Graph Collaborative Signals Denoising and Augmentation for Recommendation

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ABSTRACT

Graph collaborative filtering (GCF) is a popular technique for capturing high-order collaborative signals in recommendation systems. However, GCF's bipartite adjacency matrix, which defines the neighbors being aggregated based on user-item interactions, can be noisy for users/items with abundant interactions and insufficient for users/items with scarce interactions. Additionally, the adjacency matrix ignores user-user and item-item correlations, which can limit the scope of beneficial neighbors being aggregated.

In this work, we propose a new graph adjacency matrix that incorporates user-user and item-item correlations, as well as a properly designed user-item interaction matrix that balances the number of interactions across all users. To achieve this, we pre-train a graph-based recommendation method to obtain users/items embeddings, and then enhance the user-item interaction matrix via top-K sampling. We also augment the symmetric user-user and item-item correlation components to the adjacency matrix. Our experiments demonstrate that the enhanced user-item interaction matrix with improved neighbors and lower density leads to significant benefits in graph-based recommendation. Moreover, we show that the inclusion of user-user and item-item correlations can improve recommendations for users with both abundant and insufficient interactions. The code is in https://github.com/zfan20/GraphDA.

CCS CONCEPTS

• **Information systems** → **Recommender systems**.

KEYWORDS

Collaborative Filtering, Denoising, Augmentation, Graph Recommendation

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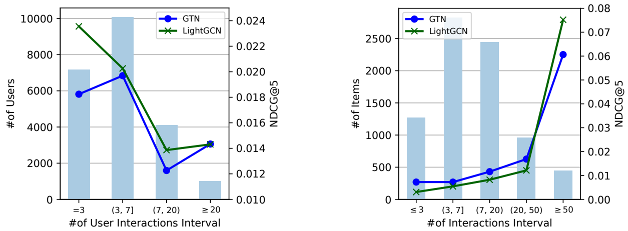
1 INTRODUCTION

Graph-based recommender systems use neighborhood information to infer user/item embeddings, where the adjacency matrix defines the neighborhood structure. High-order collaborative signals are typically aggregated by stacking multiple layers [3, 7, 13, 18, 19, 22, 29, 32, 34]. However, the quality of the neighborhood information depends on the definition of the adjacency matrix. The widely adopted adjacency matrix is built upon the user-item interaction matrix, which potentially encounters noises [10, 30, 31], sparsity [2, 11, 12, 21], biases [1, 6, 37], and long tail [9, 25, 27] issues. As shown in Fig. (1), we can observe that both users and items are following the long-tail distribution, where majority of users/items have limited interactions. Moreover, one counter-intuitive observation in Fig. (1) is that users with rich interactions (i.e., active users) are poorly modeled, compared with users with scarce interactions (i.e., inactive users) [16]. Arguably, the underlying reason is that highly active users have abundant noisy interactions, which even might be harmful to the user preference modeling. Furthermore, more noises are introduced when the graph model stacks more layers of graph convolutions [10]. From the item side, we can observe that items with limited interactions are performed unsatisfactorily.

Based on these observations, we argue that the current definition of the bipartite adjacency matrix in graph-based recommender systems is inadequate. As shown in Figure (2), the bipartite adjacency matrix **A** is constructed directly from the user-item interaction matrix **R** to define the neighborhood structure for users/items. However, **R** suffers from noisy and sparse interactions, making it insufficient to represent inactive users/items. Additionally, the bipartite adjacency matrix **A** overlooks the user-user [20, 36] and item-item correlations [8, 14, 26] in the neighborhood definition, even in the enhanced solution [5, 33]. Although high-order collaborative signals can uncover these correlations via multi-hop message passing, recent studies have shown that long-distance message passing can create new learning problems and lead to suboptimal



(a) Users **(b) Items**

Figure 1: The interactions amount distribution of users/items (bar) and corresponding NCDG@5 (line) on Amazon Beauty dataset by two graph models LightGCN [13] and GTN [10].

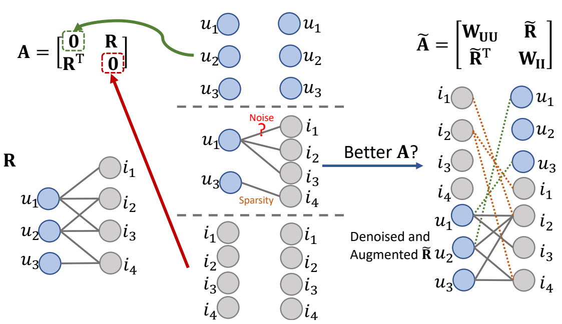


Figure 2: Motivation figure with a toy example. The A and R are the bipartite adjacency matrix and the user-item interaction matrix for graph-based recommendations, respectively.

representations [4]. Therefore, we propose a novel adjacency matrix design to improve the graph-based recommendation.

It is challenging to properly design a better adjacency matrix. Some relevant distillation methods [15, 35] learn a smaller but useful graph data for graph modeling. However, one significant difference with distillation methods is that the GCF utilizes users and items IDs as inputs, and thus existing works of graph condensation are not applicable in our GCF setting. Moreover, these distillation methods assume the availability of features while users' features are sometimes not accessible due to privacy constraints.

To this end, we propose a pre-training and enhancing pipeline framework, namely GraphDA, to denoise and augment the user-item matrix. Within GraphDA, we capture the user-user and item-item correlations in the bipartite adjacency matrix for the GCF. Specifically, we first pre-train an encoder to generate the users/items embeddings from existing user-item interactions. With pre-trained embeddings, we adopt the top-K sampling process to generate the denoised and augmented user-item matrix, non-zero user-user and item-item correlations. Our contributions include:

- We investigate the deficiency of the existing definition of the bipartite adjacency matrix for GCF and study the potential of introducing a better adjacency matrix.
- We propose a better adjacency matrix generation for the graph-based recommendation, with a novel pipeline GraphDA for denoising for active users and augmenting for inactive users.
- Comprehensive experiments show that the proposed GraphDA significantly benefits the graph-based recommendation, especially on highly active users and inactive users, who demand denoising and augmentation, respectively.

2 GRAPH COLLABORATIVE FILTERING

In the graph collaborative filtering (GCF), we denote the user set as $\mathcal{U}$ and the item set as $\mathcal{I}$, where the user and item are indexed by u and i. With either implicit or explicit feedback, the user-item interaction matrix is given as $\mathbf{R} \in \mathbb{R}^{|\mathcal{U}|\times|\mathcal{I}|}$, where $\mathbf{R}_{ui}$ denotes the feedback on the item i given by the user u. For example, $\mathbf{R}_{ui}$ of implicit feedback is either 1 or 0. As the $\mathbf{R}$ is a user-item bipartite graph, the adjacency matrix is further formatted as: $\mathbf{A} = \begin{bmatrix} \mathbf{0} & \mathbf{R} \\ \mathbf{R}^\top & \mathbf{0} \end{bmatrix}$, where $\mathbf{A} \in \mathbb{R}^{(|\mathcal{U}|+|\mathcal{I}|)\times(|\mathcal{I}|+|\mathcal{U}|)}$. This problem can also be interpreted as the link prediction problem between user and item nodes. The user and item embeddings are randomly initialized and optimized with existing user-item interactions. Specifically, we denote the user and item embeddings table as $\mathbf{E} \in \mathbb{R}^{(|\mathcal{U}|+|\mathcal{I}|)\times d}$, where d denotes the latent dimension of embeddings. GCF incorporates high-order collaborative signals [13, 29] by stacking multiple layers of graph convolution on the user-item adjacency matrix $\mathbf{A}$. Specifically, the output embeddings generation process with N graph convolution layers is given as:

$$\mathbf{E}^{(N)} = \text{Encoder}(\mathbf{A}, \mathbf{E}) = (\mathbf{L})^{N-1}\mathbf{E}^{(0)}, \tag{1}$$

where $\mathbf{E}^{(0)} = \mathbf{E}$, $\mathbf{L}$ refers to the bipartite Laplacian matrix, which is defined as the normalized symmetric Laplacian matrix $\mathbf{D}^{-\frac{1}{2}}\mathbf{A}\mathbf{D}^{-\frac{1}{2}}$, and $\mathbf{D}$ is the degree matrix. The representative work LightGCN [13] averages the generated embeddings over all layers as the final output embedding. The user preference prediction between the user u and item i is given as:

$$P(i|u, \mathbf{A}) = \sigma\left(\mathbf{e}_u^\top \mathbf{e}_i\right) \quad \text{where} \quad i \in \mathcal{I} \setminus \mathcal{I}_u^+, \tag{2}$$

where $\sigma(\cdot)$ denotes the sigmoid activation function, $\mathcal{I}_u^+$ denotes the observed interacted item set by the user u, $\mathbf{e}_u$ and $\mathbf{e}_i$ are the user and item output embeddings of $\mathbf{E}^{(N)}$.

3 PROPOSED FRAMEWORK

3.1 Pre-Trained Users/Items Embeddings

With the arguably imperfect graph Laplacian matrix $\mathbf{L}$ from the original adjacency matrix $\mathbf{A}$, we pre-train a graph encoder to obtain the users/items representations, which is shown as pre-train in the left part of Fig. (3). Specifically, we use N graph convolution layers to obtain users/items embeddings $\mathbf{E}^{(N)}$ as described in Eq. (1). The pre-train step is optimized with the training data using the BPR loss as:

$$\mathcal{L} = -\sum_{(u,i^+,i^-\in\mathbf{R})} \log\sigma(\mathbf{e}_u^\top\mathbf{e}_{i^+} - \mathbf{e}_u^\top\mathbf{e}_{i^-}), \tag{3}$$

where i^+ denotes the positively interacted item of the user u, i^- is a sampled negative item without interaction with the user u, and $\mathbf{e}_u$ and $\mathbf{e}_i$ are the user and item output embeddings in $\mathbf{E}^{(N)}$. Note that several encoders with various architectures modeling user-item interactions can be the alternative choice, such as the classical matrix factorization [28].

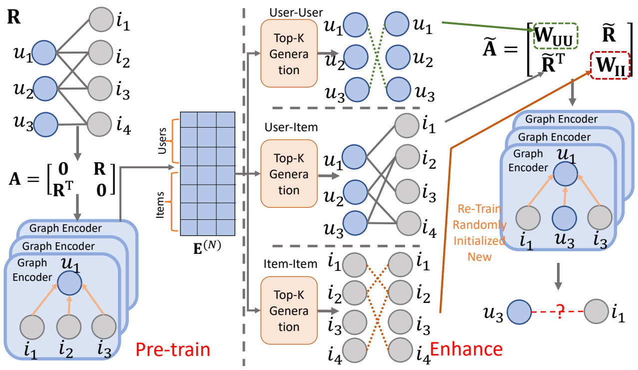


Figure 3: Workflow Diagram of GraphDA. GraphDA consists of two steps: 1. the pre-train step infers users/items embeddings; 2. utilize embeddings to generate top-K neighbors for the user-item component, the user-user component, and the item-item component, the enhanced adjacency matrix is used to re-train a graph encoder.

3.2 Enhanced Bipartite Adjacency

The pre-trained $\mathbf{E}^{(N)}$ encodes user-item collaborative signals. However, its crucial component in GCF, i.e., the adjacency matrix $\mathbf{A}$, is arguably less satisfactory for users/items embeddings learning, due to the biased interactions observed as the long-tailed distribution, noisy interactions for active users, and the ignoring of direct user-user and item-item correlations. Specifically, we enhance the adjacency matrix in three components, as shown in the central component of Fig. (3).

User-item Interactions Enhanced. With the pre-trained $\mathbf{E}^{(K)}$, we generate the top-K neighbors for both users and items. For users, the top-K neighbors define the preference while neighbors for items represent the concept of the user group being marketed. From the user side, we define a hyper-parameter U_k to control the number of neighbors being selected. For all users, the number of neighbors is the same U_k. With equal number of neighbors, users with abundant neighbors in the original data are denoised while users with scarce neighbors are augmented. Specifically, for the user u, the top-K neighbors are generated by selecting the top U_k elements with largest values from the output scores $\mathbf{e}_u^\top \mathbf{E}_{\mathcal{I}}^{(N)}$, i.e.,:

$$\underset{\{i_1,i_2,\ldots,i_{U_k}\in\mathcal{I}\}}{\arg\max} \quad \mathbf{e}_u^\top \mathbf{E}_{\mathcal{I}}^{(N)}, \tag{4}$$

where $\mathbf{E}_{\mathcal{I}}^{(N)}$ denotes output item embeddings. Similarly, for the item side, we also define the hyper-parameter I_k to generate the top-K neighbors with the similar process. We adopt the union of generated user-item interactions from both user and item sides to obtain the enhanced $\widetilde{\mathbf{R}}$.

User-User and Item-Item Correlations. For the recommender system dataset with unknown user-use/item-item interactions, the corresponding sub-matrices in conventional adjacency matrix $\mathbf{A}$ representation (as indicated at the beginning of Section 2) will be filled with zeros. We propose to complement these two all-zero sub-matrices with $\mathbf{W}_{UU}$ and $\mathbf{W}_{II}$ to further enhance the adjacency matrix. Specifically, for a user u, we extract the top-UU_k similar users as:

$$\underset{\{u_1,u_2,\ldots,u_{UU_k}\in\mathcal{U}\}}{\arg\max} \quad \mathbf{e}_u^\top \mathbf{E}_{\mathcal{U}}^{(N)}, \tag{5}$$

where $\mathbf{E}_{\mathcal{U}}^{(N)}$ denotes the output user embeddings, and $\mathbf{W}_{UU}[u, u_k] = 1$ for $u_k \in \{u_1, u_2, \ldots, u_{UU_k}\}$. The similar process is conducted for $\mathbf{W}_{II}$ with II_k to control the number of similar items being chosen. Note that we enforce the $\mathbf{W}_{UU}$ and $\mathbf{W}_{II}$ to be symmetric.

GCF Re-learn with Enhanced Bipartite Adjacency. With the enhanced graph adjacency matrix, we re-learn the graph encoder (i.e., randomly initialized) to generate embeddings for user-item interaction predictions, which is shown in the right part in Fig. (3). To better illustrate each component's contribution, we propose two version of enhancements, Enhanced-UI and GraphDA. The Enhanced-UI only adopts the user-item enhanced interactions, i.e., its adjacency matrix $\widetilde{\mathbf{A}} = \begin{bmatrix} \mathbf{0} & \widetilde{\mathbf{R}} \\ \widetilde{\mathbf{R}}^\top & \mathbf{0} \end{bmatrix}$. The complete version GraphDA includes user-user and item-item correlations, having the adjacency matrix $\widetilde{\mathbf{A}} = \begin{bmatrix} \mathbf{W}_{UU} & \widetilde{\mathbf{R}} \\ \widetilde{\mathbf{R}}^\top & \mathbf{W}_{II} \end{bmatrix}$.

4 EXPERIMENTS

This section presents experiments for demonstrating the effectiveness of the proposed framework GraphDA. We answer following research questions (RQs): **RQ1:** Does GraphDA achieve better recommendation performances than existing baselines? **RQ2:** What are the effects of hyper-parameters and each component in GraphDA? **RQ3:** Does GraphDA achieve the goals of denoising and augmentation simultaneously?

4.1 Experimental Settings

Datasets. We use the public Amazon Reviews dataset [24] with three benchmark categories [10, 13, 17, 29], including: (1) *Beauty* has 22,363 users, 12,101 items, and 198,502 interactions with 0.05% density; (2) *Toys and Games* (Toys) has 19,412 users, 11,924 items, and 167,597 interactions with 0.07% density; (3) *Tools and Home* (Tools) has 16,638 users, 10,217 items, and 134,476 interactions with 0.08% density. We follow the 5-core setting as existing works on users and the same transformation [10, 13, 29] of treating the existence of reviews as positives. We sort each user's interactions chronologically and adopt the leave-one-out setting, with the last interacted item for testing and the second last interaction for validation.

Evaluations. We adopt the widely used standard ranking evaluation metrics to evaluate the averaged ranking performance over all users, including Recall@N and NDCG@N, which are widely used in existing works [10, 13, 29].

Baselines. We compare several graph-based recommendation methods, including LightGCN [13], NGCF [29], UltraGCN [23], and GTN [10].

4.2 Overall Comparison (RQ1)

We obtain several observations from the overall comparison Table 1:

- **Enhancing the bipartite Laplancian matrix benefits the graph-based recommendation.** The proposed framework GraphDA and its variant Enhanced-UI achieve significant improvements

Table 1: Overall Comparison Table in HR@20 and NDCG@20. The best baseline and best model are underlined and in bold. 'Improv.' indicates the relative improvements over the best baseline. We observe similar improvements in other Ns.

Dataset	Beauty		Toys		Tools	
Metric	H@20	N@20	H@20	N@20	H@20	N@20
NGCF	0.0724	0.0299	0.0672	0.0306	0.0480	0.0216
UltraGCN	0.0728	0.0304	0.0675	0.0308	0.0481	0.0217
GTN	0.0680	0.0289	0.0661	0.0301	0.0484	0.0221
LightGCN	0.0730	0.0309	0.0716	0.0325	0.0482	0.0219
Enhanced-UI	0.0755	0.0317	0.0765	0.0335	0.0527	0.0236
Improv.	+3.1%	+2.9%	+6.8%	+3.3%	+4.3%	+6.6%
GraphDA	**0.0804**	**0.0336**	**0.0795**	**0.0347**	**0.0532**	**0.0245**
Improv.	+8.7%	+7.9%	+11.1%	+6.9%	+5.4%	+10.8%

over existing graph-based recommendation methods. The superiority of GraphDA and Enhanced-UI demonstrate the benefits of enhancing the bipartite Laplancian matrix.

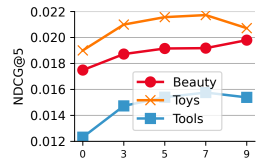
- **User-user and item-item correlations are beneficial.** The user-user and item-item correlations enhancements on the bipartite Laplacian contributes to further performance improvements. When we compare Enhanced-UI (with only the user-item component) and GraphDA (with additional user-user and item-item correlations), GraphDA outperforms Enhanced-UI.

4.3 Hyper-Parameters Sensitivity (RQ2)

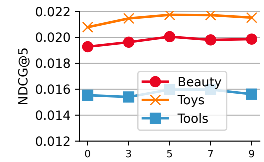
- **The user side generated neighbors U_k are important.** From Fig. (4a), we can observe that removing neighbors from the user side ($U_k = 0$) causes significant performance degradation. From Fig. (4b), having more neighbors from the item side ($I_k > 0$) benefits but with marginal improvements.
- **Small numbers of neighbors in $\mathbf{W}_{UU}$ and $\mathbf{W}_{II}$ are sufficient.** From Fig. (4c) and Fig. (4d), we can observe that non-zero neighbors on $\mathbf{W}_{UU}$ and $\mathbf{W}_{II}$ can benefit the recommendation, which is also observed in Table 1. However, the larger values of UU_k and II_k do not bring significant improvements, where the lines in Fig. (4c) and Fig. (4d) are smooth. This observation demonstrates that the potentially small UU_k and II_k can be sufficient.

4.4 Improvements Analysis (RQ3)

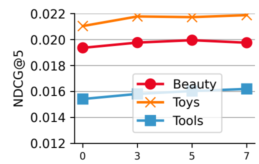
- **The augmented neighbors by GraphDA benefit inactive users significantly in the graph-based recommendation.** For inactive users with least interactions (i.e., with less than 3 interactions), the proposed GraphDA achieves significant improvements over the best baseline with range from 3.7% to 19.6%.
- **The denoised interactions by GraphDA improve highly active users with noisy interactions, especially in datasets with potentially more noises.** For highly active users with abundant interactions (i.e., with more than 7 interactions), the proposed GraphDA achieves comparative and mostly better performance than LightGCN, with improvements from 5.1% to 67.8%.



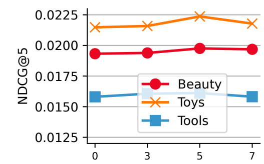
(a) Different values of U_k with best $I_k > 0$.



(b) Different values of I_k with best $U_k > 0$.

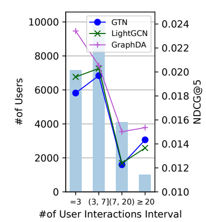


(c) Different values of UU_k

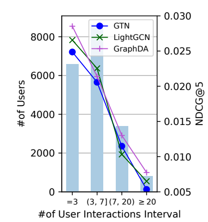


(d) Different values of II_k

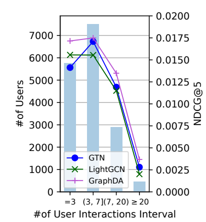
Figure 4: Different values of hyper-parameters, including U_k, I_k, UU_k for $\mathbf{W}_{UU}$, II_k for $\mathbf{W}_{II}$, with definitions in Section 3.2.



(a) Beauty



(b) Toys



(c) Tools

Figure 5: Improvements analysis of users grouped by the number of interactions. We only show two strong baselines to avoid cluttering figures.

5 CONCLUSIONS

We empirically investigate the existing deficiencies of graph-based recommendations, and arguably identify that issues come from the unsatisfactory definition of the bipartite adjacency matrix. To generate a better bipartite adjacency matrix, we propose the denoising and augmentation pipeline GraphDA with pre-training and enhancing steps to generate a better user-item matrix, user-user correlations, and also the item-item correlations. Experiments show the superiority of GraphDA, especially for highly active users and inactive users.

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