Improving Recommendation Diversity with Architectural Modifications to DGRec

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Introduction

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[2] Y. Zheng *et al.*, **"Dgcn: Diversified recommendation with graph convolutional networks,"** in *Proceedings of the Web Conference 2021*, 2021, pp. 401–412.

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- Recommender systems are essential components of online platforms, navigating users through vast amounts of data to discover relevant items.
- While maximizing accuracy has been a central concern in traditional recommender system research, studies have increasingly emphasized the importance of recommendation diversity[1][2]

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- Graph-based methods offer significant advantages, including the ability to represent users' historical interactions and diverse relationship types, leveraging the information encoded in their edges.

Diversified GNN-based Recommender System

To tackle the issue of limited recommendation diversity in current methods, the Diversified GNN-based Recommender System, Yang *et al.* [1] propose the **D**iversified **G**NN-based **Rec**ommender System (DGRec), which incorporates three key modules:

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- **Layer attention**: Applies attention weights to the outputs of each GNN layer, mitigating over-smoothing and leveraging high-order connections.
- **Loss reweighting**: Adjusts the learning process to emphasize items from long-tail categories, balancing accuracy and diversity.

Proposal

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- Specifically introducing a gated attention mechanism and additional transformations within the graph processing modules.

Methodology

Problem Statement

For diversified recommendation task, we have a set of users $U = u_1, u_2, ..., u_{|U|}$, a set of items $I = i_1, i_2, ..., i_{|I|}$, and a mapping function $C(\cdot)$ that maps each item to its category.

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The observed user-item interactions can be represented as an interaction matrix $\mathbf{R} \in \mathbb{R}^{|U| \times |I|}$, where $R_{ui} = 1$ if user u has interacted with item i, or $R_{ui} = 0$ otherwise.

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For a graph-based recommender model, the historical interactions are represented by a user-item bipartite graph $G = (U, I, E)$, where U and I are the disjoint sets of user and item nodes, and there is an edge $e_{ui} \in \mathcal{E}$ between u and i if $R_{ui} = 1$.

Training Framework

Embedding Layer is a look-up table that maps the user/item ID to a dense vector:

$$\mathbf{E}^{(0)} = \left(\mathbf{e}_1^0, \mathbf{e}_2^0, ..., \mathbf{e}_{|U|+|I|}^0\right)$$

where $e^{(0)} \in \mathbb{R}^d$ is the d-dimensional dense vector for user/item.

Training Framework

The convolution operation used in this work is Light Graph Convolution (LGC)[3].

[3] X. He *et al.*, **"Lightgcn: Simplifying and powering graph convolution network for recommendation,"** in *Proceedings of the 43rd International ACM SIGIR conference on research and development in Information Retrieval*, 2020, pp. 639–648.

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$$\mathbf{e}_{\mathcal{T}}^{\ell+1} = \sum_{i \in \mathcal{N}_{\mathcal{T}}} \frac{1}{\sqrt{|\mathcal{N}_I|}\sqrt{|\mathcal{N}_U|}} \mathbf{e}_{\mathcal{T}}^{\ell} \tag{1}$$

where $\mathbf{e}_{\mathcal{T}}^{\ell}$ are the embedding at layer ℓ for nodes of type $\mathcal{T}$. $\mathcal{N}_I$ and $\mathcal{N}_U$ represent the neighborhoods of item and user nodes.

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Each LGC layer produces an embedding vector for each user $(e_u^0, e_u^1, ..., e_u^\ell)$ and item node $(e_i^0, e_i^1, ..., e_i^\ell)$.

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An attention mechanism is then applied to these embeddings to obtain the final user and item representations.

$$e_u = \text{Attention}\left(e_u^0, e_u^1, ..., e_u^L\right)$$

$$e_i = \text{Attention}\left(e_i^0, e_i^1, ..., e_i^L\right)$$

DGRec - Submodular Neighbor Selection

In GNN-based recommender systems, user/item embedding is obtained by aggregating information from all neighbors.

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The submodular neighbor selection module aims to select a subset of neighbors that maximizes diversity and information content for aggregation.

The objective is to find a subset $\mathcal{S}_u \subseteq \mathcal{N}_u$ that maximizes the sum of the maximum similarities between each item $i \in \mathcal{N}_u \setminus \mathcal{S}_u$ and the items in $\mathcal{S}_u$

DGRec - Loss Reweighting

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Each sample (u, i) is reweighted based on the category number of items. This is achieved by incorporating a weight $w_{C(i)}$ into the loss function.

DGRec - Proposed Changes

1. Additional Transformations
2. Gated Attention

Additional Transformations

- Building upon the insights from[4] and[5], we employ a Graph Processing Module (GP Module) designed to enhance the diversity of node representations.

[4] K. Han *et al.*, **"Vision gnn: An image is worth graph of nodes,"** in *NeurIPS*, 2022.
[5] J. P. O. Batisteli *et al.*, **"Multi-scale image graph representation: A novel gnn approach for image classification through scale importance estimation,"** in *2023 IEEE International Symposium on Multimedia (ISM)*, 2023, pp. 62–68.

Additional Transformations

- Building upon the insights from[4] and[5], we employ a Graph Processing Module (GP Module) designed to enhance the diversity of node representations.
- This module incorporates linear and normalization layers before and after each graph convolution.

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$$\mathbf{e}_{\mathcal{T}}^{\ell+1} = BN(W_2(BN(\sum_{i \in \mathcal{N}_{\mathcal{T}}} \frac{1}{\sqrt{|\mathcal{N}_I|}\sqrt{|\mathcal{N}_U|}} BN(W_1 \mathbf{e}_{\mathcal{T}}^{\ell})))) \tag{2}$$

where W_1 and W_2 are linear transformations, and BN stands for Batch Normalization.

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This mechanism introduces learnable gates that modulate the flow of information, allowing the model to focus on relevant features and enhance the representation.

Experiments

Dataset

TaoBao[6]: contains user behavior on the TaoBao platform, encompassing various types of interactions such as clicking, purchasing, adding items to carts, and favoriting items.

[6] Y. Zheng *et al.*, **"Dgcn: Diversified recommendation with graph convolutional networks,"** in *Proceedings of the Web Conference 2021*, 2021, pp. 401–412.

Graph Construction

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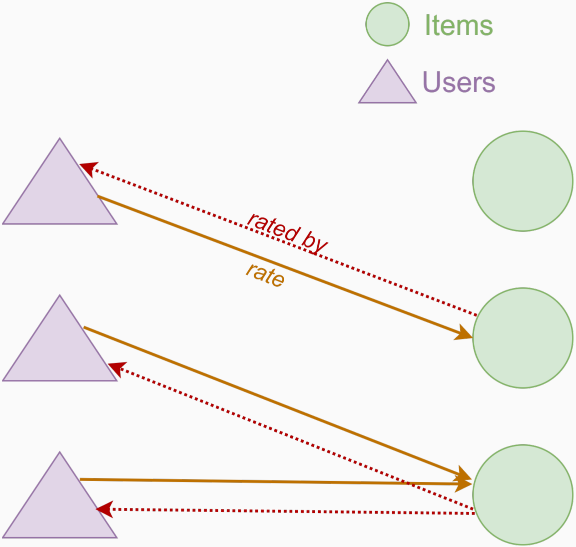
- All observed interactions are treated as positive samples, reflecting the direct connection between users and the items.
- The connections are represented by edges of type "*rated*" (user to item) and "*rated by*" (item to user).

Graph Construction



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- Accuracy: Recall and Hit Ratio (HR).
- Diversity: Coverage.

Quantitative analysis

- Table 1 presents a comparative analysis of the original DGRec model [1] and our two proposed variants, DGRec_T and DGRec_A.

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Quantitative analysis

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Method	Recall@100	Recall@300	HR@100	HR@300	Coverage@100	Coverage@300
DGRec[7]	**0.0455**	**0.0916**	**0.2946**	**0.4714**	39.5123	90.2758
DGRec_T	0.0204	0.0401	0.1569	0.2727	52.3410	**126.1431**
DGRec_A	0.0037	0.0116	0,0398	0.1075	**54.3406**	114.1998

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- Evaluation on the TaoBao dataset demonstrated that the proposed architectural changes effectively enhanced recommendation diversity.
- This increase in diversity, however, was accompanied by a decrease in accuracy metrics.
- Future work will focus on exploring architectural modifications to achieve a better balance between the diversity and accuracy of recommendations, as well as utilizing multigraph representations to explicitly model various types of user-item relationships.

Thank you!