

Adversarial Learning Data Augmentation for Graph Contrastive Learning in Recommendation

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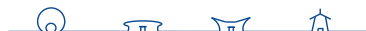
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Introduction

Learnable
Data
Augmentation



Graph
Contrastive
Learning



LDA-GCL



■ GNN-based Recommendation

- ❏ Matrix Factorization (MF) methods: BPRMF (Rendle et al., 2012), DMF (Xue et al., IJCAI2017), NeuMF (He et al., WWW2017)
- ❏ Auto-encoder (AE) methods: Mult-VAE (Liang et al., WWW2018)
- ❏ Graph Neural Networks (GNNs): NGCF (Wang et al., SIGIR2019), LightGCN (He et al., SIGIR2020), DGCF (Wang et al., WWW2020)
- ❏ Most GNN methods in recommender system follow the message-passing scheme (Gilmer et al., ICML2017) to utilize the bipartite graph structure.

■ Contrastive Learning in Recommendation

- ❏ Contrastive Learning (CL) as a self-supervised manner, has been applied in Recommender Systems (RS), including SSL+DNN (Yao et al., CIKM2021), SGL (Wu et al., SIGIR2021), SimGCL (Yu et al., SIGIR2022), NCL (Lin et al., WWW2022).
- ❏ Graph Contrastive Learning (GCL) is often used to alleviate the **data sparsity** and **popularity bias** problem.



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■ Bipartite Graph in Recommendation

□ As the fundamental recommender system, collaborative filtering (CF) can be modelled as a user-item bipartite graph as $G = (\mathcal{U}, \mathcal{I}, \mathcal{E})$, where \mathcal{U} is the user set, \mathcal{I} is the item set and $\mathcal{E} \subseteq \mathcal{U} \times \mathcal{I}$ is the inter-set edges.

□ \mathcal{E} can be denoted as the user-item interaction matrix

$\mathbf{R} \in \{0, 1\}^{|\mathcal{U}| \times |\mathcal{I}|}$. The adjacency matrix $\mathbf{A} = \begin{bmatrix} \mathbf{0} & \mathbf{R} \\ \mathbf{R}^\top & \mathbf{0} \end{bmatrix}$ is also widely used in He et al. (2020).

■ GNN-based Collaborative Filtering

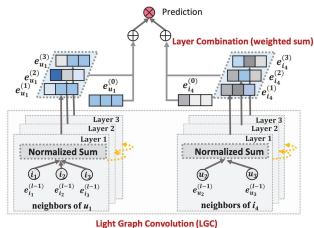
□ Based on the bipartite graph \mathbf{A} , the general GNN-based CF methods follow the message-passing scheme:

$$z_w^l = f_{\text{aggregate}} \left(\{z_v^{l-1} \mid v \in \mathcal{N}_w \cup \{w\}\} \right), z_w = f_{\text{update}} \left([z_w^0, z_w^1, \dots, z_w^L] \right),$$

where \mathcal{N} denotes the neighbor set of node w and L denotes the number of GNN layers.



■ LightGCN



□ LightGCN (He et al., SIGIR2020) applies a simple weighted sum aggregator:

$$Z^{l+1} = \left(\mathbf{D}^{-\frac{1}{2}} \mathbf{A} \mathbf{D}^{-\frac{1}{2}} \right) Z^l, Z = \frac{1}{L+1} (Z^0 + Z^1 + \dots + Z^L),$$

where $\mathbf{D}_{ii} = \sum_j \mathbf{A}_{ij}$ is the diagonal matrix and Z^0 is initial trainable embeddings.



■ Loss Function

- Most GNN-based CF methods (e.g., NGCF (Wang et al., SIGIR2019), DGCF (Wang et al., WWW2020), and LightGCN (He et al., SIGIR2020)) use the pairwise Bayesian Personalized Ranking (BPR) loss function for the model training:

$$\mathcal{L}_{\text{BPR}} = \sum_{(u,i,j) \in \mathcal{O}} -\log \sigma(\hat{y}_{ui} - \hat{y}_{uj}),$$

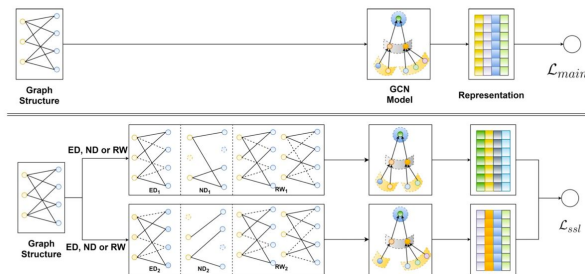
where $\mathcal{O} = \{(u, i, j) | (u, i) \in \mathcal{O}^+, (u, j) \in \mathcal{O}^-\}$, \mathcal{O}^+ and \mathcal{O}^- are the observed and unobserved interactions, respectively.



■ Graph Contrastive Learning in Recommendation

📄 Data Augmentation

- Common data augmentation is the perturbation of the graph structure due to the absence of node features.(e.g., Edge-dropping (Wu et al., SIGIR2021).)
- **InfoMin** principle that the good set of views shares the *minimal* information



SGL (Wu et al., SIGIR2021)



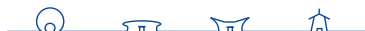
■ Contrastive Loss

- Augmented views of the same user node are treated as the positive pairs (i.e., $\{(z'_u, z''_u)\}$), and the views of different user nodes are treated as the negative pairs (i.e., $\{(z'_u, z''_v)\}$).
- InfoNCE Loss: Maximization principle (**InfoMax**) that aims to *maximize* the correspondence between the representations of the nodes in its different augmented graphs.

$$\mathcal{L}_{\text{NCE}}^{\mathcal{U}} = \sum_{u \in \mathcal{U}} -\log \frac{\exp(\text{sim}(\mathbf{z}'_u, \mathbf{z}''_u) / \tau)}{\sum_{v \in \mathcal{U}} \exp(\text{sim}(\mathbf{z}'_u, \mathbf{z}''_v) / \tau)},$$

where τ is the temperature hyper-parameters and *sim* is the similarity function (e.g., cosine function).

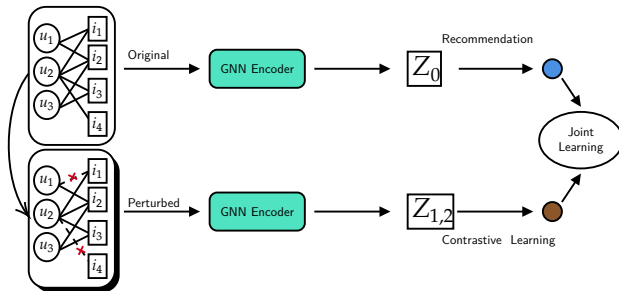
- Analogously, contrastive loss is also adopted on the item side (i.e., $\mathcal{L}_{\text{NCE}}^{\mathcal{I}}$). The final contrastive loss is the combination of two losses as $\mathcal{L}_{\text{NCE}} = \mathcal{L}_{\text{NCE}}^{\mathcal{U}} + \mathcal{L}_{\text{NCE}}^{\mathcal{I}}$.



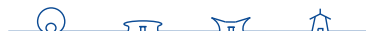
GCL in Recommendation III

■ Joint training scheme $\mathcal{L} = \mathcal{L}_{\text{Rec}} + \lambda_1 \mathcal{L}_{\text{NCE}} + \lambda_2 \mathcal{L}_{\text{Reg}}$

- Contrastive learning in recommender systems usually adopts the joint learning strategy to train their model instead of pre-training and fine-tuning strategies.
- Both pretext tasks and downstream tasks are optimized jointly.
- SGL (Wu et al., SIGIR2021) demonstrate that joint training will achieve better performance, the pretext tasks and downstream tasks are mutually enhanced with each other.



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Graph Data Augmentation With Edge Operating I

■ Edge-Dropping Data Augmentations

□ Generally edge-dropping is as follows:

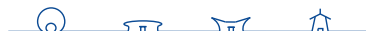
$$s_1(G) = \mathbf{A}_1 = \mathbf{A} \odot \mathbf{M}_1, \quad s_2(G) = \mathbf{A}_2 = \mathbf{A} \odot \mathbf{M}_2,$$

where \odot is the Hadamard product and $\mathbf{M}_1, \mathbf{M}_2 \in \{0, 1\}^{|V| \times |V|}$ are two masking matrices to be applied on the original graph G to generate two augmented graph adjacency matrix \mathbf{A}_1 and \mathbf{A}_2 .

□ Sampling edges follow a uniform distribution to keep $(1 - \rho) \times |\mathcal{E}|$ edges, where ρ is the edge-dropping ratio. ρ is usually set to a small value (e.g., 0.1).

□ Weakness:

- High complexity of randomly sampling edges from \mathbf{A} is $\mathcal{O}(|V|^2)$.
- Introduce noises by randomly adding edges.

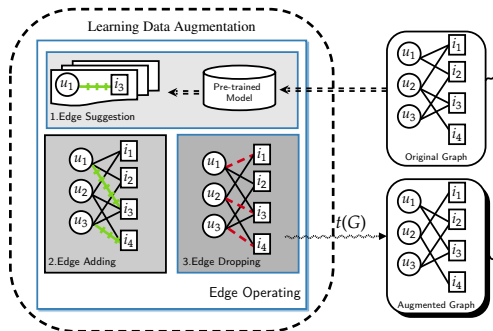


Graph Data Augmentation With Edge Operating II

■ Edge-Operating Data Augmentation

□ A new data augmentation in recommender systems (i.e., **edge-operating** including both edge-adding and edge-dropping).

- Edge Suggestion
- Edge Adding
- Edge Dropping



■ Learnable edge operator model t

- We use a Multi-layer Perception (MLP) to learn the weight for every edge candidate $e_{u,i}$ as follows:

$$\omega_{u,i} = \text{MLP}([z_u \odot z_i] \parallel \mathbb{1}_{\mathcal{E}}(e_{u,i})),$$

where \odot is the Hadamard product, z_u and z_i are the embeddings for user u and item i , \parallel is the concatenation operator and $\mathbb{1}_{\mathcal{E}}(e_{u,i})$ indicates if edge $e_{u,i}$ belongs to original or added edges.

- Gumbel-Max reparameterization (Jang et al., ICRL2017) to get the probability $p_{u,i}$ for edge $e_{u,i}$ by

$$p_{u,i} = \text{sigmoid}\left(\frac{(\log \delta - \log(1 - \delta) + \omega_{u,i})}{\tau}\right),$$

where $\delta \sim \text{Uniform}(0,1)$ and τ is the temperature hyperparameter.

- We use $p_{u,i}$ to construct augmented graphs

$t(G) = \mathbf{A}' = \begin{pmatrix} \mathbf{0} & \mathbf{P} \\ \mathbf{P}^\top & \mathbf{0} \end{pmatrix}$, where $\mathbf{P} \in R^{|\mathcal{U}| \times |\mathcal{I}|}$ is the probability matrix.



Objective Function I

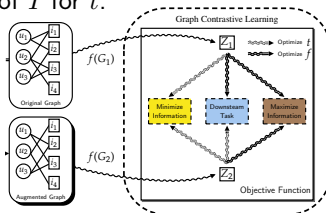
■ InfoMin and InfoMax:

□ Overall Objective Functions:

$$\min_t \lambda_t I(f(G); f(t(G))) + \mathcal{L}(f(t(G)), y)$$
$$\max_f I(f(G); f(t(G))) - \mathcal{L}(f(G), y),$$

where $I(X_1; X_2)$ is the mutual information between two random variables X_1 and X_2 , t is the data augmentation learner, f is the GNN encoder and \mathcal{L} is the task relevant supervised loss function. λ_t is used to control the influence of I for t .

- t : MLP
- f : LightGCN
- \mathcal{L} : BPR
- I : InfoNCE Estimator



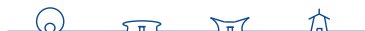
Objective Function II

■ Mutual Information (MI) Estimator:

□ We use InfoNCE as the MI Estimator

$$I(f(G), f(t(G))) \rightarrow -\mathcal{L}_{\text{NCE}} = \frac{1}{B} \sum_{i=1}^B \log \frac{\exp(\text{sim}(z_{i,1}, z_{i,2}))}{\sum_{i'=1, i' \neq i}^B \exp(\text{sim}(z_{i,1}, z_{i',2}))},$$

where *sim* is the cosine similarity to measure the agreement between two representations, z is the node representation encoded by $f(G)$ and $f(t(G))$, and B is the batch size.



Objective Function III

■ Training LDA-GCL

□ Fix t :

$$\mathcal{L}_f = \mathcal{L}_{\text{BPR}}(f(G), y) + \lambda_{ssl} \mathcal{L}_{\text{NCE}}(f(G), f(t(G))) + \lambda_{reg} \|f\|_2^2,$$

where λ_{ssl} and λ_{reg} are the hyper-parameters to control the weights of the InfoNCE loss function and the regularization term.

□ Fix f :

$$\mathcal{L}_t = \mathcal{L}_{\text{BPR}}(f(t(G)), y) - \lambda_2 \mathcal{L}_{\text{NCE}}(f(G), f(t(G))) + \lambda_{reg} \|t\|_2^2,$$

where $\lambda_2 = \lambda_t \times \lambda_{ssl}$ and λ_{reg} are the hyper-parameters to control the weights of the InfoNCE loss function and the regularization term.



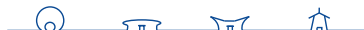
Training LDA-GCL

Input: Original bipartite graph $G(\mathcal{U}, \mathcal{I}, \mathcal{E})$; Pre-trained GNN encoder f_0 ; GNN encoder f ; Edge operator model t ; Epoch T ;

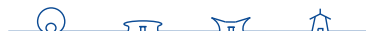
Output: Node representation Z

```
1: Generate added edges  $\mathcal{E}_1$  from pre-trained model  $f_0$ .
2: Merge added edges  $\mathcal{E}_1$  and original edges  $\mathcal{E}$  into edge
   candidates  $\mathcal{E}_2$ .
3: Initialize the parameters of edge operator model  $t$  and GNN
   encoder  $f$ 
4: for  $epoch = 1, \dots, T$  do
5:   for each mini-batch interactions  $B = \{(u_1, i_1, i_2)\}$  do
6:     Get node set  $V$  with user set  $U$  and item set  $I$  in
       mini-batch data
       /* Optimize  $t$  */
7:     Freeze GNN encoder  $f$ ; unfreeze edge operator  $t$ 
8:     Apply  $t$  on  $\mathcal{E}_2$  to get augmented graph  $t(G)$  and Apply  $f$ 
       to get the embeddings  $Z_1, Z_2$  for node  $V$  from  $G$ 
9:     Compute loss in Eq 15 with  $Z_1$  and  $Z_2$ ; Back
       propagation, update  $t$ .
       /* Optimize  $f$  */
10:    Freeze edge operator  $t$ ; unfreeze of GNN encoder  $f$ 
11:    Apply  $t$  on  $\mathcal{E}_2$  to get augmented graph  $t(G)$  and Apply  $f$ 
       to get the embeddings  $Z_1, Z_2$  for node  $V$  from  $G$ 
12:    Compute loss in Eq 15 with  $Z_1$  and  $Z_2$ ; Back
       propagation, update  $f$ .
       /* Judge early stopping condition */
13:    if  $Z_1$  match the early stopping condition then
14:      Stop training algorithm; Return the best GNN encoder
         $f_{opt}$ 
15:    end if
16:  end for
17: end for
18: return  $Z = f_{opt}(G)$ 
```

Algorithm 1: LDA-GCL Training Algorithm



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- **RQ1:** How does LDA-GCL perform in recommendation tasks as compared with the state-of-the-art CF models and GCL models?
- **RQ2:** If LDA-GCL performs well, what component benefits our LDA-GCL in collaborative filtering tasks?
- **RQ3:** What hyper-parameters affect the effectiveness of the proposed LDA-GCL?

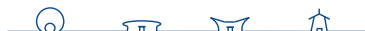


Experimental Settings

Table: Statistics of the datasets used in this paper.

| Datasets | #Users | #Items | #Interactions | %Density |
|------------------|---------|--------|---------------|----------|
| Yelp | 45,478 | 30,709 | 1,777,765 | 0.127 |
| Gowalla | 29,859 | 40,989 | 1,027,464 | 0.084 |
| Amazon-Book | 58,145 | 58,052 | 2,517,437 | 0.075 |
| Alibaba-iFashion | 300,000 | 81,614 | 1,607,813 | 0.007 |

- Datasets: Yelp, Gowalla, Amazon-Book and Alibaba-iFashion.
- Data splits: 80/10/10 - training/validation/testing data split 5 times
- Baselines:
 - Matrix Factorization: **BPRMF/NeuMF/DMF**
 - Graph Neural Networks: **NGCF/DGCF/ LightGCN**
 - Graph Contrastive Learning: **SGL/SimGCL/NCL**
- Metrics: Recall@ N and NDCG@ N (10, 20, 50)



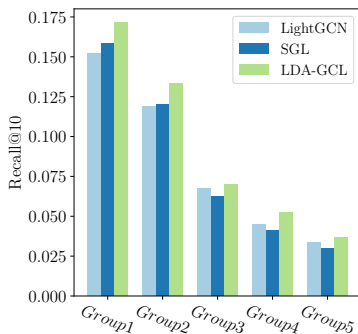
Performance Comparison

Table: Performance Comparison of Different Baseline Models. The best result is **bolded** and the second result is underlined. * indicates the statistical significance for $p < 0.05$

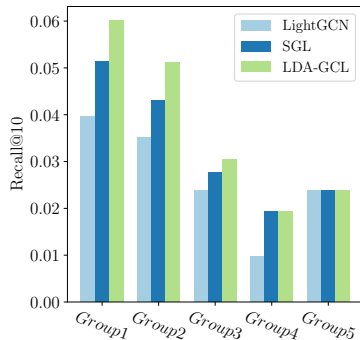
| Dataset | Metric | Matrix Factorization | | | Graph Neural Networks | | | Graph Contrastive Learning | | | |
|------------------|-----------|----------------------|--------|--------|-----------------------|--------|----------|----------------------------|---------------|---------------|----------------|
| | | BPRMF | NeuMF | DMF | NGCF | DGCF | LightGCN | SGL | SimGCL | NCL | LDA-GCL |
| Yelp | Recall@10 | 0.0499 | 0.0367 | 0.0372 | 0.0514 | 0.0606 | 0.0616 | 0.0664 | <u>0.0743</u> | 0.0713 | 0.0751* |
| | Recall@20 | 0.0829 | 0.0629 | 0.0631 | 0.0857 | 0.0987 | 0.1001 | 0.1072 | <u>0.1185</u> | 0.1135 | 0.1190* |
| | Recall@50 | 0.1549 | 0.1227 | 0.1215 | 0.1596 | 0.1798 | 0.1817 | 0.1928 | <u>0.2068</u> | 0.1997 | 0.2101* |
| | NDCG@10 | 0.0335 | 0.0242 | 0.0248 | 0.0346 | 0.0412 | 0.0419 | 0.0456 | <u>0.0515</u> | 0.0489 | 0.0518* |
| | NDCG@20 | 0.0438 | 0.0324 | 0.0327 | 0.0453 | 0.0530 | 0.0538 | 0.0581 | <u>0.0652</u> | 0.0619 | 0.0653* |
| | NDCG@50 | 0.0622 | 0.0477 | 0.0476 | 0.0642 | 0.0738 | 0.0748 | 0.0801 | <u>0.0878</u> | 0.0841 | 0.0886* |
| Amazon-Book | Recall@10 | 0.0619 | 0.0442 | 0.0313 | 0.0575 | 0.0787 | 0.0783 | 0.0844 | 0.0872 | <u>0.0947</u> | 0.0975* |
| | Recall@20 | 0.0971 | 0.0726 | 0.0522 | 0.0920 | 0.1191 | 0.1210 | 0.1281 | 0.1251 | <u>0.1395</u> | 0.1456* |
| | Recall@50 | 0.1676 | 0.1331 | 0.0984 | 0.1624 | 0.1965 | 0.2055 | 0.2117 | 0.1934 | <u>0.2201</u> | 0.2346* |
| | NDCG@10 | 0.0431 | 0.0295 | 0.0216 | 0.0400 | 0.0563 | 0.0553 | 0.0606 | 0.0643 | <u>0.0685</u> | 0.0699* |
| | NDCG@20 | 0.0537 | 0.0382 | 0.0280 | 0.0505 | 0.0681 | 0.0682 | 0.0739 | 0.0758 | <u>0.0822</u> | 0.0845* |
| | NDCG@50 | 0.0721 | 0.0539 | 0.0400 | 0.0688 | 0.0887 | 0.0902 | 0.0956 | 0.0936 | <u>0.1034</u> | 0.1078* |
| Gowalla | Recall@10 | 0.1040 | 0.0882 | 0.0634 | 0.0992 | 0.1343 | 0.1355 | 0.1386 | 0.1487 | <u>0.1496</u> | 0.1505 |
| | Recall@20 | 0.1525 | 0.1307 | 0.0945 | 0.1462 | 0.1917 | 0.1969 | 0.1969 | 0.2123 | <u>0.2131</u> | 0.2144 |
| | Recall@50 | 0.2476 | 0.2161 | 0.1559 | 0.2383 | 0.2972 | 0.3093 | 0.3055 | 0.3208 | <u>0.3228</u> | 0.3284* |
| | NDCG@10 | 0.0738 | 0.0603 | 0.0450 | 0.0703 | 0.0963 | 0.0961 | 0.0999 | 0.1078 | <u>0.1081</u> | 0.1085 |
| | NDCG@20 | 0.0878 | 0.0727 | 0.0540 | 0.0838 | 0.1127 | 0.1136 | 0.1166 | 0.1259 | <u>0.1263</u> | 0.1268 |
| | NDCG@50 | 0.1109 | 0.0935 | 0.0692 | 0.1062 | 0.1384 | 0.1411 | 0.1431 | 0.1525 | <u>0.1534</u> | 0.1547 |
| Alibaba-iFashion | Recall@10 | 0.0297 | 0.0157 | 0.0138 | 0.0355 | 0.0361 | 0.0402 | <u>0.0518</u> | 0.0450 | 0.0490 | 0.0605* |
| | Recall@20 | 0.0458 | 0.0264 | 0.0229 | 0.0565 | 0.0549 | 0.0612 | <u>0.0774</u> | 0.0651 | 0.0729 | 0.0882* |
| | Recall@50 | 0.0784 | 0.0501 | 0.0443 | 0.0994 | 0.0910 | 0.1015 | <u>0.1258</u> | 0.1029 | 0.1178 | 0.1381* |
| | NDCG@10 | 0.0158 | 0.0079 | 0.0071 | 0.0185 | 0.0194 | 0.0216 | <u>0.0280</u> | 0.0252 | 0.0267 | 0.0335* |
| | NDCG@20 | 0.0199 | 0.0106 | 0.0094 | 0.0237 | 0.0241 | 0.0269 | <u>0.0344</u> | 0.0303 | 0.0328 | 0.0405* |
| | NDCG@50 | 0.0264 | 0.0152 | 0.0137 | 0.0323 | 0.0313 | 0.0350 | <u>0.0440</u> | 0.0378 | 0.0417 | 0.0504* |



Sparsity Analysis



(a) Gowalla



(b) Alibaba-iFashion

Figure: Performance analysis over different users groups. G_1 is the group of users with the *lowest* interaction number.



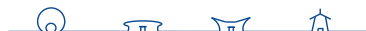
Ablation Study

Table: Performance comparison of different variants of LDA-GCL.

| Method | Gowalla | | Alibaba-iFashion | |
|------------------|-----------|---------|------------------|---------|
| | Recall@10 | NDCG@10 | Recall@10 | NDCG@10 |
| LightGCN | 0.1342 | 0.0962 | 0.0395 | 0.0212 |
| DA-GCL(0.0,0.0) | 0.1488 | 0.1085 | 0.0497 | 0.0274 |
| DA-GCL(0.1,0.0) | 0.1492 | 0.1083 | 0.0529 | 0.0289 |
| DA-GCL(0.0,0.1) | 0.1487 | 0.1067 | 0.0544 | 0.0299 |
| DA-GCL(0.1,0.1) | 0.1479 | 0.1063 | 0.0553 | 0.0303 |
| DA-GCL(0.0,0.5) | 0.1412 | 0.1010 | 0.0533 | 0.0290 |
| DA-GCL(0.1,0.5) | 0.1409 | 0.1003 | 0.0542 | 0.0296 |
| DA-GCL(0.0,1.0) | 0.1369 | 0.0973 | 0.0520 | 0.0282 |
| DA-GCL(0.1,1.0) | 0.1359 | 0.0963 | 0.0526 | 0.0285 |
| LDA-GCL (w NGCF) | 0.1488 | 0.1078 | 0.0589 | 0.0322 |
| LDA-GCL (w/o EA) | 0.1499 | 0.1087 | 0.0579 | 0.0319 |
| LDA-GCL | 0.1512 | 0.1090 | 0.0599 | 0.0330 |



- ① Introduction
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 - ▶ Framework
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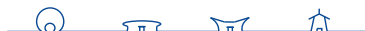
Conclusion and Future Work

■ Conclusion

- A theoretically motivated learnable data augmentation model for GCL in recommendation, instead of heuristic designs. (**InfoMin** and **InfoMax**)
- An adversarial framework that can better enhance the effect of GCL in the recommendation.
- Our model achieves state-of-the-art performance on several public benchmark datasets.
- The relevant analytical experiments prove the efficiency of the model design.

■ Future work

- To make improvements on the efficiency in future work. A potential boosting scheme is the pre-trained edge operator models.



Q&A

Thank you!

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