	93.36	91.89	92.63	2.23

3.2 Simulation testing of the POI interactive recommendation model between cities

This study randomly selects two groups of cities with the top four user POI click-through rates in Baidu's public database and Gaode's public database from 2012 to 2022 for visual comparison, namely Chengdu and Chongqing, and Shanghai and Beijing. The first step of the simulation process is to preprocess the two datasets to extract the user's POI features and generate feature vectors. Next, a model based on the PyTorch framework is trained with the parameters set to an embedding layer size of 128, a learning rate of 0.001, and an optimizer of Adam. The transfer loss and attention weight coefficients are adjusted through multiple iterations during model training to ensure the accuracy and convergence of the recommendation system. After completing the training, the model predicts the input user data, recommends the corresponding POI, and evaluates the performance of the recommendation results. Advanced recommendation models have been introduced, such as the deep multi-view sequential model (DeepMove), spatial-temporal attention network (STAN), and geographic information embedding (GeoIE). Seven types of POIs with high user click-through rates are selected for testing, namely leisure and entertainment, transportation facilities, food and beverage, healthcare, business residences, tourist attractions, and science, education, and culture. The test results are shown in Figure 9.

Figure 9(a) and (b) shows the recommended coverage of seven types of POI labels for four models between cities in Chengdu and Chongqing and Shanghai and Beijing. In Figure 9(a), the recommendation coverage rate of the research model in the POI of food and beverage is the highest at 96.72%, which is much higher than other models. Chongqing's hotpot and Chengdu's snack culture are typical representatives of this type of POI, indicating that the research model has advantages in capturing and recommending local cuisine and dining venues and can maintain high coverage of local specialty foods. In Figure 9(b), the recommended coverage rates for all seven types of POIs are relatively high, especially for commercial residential and educational cultural areas. The reason behind this is that Shanghai is the economic center of the country, and Beijing is the political center of the country. Therefore, the click-through rates for business residential and science, education, and culture in social network POI recommendations in both places are generally high. The research model can achieve a recommendation coverage rate of 95.17%. GeoIE and research models with better performance are selected for visual comparison using a confusion matrix, as shown in Figure 10.

Figure 10(a) and (b) shows the POI recommendation classification results of GeoIE and the research model. In Figure 10(a), among the 7 types of POI recommendations, only 4 types of POI classification recommendations score above 90 points, and 2 types of POIs score above 80 points. Among them, GeoIE has a high similarity in recommending food and transportation facilities, which can lead to recommendation bias. The average recommendation classification of the research model for 7 types of POIs is 95%, and the classification of each type of POI is very accurate, maintaining above 90 points. This shows that the proposed

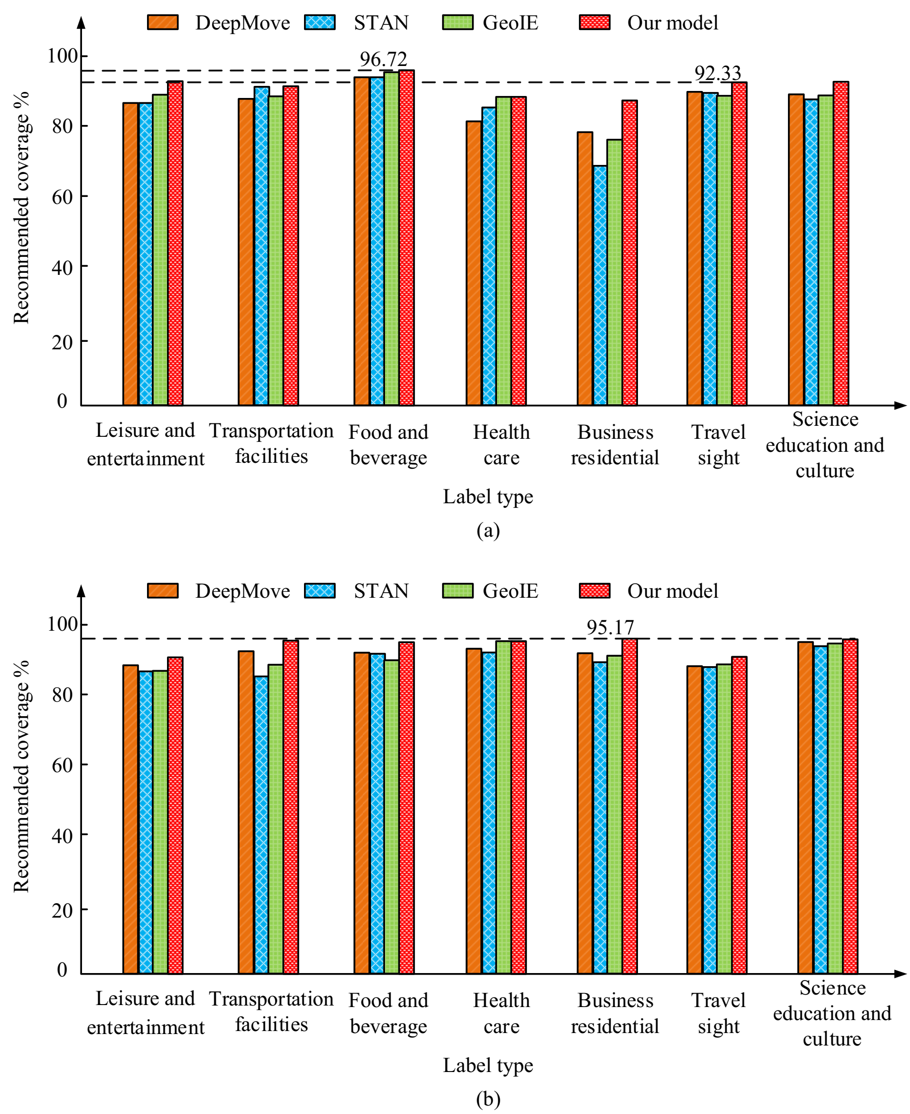

Figure 9: Recommendation coverage test results for different models. (a) Chengdu–Chongqing and (b) Shanghai–Beijing.

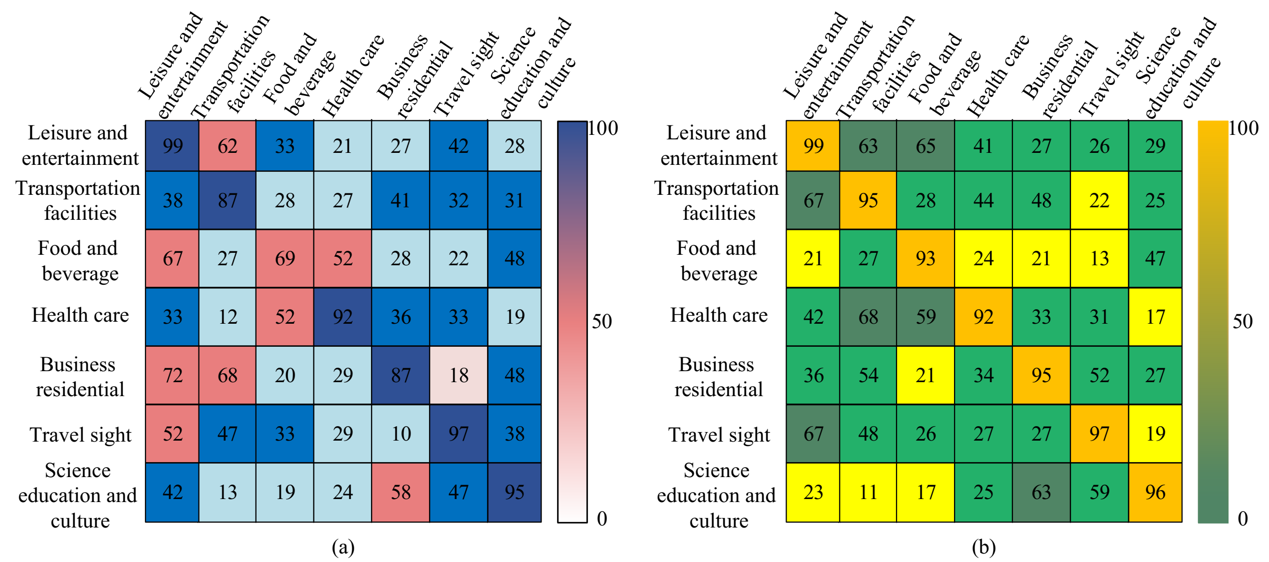

Figure 10: POI recommendation obfuscation results for the two classes of models. (a) GeoIE and (b) our model.

model performs more consistently in the multi-interest point recommendation task, especially in the cross-city recommendation, and is able to match user interest points more accurately. The results demonstrate the efficacy of GNN combined with the attention mechanism for the task of user interest point categorization, thereby substantiating the robust adaptability of the proposed model in complex social network structures. This study compares four models for recommending seven types of POIs based on recommendation time, as listed in Table 3.

In Table 3, in the recommendation test for seven types of POIs, the longest recommendation time for DeepMove is 6.32 s in transportation facilities, the shortest time is 3.15 s in tourist attractions, and the average running time is 4.68 s. GeoIE combines geographic location information to significantly improve recommendation efficiency, with an average recommendation time of 3.49 s for seven types of POIs. Relatively speaking, the average recommendation time for the research model is the shortest at 2.61 s. This value is reduced by 2.07, 1.8, and 0.88 s compared to DeepMove, STAN, and GeoIE, respectively. The proposed model greatly improves computational efficiency while ensuring the recommendation accuracy. Particularly in the recommendation of key POIs such as transportation facilities, food, and beverages, the proposed model can respond to the user's needs quickly, and the recommendation efficiency is far better than other models.

4 Conclusion and future work

In response to the challenges posed by the diversity of user demands and the complexity of social relationships between cities, this study introduced SA and CA mechanisms to capture the POI preference migration of users between source and target cities. Subsequently, a user POI popularity topology framework was constructed using

Table 3: Comparison results of recommendation times of four models for seven categories of POIs

POI	DeepMove	STAN	GeoIE	Research model
Leisure and entertainment	6.17	6.12	5.11	4.17
Transportation facilities	6.32	5.45	5.03	3.57
Food and beverage	5.18	3.29	3.28	2.14
Health care	3.29	3.51	2.59	2.09
Business residential	4.24	4.36	2.44	2.13
Travel sight	3.15	3.57	2.46	2.01
Science education and culture	4.44	4.59	3.54	2.18
Average value	4.68	4.41	3.49	2.61

the attention-derived model GAT in GNN, and a novel recommendation model was proposed. In the experiment, when the transfer loss function was 0.6, and the attention weight coefficient was 1.0, the highest recommendation accuracy of the model was 90%. Compared to HetGN, RGCN, and AGNN, the research model had a preference transfer rate of up to 93%, with a minimum error of 2%. The key results showed that the proposed model achieved 93.52 and 93.36% recommendation accuracy in the Yelp and Brightkite datasets, respectively, while the $F1$ value reached 92.63%, which was much higher than the other comparison models. Especially in the tests of Chengdu–Chongqing, and Shanghai–Beijing, the model achieved 96.72 and 95.17% recommendation coverage for dining and food, business residential and science, and education and culture, respectively. In addition, the recommendation speed was significantly improved, and the average recommendation time was reduced to 2.61 s, with a maximum reduction of 2.07 s compared to other models. In summary, the contribution of the study is that a model combining the SA and CA mechanisms is proposed to successfully solve the cross-city user POI preference migration problem. Meanwhile, the GAT-based POI heat modeling method significantly improves the accuracy and stability of the recommender system. However, the proposed method still has limitations in geographic information processing when dealing with recommendations in complex geographic environments, especially in scenarios with complex spatial structures. Second, the model lacks the ability to respond dynamically to rapid changes in user preferences and performs poorly in recommendations across time dimensions. Subsequent work will focus on optimizing the application of the model in complex geographic environments to further improve the responsiveness to rapid changes in user preferences. In addition, future research will incorporate more external data sources, such as social network relationships and time factors, to improve the accuracy and diversity of recommendations.

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