
Heterogeneous Graph Neural Network for Recommendation

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Abstract

The prosperous development of e-commerce has spawned diverse recommendation systems. As a matter of fact, there exist rich and complex interactions among various types of nodes in real-world recommendation systems, which can be constructed as heterogeneous graphs. How learn representative node embedding is the basis and core of the personalized recommendation system. Meta-path is a widely used structure to capture the semantics beneath such interactions and show potential ability in improving node embedding. In this paper, we propose **Heterogeneous Graph** neural network for **Recommendation** (HGRec) which injects high-order semantic into node embedding via aggregating multi-hops meta-path based neighbors and fuses rich semantics via multiple meta-paths based on attention mechanism to get comprehensive node embedding. Experimental results demonstrate the importance of rich high-order semantics and also show the potentially good interpretability of HGRec.

1. Introduction

In the era of information explosion, the recommender system has become one of the most effective ways to help users to discover what they are interested in enormous data. Generally speaking, the recommender systems usually follow two steps: learn vectorized representations (aka. embeddings) of users and items and then model interactions among them (e.g., whether a user buy an item). Collaborative filtering (CF) learns node embedding based on the historical interactions on user-item bipartite graph and performs item recommendation based on the parameters.

As a matter of fact, there exist diverse relations among various types of nodes (e.g., buy relation and social relation) in real-world recommendation scenario, also widely known

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as heterogeneous graph (Shi et al., 2017). Taking the dataset Movielens as an example, it contains three types of nodes include movie, user and genre. Meta-path (Sun et al., 2011), a composite relation connecting two objects, is a widely used structure to capture the semantics. The semantics revealed by different meta-paths are able to describe the characteristics of nodes from different aspects. For example, meta-path User-Movie (U-M) describes the preference of user, while meta-path User-User (U-U) describes social influence among users. Besides basic meta-path, multi-hop meta-path (e.g., U-U-U) which captures high-order semantics and enrich the connections among users is able to improve the node embedding and alleviate the cold-start problem.

Based on the above analysis, when designing heterogeneous graph neural network for recommendation, we need to address the following requirements.

- **Heterogeneity of graph.** The heterogeneity is an intrinsic property of heterogeneous graph, i.e., various types of nodes and edges. How to handle such complex structural information for recommendation is an urgent problem that needs to be solved.
- **High-order semantic preservation.** High-order semantic information which captures diverse long-term dependencies among nodes plays the key role in improving node embedding and alleviating the cold-start problem in recommender system. How to inject high-order semantic into node embedding is a fundamental problem in recommender system.
- **Rich semantics fusion.** Different meaningful and complex semantic information are involved in heterogeneous graph, which are usually reflected by diverse meta-paths. For example, meta-path U-M and U-U can describe the preference and social influence of user and then comprehensively describe the characteristics of user from different aspects. How to select the most meaningful meta-paths and fuse rich semantics to improve node embedding is an open problem.

In this paper, we propose **Heterogeneous Graph** neural network for **Recommendation**, named HGRec, which mainly considers high-order semantic preservation and rich semantics fusion. Specifically, semantic aggregation layer injects

high-order semantic into node embedding via multi-hop meta-path and semantic fusion layer fuse rich semantics revealed by multiple meta-paths. After that, the overall model can be optimized via back propagation in an end-to-end manner.

The contributions of our work are summarized as follows:

- We highlight the critical importance of rich high-order semantics in improving node embedding for recommendation system.
- We propose a heterogeneous graph neural network based recommendation system, which explicitly injects high-order semantic into node embedding via multi-hops meta-path and fuses rich semantics via multiple meta-paths for comprehensive node embedding.
- Empirical studies on real-world heterogeneous graphs demonstrate the state-of-the-art performance of HGRec and potentially good interpretability for the recommendation results.

2. METHODOLOGY

In this section, we present the proposed model **Heterogeneous Graph neural network for Recommendation (HGRec)**. The basic idea of HGRec is to learn representative node embedding of users and items by injecting and fusing high-order semantics. The proposed HGRec first adopts embedding layer to initialize node embedding. Then, semantic aggregation layer and semantic fusion layer will inject high-order semantic into node embedding via multi-hops meta-path and fuses rich semantics via multiple meta-paths, respectively. Lastly, we leverage the fused embedding of user and item for recommendation.

2.1. Embedding Initialization

Following the previous works (He et al., 2017; Wang et al., 2019), we random initialize node embedding matrix and use look-up to get the initial embedding of user u and item i , denoted as $\mathbf{e}_u \in \mathbb{R}^d$ and $\mathbf{e}_i \in \mathbb{R}^d$, respectively. Here d is the dimension of node embedding.

2.2. Semantic Aggregation Layer

After obtain initial node embedding, we propose semantic aggregating layer to aggregate multi-hops meta-path based neighbors and update node embedding, so the high-order semantic information is well preserved. For clearly, we first introduce the first-order aggregation in semantic aggregation layer and then generalize it to multiple successive layers (aka. high-order semantic aggregation).

First-order Semantic Aggregation Taking one user u and one user-related meta-path Φ^U as an example, we propose

semantic aggregation layer \mathcal{A} to aggregate meta-path based neighbors $\mathcal{N}_u^{\Phi^U}$ and get the first-order user embedding $\mathbf{e}_u^{\Phi^U,1}$, shown as follows:

$$\mathbf{e}_u^{\Phi^U,1} = \mathcal{A}(u, \Phi^U). \quad (1)$$

Rather than simple neighbor combination, we consider the complex interaction between node and its neighbors in aggregating process. Specifically, we encode the interaction between node u and its neighbor k into aggregating process via $\mathbf{e}_k \odot \mathbf{e}_u$, where \odot denotes the element-wise product. The overall aggregating process is shown as follows:

$$\mathbf{e}_u^{\Phi^U,1} = \mathbf{W}_1^{\Phi^U} \mathbf{e}_u + \sum_{k \in \mathcal{N}_u^{\Phi^U}} \left(\mathbf{W}_1^{\Phi^U} \mathbf{e}_k + \mathbf{W}_2^{\Phi^U} (\mathbf{e}_k \odot \mathbf{e}_u) \right), \quad (2)$$

where $\mathbf{W}_1^{\Phi^U}$, $\mathbf{W}_2^{\Phi^U}$ are weight matrixes. The first-order semantic aggregation only aggregates one-hop meta-path based neighbors into node embedding, while high-order semantic revealed by multi-hops meta-path plays a crucial role in improving node embedding.

High-order Semantic Aggregation Considering the high-order semantic revealed by multi-hops meta-path, we stack first-order semantic aggregation for multiple layers and recurrently aggregate corresponding meta-path based neighbors, so the high-order semantic is injected into node embedding, shown as follows:

$$\mathbf{e}_u^{\Phi^U,L} = \mathcal{A}^L(\dots \mathcal{A}^2(\mathcal{A}^1(u, \Phi^U))), \quad (3)$$

where $\mathbf{e}_u^{\Phi^U,L}$ denotes the L -order user embedding. Then, we concatenate different order user embedding and get the semantic-specific embedding of user u , shown as follows:

$$\mathbf{e}_u^{\Phi^U} = \mathbf{e}_u^{\Phi^U,1} || \mathbf{e}_u^{\Phi^U,2} || \dots || \mathbf{e}_u^{\Phi^U,L}, \quad (4)$$

where $||$ is the concatenation operation. However, one meta-path cannot comprehensively describe the characteristics of node from different aspects. Considering a set of user-related meta-paths $\{\Phi_1^U, \Phi_2^U, \dots, \Phi_{K_1}^U\}$, we can get K_1 groups of user embeddings $\{\mathbf{E}_u^{\Phi_1^U}, \mathbf{E}_u^{\Phi_2^U}, \dots, \mathbf{E}_u^{\Phi_{K_1}^U}\}$.

Similar to user embedding, given a set of item-related meta-paths $\{\Phi_1^I, \Phi_2^I, \dots, \Phi_{K_2}^I\}$, we can get K_2 groups of item embeddings $\{\mathbf{E}_i^{\Phi_1^I}, \mathbf{E}_i^{\Phi_2^I}, \dots, \mathbf{E}_i^{\Phi_{K_2}^I}\}$.

2.3. Semantic Fusion Layer

After obtaining multiple higher-order node embedding, we need to learn the importance of different meta-paths and fuse them properly for better recommendation. Given K_1 groups of user embeddings $\{\mathbf{E}_u^{\Phi_1^U}, \mathbf{E}_u^{\Phi_2^U}, \dots, \mathbf{E}_u^{\Phi_{K_1}^U}\}$, we

propose semantic fusion layer \mathcal{F} to learn the weights of different meta-paths (e.g., $w^{\Phi_1^U}, w^{\Phi_2^U}, \dots, w^{\Phi_{K_1}^U}$), shown as follows:

$$(w^{\Phi_1^U}, w^{\Phi_2^U}, \dots, w^{\Phi_{K_1}^U}) = \mathcal{F}(\mathbf{E}_{u_1^U}, \mathbf{E}_{u_2^U}, \dots, \mathbf{E}_{u_{K_1}^U}). \quad (5)$$

To learn the importance of each meta-path (e.g., $\alpha_{\Phi_k^U}$), we first project node embedding into the attention space and then use a semantic attention vector \mathbf{q}_U to measure the importance of meta-path specific embedding,

$$\alpha_{\Phi_k^U} = \frac{1}{|V|} \sum_{i \in V} \mathbf{q}_U^\top \cdot \tanh(\mathbf{W}_U \cdot \mathbf{e}_i^{\Phi_k^U} + \mathbf{b}_U), \quad (6)$$

where \mathbf{W}_U and \mathbf{b}_U are weight and bias, respectively. Then, we normalize them via softmax function and get meta-path weights $w_{\Phi_k^U}$, shown as follows:

$$w_{\Phi_k^U} = \frac{\exp(w_{\Phi_k^U})}{\sum_{k=1}^{K_1} \exp(w_{\Phi_k^U})}. \quad (7)$$

With the learned weights as coefficients, we can fuse multiple user embeddings to obtain the final embedding \mathbf{E}_u as follows:

$$\mathbf{E}_u = \sum_{k=1}^{K_1} w_{\Phi_k^U} \cdot \mathbf{E}_{u_k^U}. \quad (8)$$

Similar to user embedding, we can fuse K_2 groups of item embeddings $\{\mathbf{E}_i^{\Phi_1^U}, \mathbf{E}_i^{\Phi_2^U}, \dots, \mathbf{E}_i^{\Phi_{K_2}^U}\}$ and obtain the final embedding of item \mathbf{E}_i .

2.4. Model Prediction

The final part of the model is to recommend items for users based on their embedding. Here we calculate the inner product of user and item for recommendation, as follows:

$$\hat{y}_{ui} = (\mathbf{E}_u)^\top \mathbf{E}_i. \quad (9)$$

Then, we calculate BPR loss (Wang et al., 2019) and optimize the parameters, as follows:

$$L = \sum_{(u,i,j) \in \mathcal{O}} -\ln \sigma(\hat{y}_{ui} - \hat{y}_{uj}) + \lambda \|\Theta\|_2^2, \quad (10)$$

where $\mathcal{O} = \{(u, i, j) | (u, i) \in \mathcal{R}^+, (u, j) \in \mathcal{R}^-\}$ denotes the pairwise training data, \mathcal{R}^+ indicates the observed interactions, \mathcal{R}^- is the unobserved interactions, Θ denotes all trainable model parameters, and λ controls the L2 regularization strength to prevent overfitting.

Table 1. Statistics of the datasets.

Datasets	Relation(A-B)	#A	#B	#A-B
Movielens	User - Movie	943	1,682	100,000
	User - User	943	943	47,150
	Movie - Genre	1,682	18	2,861
Amazon	User - Item	6,170	2,753	195,791
	Item - Category	2,753	22	5,508
	Item - Brand	2,753	334	2,753
Yelp	User - Item	16,239	14,284	198,397
	User - User	16,239	16,239	158,590
	Item - City	14,284	47	14,267

Table 2. Overall Performance Comparison

Model	Movielens			
	Pre@10	Rec@10	NDCG@10	HR@10
BMF	0.3251	0.2096	0.4081	0.8928
NMF	0.1704	0.1163	0.2336	0.7739
GAT	0.2068	0.1210	0.2556	0.7548
MCFRec	0.3310	0.2129	0.2624	0.9025
NGCF	0.3369	0.2179	0.4178	0.9045
HGRec-	0.3670	0.2412	0.4551	0.9172
HGRec	0.3667	0.2405	0.4547	0.9193
%Improv.	6.70%	6.80%	8.19%	1.36%

3. EXPERIMENTS

We conduct experiments on three heterogeneous graphs: Amazon, Yelp and Movielens (details are shown in Table 1). We compare with some state-of-art baselines, include BPRMF (Rendle et al., 2009), NMF (He et al., 2017), GAT (Veličković et al., 2018), MCFRec (Hu et al., 2018), NGCF (Wang et al., 2019), to verify the effectiveness of the proposed model. We also test a variant of HGRec, denotes as HGRec-, which assigns the same importance to each meta-path.

For evaluation, we split datasets into training set and test set with 8:2 ratio and employ Pre@10, Recall@10, HR@10 and NDCG@10 as evaluation metrics.

We randomly initialize parameters and optimize models with Adam. For the proposed HGRec, we set the L2 regularization to 1e-2, the dimension of the semantic attention vector \mathbf{q} to 64, the dropout to 0.8, and the learning rate to 5e-4, 1e-3 and 5e-3 on Movielens Amazon and Yelp, respectively. We also use early stopping with a patience of 100 to avoid overfitting.

3.1. Overall Performance Analysis

The experiment results are shown in Table 2 and we have the following observations:

- The proposed HGRec consistently performances better

Models	Amazon			
	Pre@10	Rec@10	NDCG@10	HR@10
BMF	0.0490	0.0881	0.1176	0.3232
NMF	0.0168	0.0264	0.0463	0.1371
GAT	0.0410	0.0810	0.1096	0.2998
MCF	0.0309	0.0697	0.1131	0.3027
NGCF	0.0495	0.0870	0.1150	0.3224
HGRec-	0.0553	0.0988	0.1313	0.3503
HGRec	0.0588	0.1054	0.1384	0.3746
%Improv.	5.95%	6.26%	5.13%	6.48%

Models	Yelp			
	Pre@10	Rec@10	NDCG@10	HR@10
BMF	0.0039	0.0287	0.0150	0.0291
NMF	0.0012	0.0264	0.0233	0.0398
GAT	0.0038	0.0240	0.0171	0.0363
MCF	0.0031	0.0531	0.0201	0.0432
NGCF	0.0073	0.0410	0.0271	0.0667
HGRec-	0.0076	0.0433	0.0237	0.0506
HGRec	0.0078	0.0447	0.0310	0.0671
%Improv.	6.41%	3.13%	12.6%	1.03%

than baselines with significant gap on all the datasets. In particular, HGRec improves over the strongest baseline NGCF w.r.t. Recall@10 by 6.80%, 17.49%, 3.13% in MovieLens Amazon and Yelp, respectively. The results demonstrate that injecting rich high-order semantics into the node embedding indeed improves the recommendation performance.

- Compare HGRec with HGRec-, we can observe that HGRec outperforms HGRec- on all datasets. This proves that the semantic fusion layer is able to identify the importance of meta-paths and then enhance the performance of HGRec.

- Graph neural network based recommendation models show their superiorities over traditional MF based models, demonstrating the importance of nonlinear structural interactions among nodes.

Effect of Layer Numbers. To investigate the whether high-order semantic improves node embedding, we vary the model depth (e.g., $L = 1, 2, 3, 4$) and show the results on Table 3. We can find that with the growth of model

Table 3. Effectiveness of Layer Number

L	MovieLens		Amazon	
	Rec@10	NDCG@10	Rec@10	NDCG@10
1	0.2390	0.4506	0.0947	0.1251
2	0.2391	0.4526	0.0864	0.1151
3	0.2405	0.4547	0.1054	0.1384
4	0.2391	0.4513	0.0743	0.1064

depth, the performance of HGRec are sustainable growth and achieves the best performance when L is set to 3, indicating the effectiveness of high-order semantic. After that, the performance of HGRec starts to degenerate which may be because of overfitting.

4. Conclusion and Future Work

In this work, we highlight the critical importance of rich high-order semantics in improving node embedding for better recommendation. Specifically, we design a semantic aggregation layer which aggregates multi-hop meta-path neighbors so as to inject high-order semantic into node embedding. To describe the characteristics of node comprehensively, we leverage a semantic fusion layer to fuse rich semantic revealed by multiple meta-paths. Experimental results demonstrates the superiority of the proposed model and show the potentially good interpretability for the recommendation results.

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