MIGNN: A Multiple Intention-aware Graph Convolutional Neural Network for POI Recommendation

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Abstract: In recent years, the rapid development of urbanization and mobile communication motivated the point-of-interest (POI) recommendation systems. Many models adopt deep learning methods to learn user and POI embedding, and achieved some improvements. However, existing models seldom pay attention to user check-in intentions. To address this problem, we propose a novel deep learning model to extract user check-in intentions using graph network, namely Multiple Intention-aware Graph Convolutional Neural network (MIGCN). We set four key modules in the proposed model, the embedding module for data preparation, the intention decomposition module for intention learning, the intention integrating module for intention embedding generating and the prediction module for future check-in prediction. We carried out a series of experiments on two real-world datasets. The experimental results verified the superiority of the proposed model compared with several the state-of-the-art methods.

1 INTRODUCTION

The rapid development of mobile phones and wearable devices motivated the development of point-of-interest (POI) recommender systems. In POI recommendation systems, following the collaborative filtering (CF) algorithm (Zeng 2021), the user and the POI are represented by a dense vector, and the future check-in is predicted by the matching score of user and POI embeddings. Recently, researchers attempted to leverage some context information to improve recommendation performance, such as geographical location, check-in time, POI category (Rahmani 2019) and social network (WANG 2021). Nowadays, many researchers adopted the graph neural network (GNN) (Wang 2018) in recommendation systems, to extract hidden features to generate better user/POI embedding (Hamilton 2017, Kim 2018). Several research found that grasping intention features help to enhance the representations of users (Chang 2020, Chang 2020). Hence, some researchers proposed different methods of feature disentangling to discover user intentions, such as auto-encoders (Tang 2021) and generative models (Yang 2020), which enhance the interpretability of user preference (Trieu 2021). However, the difference between multiple user intentions were ignored (Chen 2019). Specifically, in POI recommendation systems, the real-world check-in is influenced by different intentions. Therefore, it is necessary to extract different intention features from user-POI interactions. Similar tasks adopted heterogeneous graphs to analyse various user intentions (Guo 2020). For example, the neural graph collaborative filtering model (NGCF) (Wang 2019), was proposed in recommendation systems to decouple user intentions. However, it leaves the work of distinguish various intentions not well explored, resulting in the loss of potential available information. To overcome this problem, we proposed a multiple intention-aware graph convolutional neural network (MIGCN) to simultaneously extract features of various users' intentions and describe the weight of different intention embedding.

2 THE FRAMEWORK OF MIGCN

2.1 Overview

As shown in Figure 1, the proposed MIGCN model contains four modules: embedding module, intention

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decomposition module, intention integration module and prediction module.

In Embedding Module, we construct homogeneous graphs for both users and POIs and generate embedding for users, POIs, and check-ins via GCN in the embedding module. First, we generate user embedding and POI embedding in embedding module for data preparation.

Then, we extract the features of multiple user intentions by decomposing the user embedding in user graph constructed by user-POI interactions.

As for the Intention Extraction Module, we extract the features of user intentions by disentangling the check-in embedding in the user-POI graph. By calculating the weight of each intention, we achieved the fusion of the embedding of both users and POIs by feeding them into a GCN via an adjacent matrix. Then, we obtained all the embedding by disentangling by a multi-head attention mechanism and input them into the prediction module. By calculating the weight of each intention, we fuse the intention features in integration module.

Finally, we put the intention embedding and POI embedding into prediction module, to get the predicted probability of future check-ins. In Prediction Module, we added an attention mechanism to form the historical POIs embedding of the target users, and calculated the weights of historical POIs for the user. The prediction probability was obtained by weighting the auxiliary reference value of the predicted POI (the weight was adjusted as a hyperparameter). Finally, according to the calculated prediction probability, we ranked the POIs in descending order as a recommendation for each user.

2.2 Embedding Module

At the beginning of the model, we use two embedding layers to conduct the data preparation for intention feature learning. The user id and POI id are mapped into two dense vectors by user embedding layer and POI embedding layer.

$$u = \mathbf{W}_u^E * user\_id \tag{1}$$

$$p = \mathbf{W}_p^E * POI\_id \tag{2}$$

Where, $\mathbf{W}_u^E$ and $\mathbf{W}_p^E$ represent the weight matrix in user embedding and POI embedding layers.

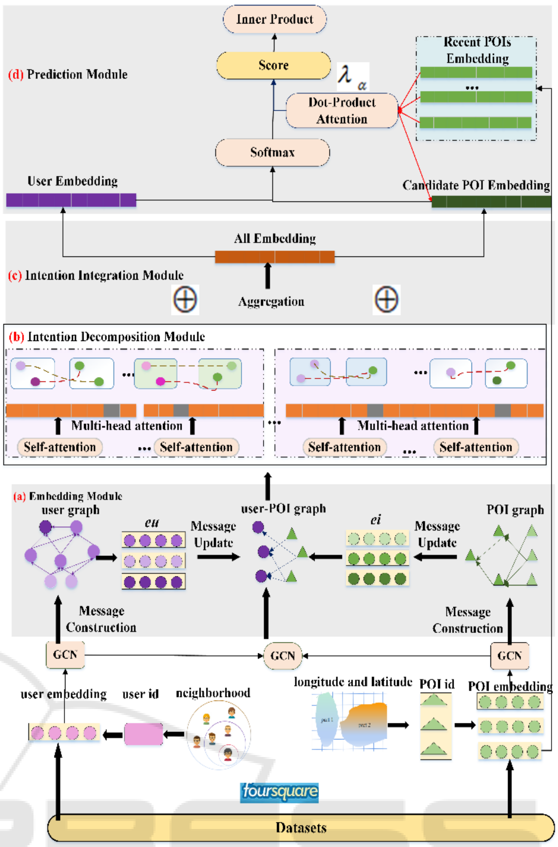

Figure 1: Overview of MIGCN model.

2.3 Intention Decomposition Module

As for intention extraction, we first build a intention decomposition module to extract different weights of various intentions. Since user intentions existed in user and POI embedding, we try to explore more information of the users' intentions from the interactions of users and POIs via disentangling the embedding of the user-POI pair (u,i). Then, we build two graphs for users and POIs respectively. In the user-POI graph, $m_{u\leftarrow p}^{(l)}$ and $m_{u\leftarrow u}^{(l)}$ denote the message propagation mechanisms for users and POIs in *l-th* layer of the GCN. $eu^{(l-1)}$ represents the presentation of the node and its *l*-1 order neighbors. $w^{(l)}$ is a parameter matrix, whose parameters are shared in the same order.

$$m_{u\leftarrow p}^{(l)} = \mathbf{W}_1^{(l)} ei^{(l-1)} + \mathbf{W}_2^{(l)} (eu^{(l-1)} * ei^{(l-1)}) \tag{3}$$

we obtain the updated embedding of users in *l-th* layer in the user-POI graph using GCN, as shown in Equation (4):

$$eu^{(l)} = LeakyRelu(m_{u\leftarrow u}^{(l)} + \sum\nolimits_{i\in N_u} m_{u\leftarrow p}^{(l)}) \tag{4}$$

The interaction of check-ins is represented by the Laplace matrix $\mathbf{\Gamma}_{u,p}$, where $\mathbf{R}$ is the interaction matrix between a user and a POI, and $\mathbf{D}$ is the degree matrix. In matrix $\mathbf{R}$, if the user checked-in at the POI, we define the corresponding value as 1:

$$\mathbf{\Gamma} = \mathbf{D}^{\frac{1}{2}} \begin{bmatrix} 0 & \mathbf{R} \\ \mathbf{R}^T & 0 \end{bmatrix} \mathbf{D}^{\frac{1}{2}} \tag{5}$$

As shown in Equation (6) – (7), after the propagation in the *l-th* layer, we obtain the updated user embedding eu^*. We also update the POI embedding, namely ei^* ei^*.

$$eu^* = LeakyRelu(\mathbf{\Gamma}+\mathbf{I})\mathbf{W}_1^{(l)} eu^{*(l-1)} + \mathbf{\Gamma}\mathbf{W}_2^{(l)} eu^{*(l+1)} eu^{*(l-1)} \tag{6}$$

$$ei^* = LeakyRelu(\mathbf{\Gamma}+\mathbf{I})\mathbf{W}_1^{(l)} ei^{*(l-1)} + \mathbf{\Gamma}\mathbf{W}_2^{(l)} ei^{*(l+1)} ei^{*(l-1)} \tag{7}$$

After the last layer, and are updated as follows:

$$eu = eu^* \tag{8}$$

$$ei = ei^* \tag{9}$$

2.4 Intention Integration

In intention integration module, we use the user-POI embedding after the message propagation of the disentangling mechanism to generate the integrated multiple intention vector h_i, which was composed of $h_i^{(l)}$ in *l*-th layer, as shown in Equation (10). Where $\mathbf{W}$ represents the weight matrix. The weight matrix is obtained via multi-head attention mechanism, as shown in Equation (11)-(12).

$$h_p^{(l)} = \mathbf{W}^{(1)}(eu^{(1)} * ei^{(1)}) \tag{10}$$

$$\alpha_p^{(l)} = \frac{\exp(h_i^{(l)})}{\sum_{k \in N_i} \exp(h_{ik}^{(l)})} \tag{11}$$

$$h_i^{(l+1)} = \Vert_{k=1\ldots,K-1}\ \delta\left(\sum_{j \in N_i} \alpha_{ij}^k \mathbf{W}^k h_j^{(l)}\right) \tag{12}$$

Where $\alpha_p^{(l)}$ represents the coefficient of multi-head attention.

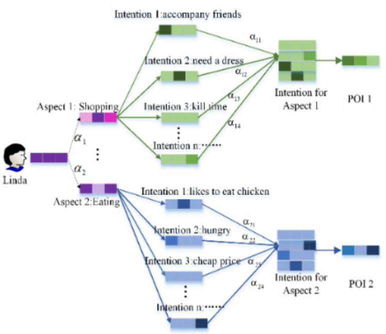

Figure 2: The explanation of intention decomposition and integration.

The final intention decoupling is shown in Figure 2. Through decoupling the intention to “accompany friends”, “need a dress”, “kill time”, and so on of aspect 1, and “hungry”, “cheap price”, and so on of aspect 2, we can obtain a more adequate representation of features.

2.5 Prediction

In order to make the difference between the positive sample and the negative sample as large as possible, we use the loss function of BPR. We regard check-in samples as positive samples (eu, ei), and regarded no check-in samples as negative samples (eu, ei') [50]. To facilitate data processing, we randomly choose a negative sample to match a positive one. The formula derivation is shown in Eq. (13).

$$\text{Loss} = \sum_{(eu,ei,ei')\in O} -\ln \sigma(\hat{y}_{eu,ei} - \hat{y}_{eu,ei'}) + \lambda \Vert \theta \Vert_2^2 \tag{13}$$

Further, we joined the regularization $\lambda\Vert\theta\Vert_2^2$ to reduce over-fitting. Here, δ represents the function of sigmoid. $\hat{y}_{eu,ei}$ indicates that the probability user u will check-in at POI i, and $\hat{y}_{eu,ei'}$ indicates that the predicted user will not check-in at POI i'.

3 EXPERIMENTS

3.1 Experiment Settings

Table 1: Experimental datasets.

Datasets	Users	POIs	Check-ins	Density
Foursquare	3,705	53,383	836,280	$7.2*10^{-7}$
Gowalla	29,858	40,981	1,027,370	$6.4*10^{-7}$

To evaluate the performance of MIGCN model, we choose two real-world check-in datasets, Foursquare and Gowalla, in our experiments. The datasets cover user id, POI id and check-in timestamp. The statistic of the datasets is shown in Table 1. The dataset was divided into training and test sets in chronological order, the first 70% check-ins are included in training set, and the last 30% check-ins are included in test set. The negative samples are generated by random sampling.

We adopt two widely used metrics, Recall and NDCG at top 10 to access the recommendation performance. We compare the proposed model with the following baselines: MF (Lian 2020) is a typical recommendation method. Both user and POI are mapped into a hidden space by the matrix factorization algorithm. NGCF (Wang 2019) is a combination model of graph neural network and collaborative filtering. The encoding of user-POI interaction is explicitly embedded in the embedding representation. DGCF (Wang 2020) is a model based on graph neural network for feature disentangling, which combines a new neighbor routing mechanism into a message propagation mechanism.

3.2 Performance Comparison

We compared the proposed MIGCN model with the baselines on two datasets in terms of Recall and NDCG.

The experimental results are shown in Table 2:

The proposed model outperforms the traditional MF model. For example, in terms of Recall, MIGCN achieves ~45.11% improvement compared with MF. In terms of NDCG, MIGCN achieves ~43.82% improvement compared with MF.

As for the advance graph neural network model, such as NGCF and DGCF, MIGCN also achieves significant improvement. For example, MIGCN achieves ~19.79% and ~14.29% improvements than NGCF and DGCF models in terms of Recall, and achieves ~25.38% and ~19.27% improvements than NGCF and DGCF models in terms of NDCG.

These results illustrate the MIGCN model was better than MF, NGCF, DGCF, and verify the superiority of the weighted intention decoupling and intention combination in the proposed model.

Table 2: Performance of models.

Dataset	Metric	MF	NGCF
Gowalla	Recall@10	0.3137	0.3800
	Recall@20	0.4632	0.5200
	NDCG@10	0.3400	0.3900
	NDCG@20	0.4900	0.5250
Foursquare	Recall@10	0.3240	0.3890
	Recall @20	0.4770	0.5380
	NDCG@10	0.3500	0.3920
	NDCG@20	0.5200	0.5960
Dataset	Metric	DGCF	MIGCN
Gowalla	Recall@10	0.3983	0.4552
	Recall@20	0.5410	0.6152
	NDCG@10	0.4100	0.4890
	NDCG@20	0.5310	0.5860
Foursquare	Recall@10	0.4150	0.4452
	Recall @20	0.5760	0.6350
	NDCG@10	0.4130	0.4991
	NDCG@20	0.6030	0.6130

3.3 Visualization of Check-in based on MIGCN

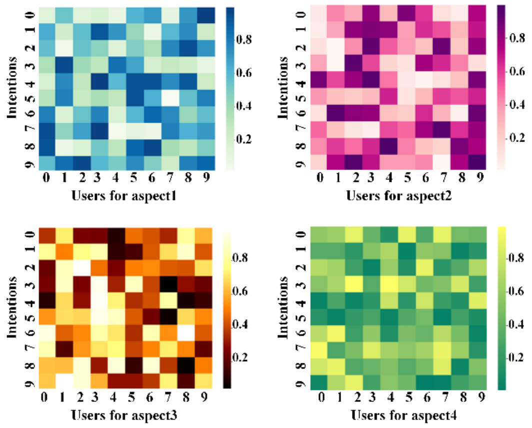

Figure 3: Visualization of Check-in based on MIGCN.

In order to explore the ability of the proposed model in depicting different user intentions, we visualize the intention vectors of several selected users. as shown in Figure 3, we find that user intentions in different aspects have different weights, which determines user's check-in decision in real-world. The differences in the colour of the four intention aspects show that the proposed model indeed distinguish different user intentions.

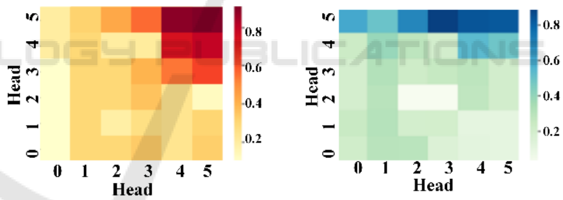

Figure 4: Visualization of weights in multi-head attention.

Further, we visualize the weights in multi-head attention module to verify the positive effect of attention mechanism on intention feature learning. As shown in Figure 4. The dimensions of x axis and y axis represented the six dimensions of user intention feature, and different shades of colour represent different weights of attention. From Figure 3 (a), we see the red area on the (5, 5) head, which illustrated that the intention represented by the 5-th head is the most important one for predicting user check-ins. However, the 0-th head has tiny contribution on future check-in prediction, as the area around the 0-th head is filled with the lightest colour. As shown in Figure 3 (b), the (3, 5) head is coloured in dark blue, it illustrated that the 3-th head had the great importance on MIGCN.

4 CONCLUSION AND FUTURE WORK

There may be multiple intentions that motivate users to check-in in real life. We think different intentions have different influence on user's check-in decision. Only a few existing studies address the learning of multiple intentions. However, using the features of multiple intention in recommendation algorithm is conducive to the understanding of user preference, and then to improve the recommendation performance. In this paper, we aim to design an intention representation model to enrich the characterization of users and POIs for recommendation. To make up for the deficiency of GNN, we used the multi-head attention mechanism and self-attention mechanism to focus on more important POIs. The designs of the intention extraction module and prediction module can capture complex relationships between users and POIs, hence, we can learn features and obtain more accurate recommendations. Furthermore, the intention that is extracted from our model has the ability to explain the user's check-in. This helps alleviate the problem of insufficient features. We conducted a series of experiments on two datasets to verify the effectiveness of the proposed model. The comparison results show that the proposed model outperforms the state-of-the-art recommendation models.

For discussion, we attribute the effective performance of the proposed model into the following aspects:

(1) The proposed multiple intention graph neural network model not only effectively describes user's multiple intention, but also calculates the weights of different intentions from different views when integrating it.

(2) The proposed method conducts an exhaustive mining from user-POI interactions, it aggregated and updated the embedding vectors of users and POIs. Through the analysis of the datasets, we found that users generally have different check-ins under different intentions.

(3) The proposed model adopted an attention mechanism to capture user intention in different layers. We added multi-head attention mechanism in the proposed model to integrate the multiple intention features, serving to future prediction.

(4) The proposed model combines different intention features with the model of historical check-in interactions. The greater the weight, the more important the corresponding intention feature plays in future check-in prediction.

However, we do not consider other information, such as comments, time, etc., which results in single-dimensional information and thus cannot dynamically capture dynamic user preference. In future work, we will introduce additional auxiliary information to capture dynamic changes for user intention and further interpret dynamic intention representations, such as in conjunction with the temporal information of check-in data, which will make feature representation more complete.

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