Dual Intents Graph Modeling for User-centric Group Discovery

Xixi Wu
Yun Xiong*
Yao Zhang
21210240043@m.fudan.edu.cn
yunx@fudan.edu.cn
yaozhang@fudan.edu.cn
Shanghai Key Laboratory of Data Science, School of Computer Science, Fudan University
Shanghai, China

Yizhu Jiao
yizhuj2@illinois.edu
University of Illinois at Urbana-Champaign
IL, USA

Jiawei Zhang
jiawei@ifmlab.org
IFM Lab, Department of Computer Science, University of California, Davis
CA, USA

code:https://github.com/WxxShirley/CIKM2023DiRec

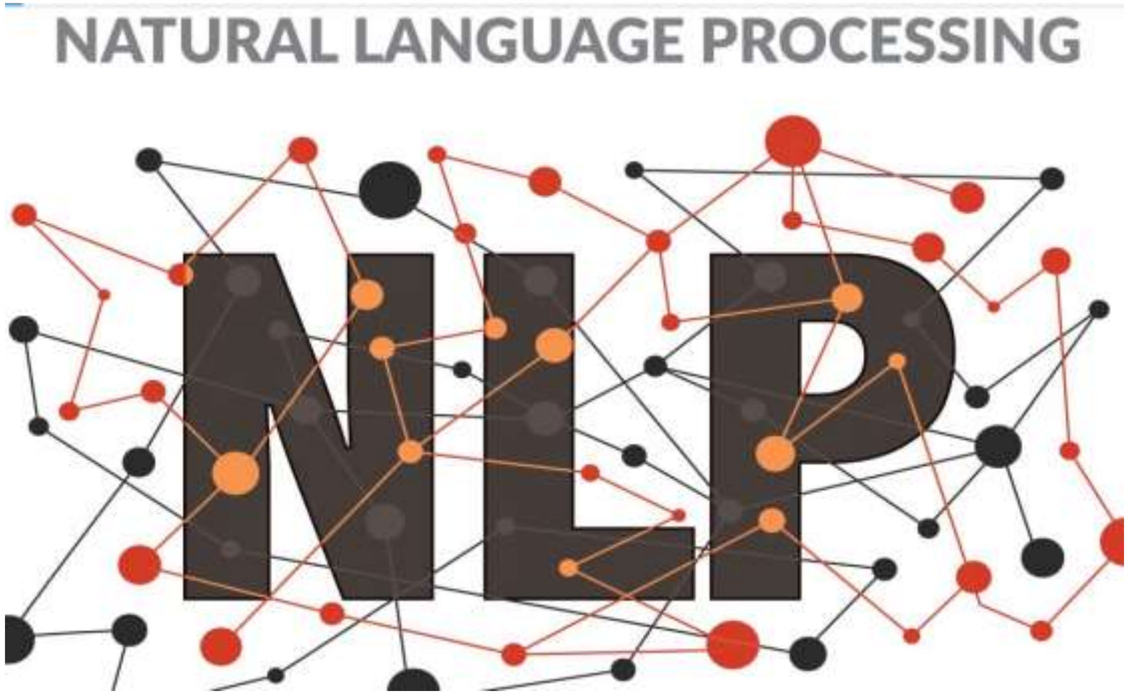
2023.11.5 • ChongQing

2023_CIKM

gesis
Leibniz-Institut für Sozialwissenschaften

Forschungszentrum · Research Center
L3S

Reported by Junhao Cao



1.Introduction

2.Method

3.Experiments

Introduction

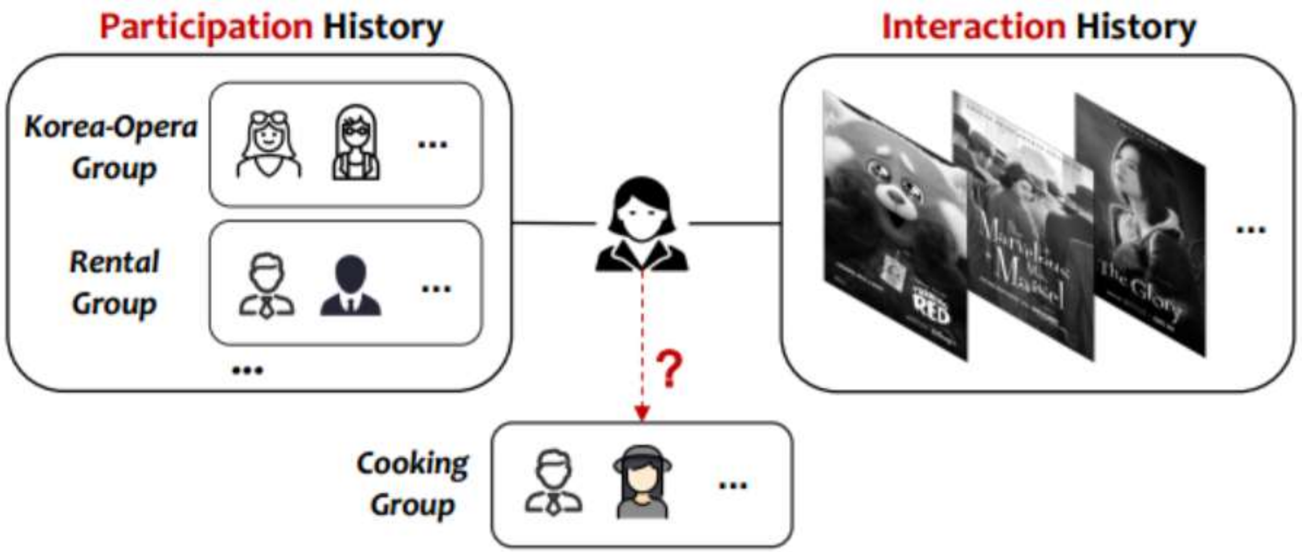
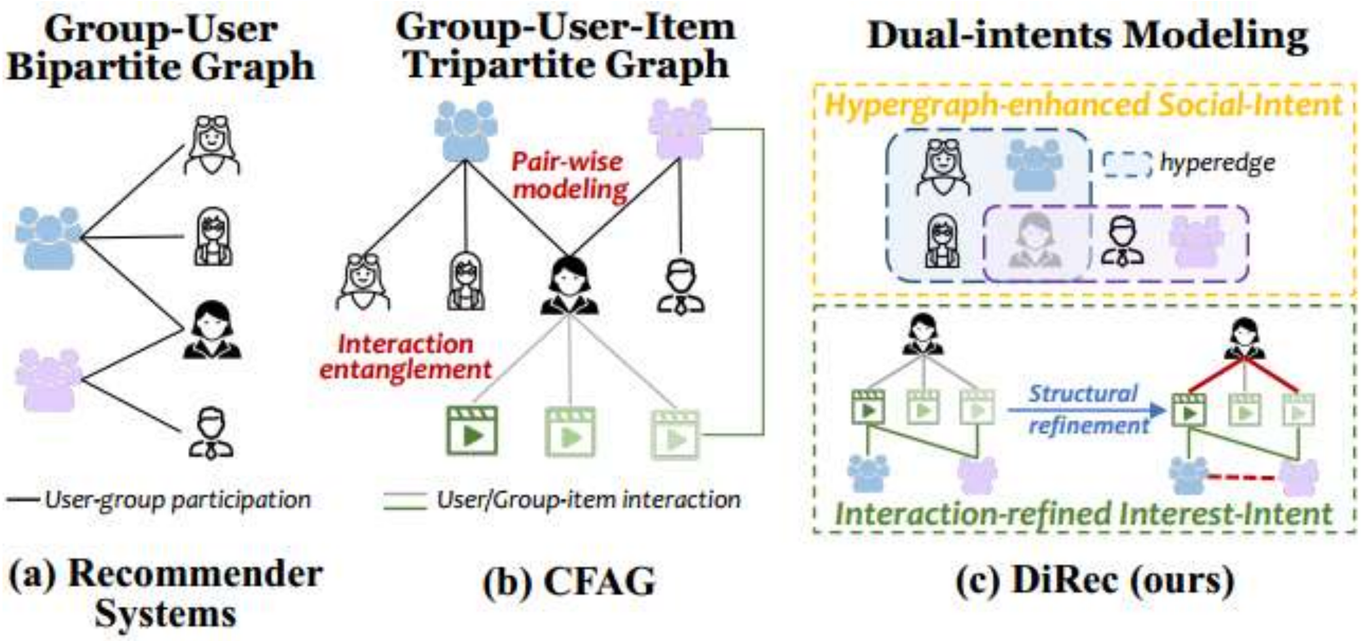


Figure 1: Illustration of User-centric Group Discovery (UGD) task on Douban platform. With group participation and item interactions, UGD aims to suggesting groups for users.

Introduction

Existing recommender methods can not deal with this task as modeling user-group participation into a bipartite graph overlooks their item-side interests.
Although there exist a few works attempting to address this task, they still fall short in fully preserving the social context and ensuring effective interest representation learning.



Method

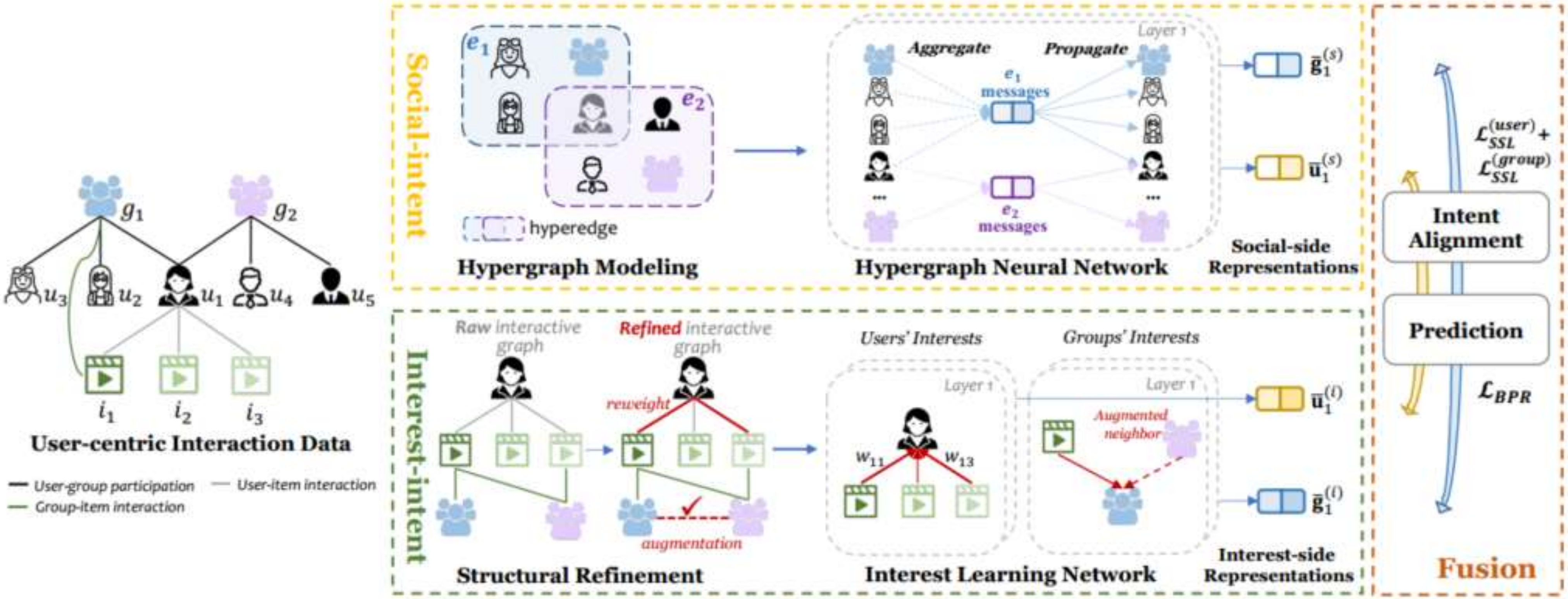


Figure 3: DiRec overview. In the left part, we present the interactive data between users, groups, and items (omit some group-item edges to avoid link interference). We model users' inclination towards groups from dual intents, including social-intent and interest-intent. For social-intent, we leverage hyperegraph for relationship preservation and employ hypergraph neural networks for representation learning. As to interest-intent, we conduct structural refinement to uncover intricate user behavior patterns and item characteristics, leading to better interests learning. Finally, dual intents are fused for optimization.

Method

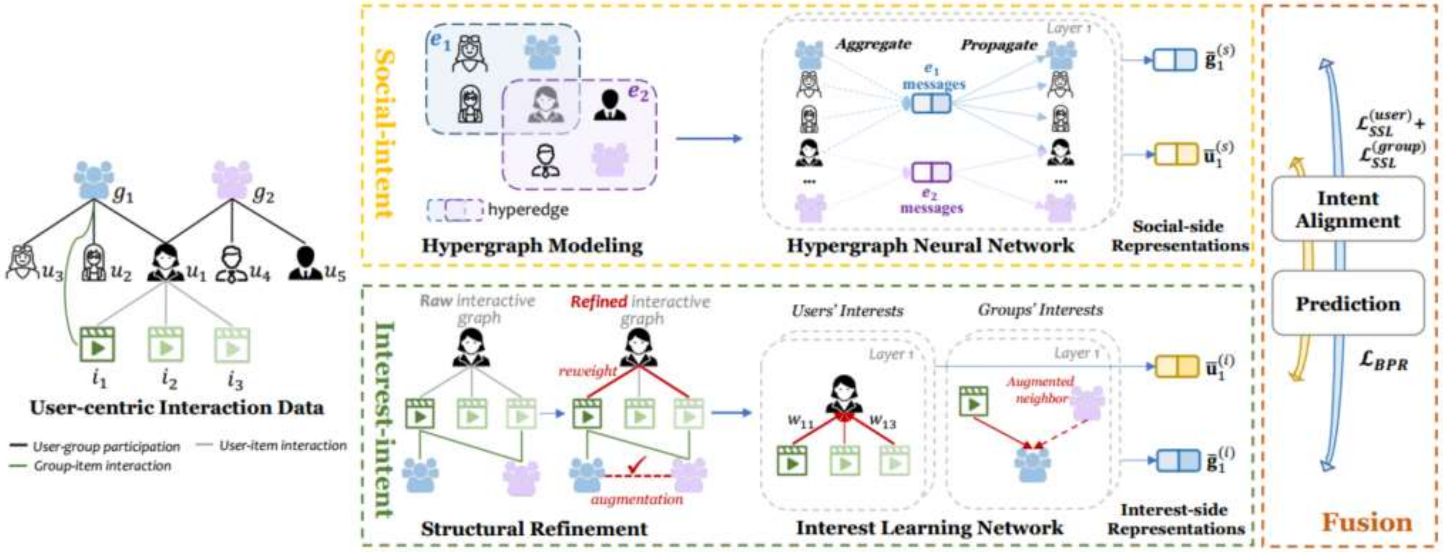


Figure 3: DiRec overview. In the left part, we present the interactive data between users, groups, and items (omit some group-item edges to avoid link interference). We model users' inclination towards groups from dual intents, including social-intent and interest-intent. For social-intent, we leverage hyperegraph for relationship preservation and employ hypergraph neural networks for representation learning. As to interest-intent, we conduct structural refinement to uncover intricate user behavior patterns and item characteristics, leading to better interests learning. Finally, dual intents are fused for optimization.

$$\mathbf{u}_j^{(s)}, \mathbf{u}_j^{(i)} = \mathbf{ExtractLayer}(\mathbf{u}_j), \quad (1)$$

$$\overline{\mathbf{U}}^{(s)}, \overline{\mathbf{G}}^{(s)} = \mathbf{HyperGNN}_{\Theta_1}([\mathbf{U}^{(s)} \| \mathbf{G}^{(s)}], \mathbf{H}^{(s)}), \quad (2)$$

$$\overline{\mathbf{U}}^{(i)} = \mathbf{GNN}_{\Theta_2}([\mathbf{U}^{(i)} \| \mathbf{I}], \mathbf{A}^{(u)}), \quad (3)$$

$$\overline{\mathbf{G}}^{(i)} = \mathbf{GNN}_{\Theta_3}([\mathbf{G}^{(i)} \| \mathbf{I}], \mathbf{A}^{(g)}), \quad (4)$$

Method

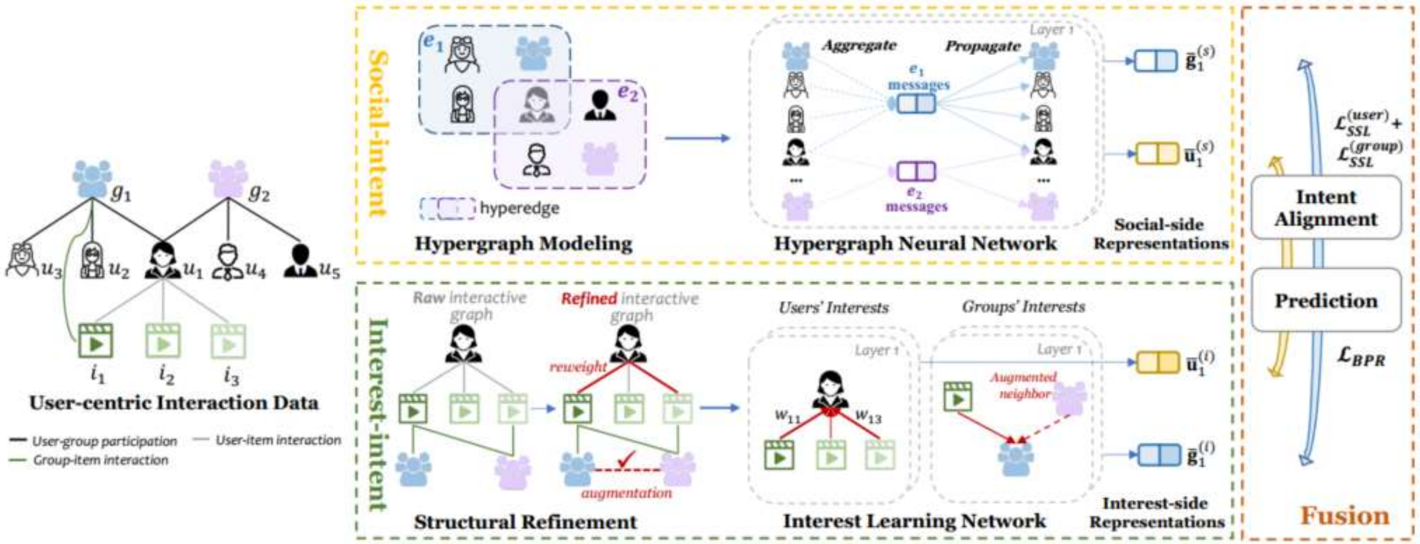


Figure 3: DiRec overview. In the left part, we present the interactive data between users, groups, and items (omit some group-item edges to avoid link interference). We model users' inclination towards groups from dual intents, including social-intent and interest-intent. For social-intent, we leverage hyperegraph for relationship preservation and employ hypergraph neural networks for representation learning. As to interest-intent, we conduct structural refinement to uncover intricate user behavior patterns and item characteristics, leading to better interests learning. Finally, dual intents are fused for optimization.

$$\mathcal{L}_{SSL}^{(user)_1} = -\sum_{u_j \in \mathcal{U}} \log \frac{\exp(\mathrm{sim}(\bar{\mathbf{u}}_j^{(s)}, \bar{\mathbf{u}}_j^{(i)}))}{\sum_{u_k \in \mathcal{U}} \exp(\mathrm{sim}(\bar{\mathbf{u}}_j^{(s)}, \bar{\mathbf{u}}_k^{(i)}))}, \quad (5)$$

$$\mathcal{L}_{SSL}^{(user)_2} = -\sum_{u_j \in \mathcal{U}} \log \frac{\exp(\mathrm{sim}(\bar{\mathbf{u}}_j^{(i)}, \bar{\mathbf{u}}_j^{(s)}))}{\sum_{u_k \in \mathcal{U}} \exp(\mathrm{sim}(\bar{\mathbf{u}}_j^{(i)}, \bar{\mathbf{u}}_k^{(s)}))}. \quad (6)$$

$$\mathcal{L}_{SSL}^{(user)} = \mathcal{L}_{SSL}^{(user)_1} + \mathcal{L}_{SSL}^{(user)_2} \quad (7)$$

$$\hat{s}_{jt} = \bar{\mathbf{u}}_j \cdot \bar{\mathbf{g}}_t, \quad (8)$$

$$\bar{\mathbf{U}} = [\bar{\mathbf{U}}^{(s)} \| \bar{\mathbf{U}}^{(i)}], \bar{\mathbf{G}} = [\bar{\mathbf{G}}^{(s)} \| \bar{\mathbf{G}}^{(i)}], \quad (9)$$

$$\mathcal{L}_{BPR} = \sum_{(u_j, g_t, g_{t'}) \in \mathcal{D}} -\log \sigma(\hat{s}_{jt} - \hat{s}_{jt'}) + \lambda_2 \|\Theta\|_2^2, \quad (10)$$

Table 2: Statistics of datasets

Dataset	Mafengwo	Weeplaces	Steam
# Users	1,269	1,501	11,099
# Groups	972	4,651	1,085
# Items	999	6,406	2,351
# User-Group Participation	5,574	12,258	57,654
# User-Item Interactions	8,676	43,942	444,776
# Group-Item Interactions	2,540	6,033	22,318
Avg. # Groups/user	4.39	8.17	5.19
Avg. # Items/user	6.84	29.28	40.07
Avg. # Items/group	2.61	1.29	20.57

Experiment

Table 3: UGD Performance comparison on three datasets with Recall (R) reported.

Method Type	Dataset / Metric	Mafengwo R@5	Mafengwo R@10	Mafengwo R@20	Weeplaces R@5	Weeplaces R@10	Weeplaces R@20	Steam R@5	Steam R@10	Steam R@20
Group Recommendation	**AGREE**(SIGIR'18)	0.1216	0.1716	0.2368	0.1680	0.2270	0.2911	0.1168	0.1768	0.2577
	ConsRec(WWW'23)	0.2204	0.3141	0.4063	0.2514	0.3472	0.4391	0.1690	0.2440	0.3330
Recommender Systems	**MF-BPR**	0.1832	0.2407	0.2973	0.1734	0.2278	0.2822	0.1207	0.1848	0.2671
	NGCF(SIGIR'19)	0.1999	0.2650	0.3284	0.1787	0.2392	0.2961	0.1330	0.2010	0.2903
	LightGCN(SIGIR'20)	0.2293	0.2930	0.3596	0.1791	0.2431	0.3069	0.1543	0.2343	0.3273
	SGL(SIGIR'21)	0.2259	0.2956	0.3555	0.1810	0.2443	0.3046	0.1535	0.2336	0.3276
	SimGCL(SIGIR'22)	0.2309	0.2925	0.3585	0.1808	0.2477	0.3079	0.1544	0.2332	0.3271
	DCCF(SIGIR'23)	0.2049	0.2649	0.3216	0.1858	0.2507	0.3171	0.1614	0.2417	0.3423
User-centric Group Discovery	**CFAG**(WSDM'23)	0.2274	0.3242	0.4194	0.2855	0.3824	0.4893	0.1597	0.2485	0.3502
	DiRecours	**0.2653**	**0.3585**	**0.4549**	**0.3177**	**0.4119**	**0.4987**	**0.1702**	**0.2685**	**0.3708**

Experiment

Table 4: UGD Performance comparison on three datasets with NDCG (N) reported.

Method Type	Dataset / Metric	Mafengwo N@5	Mafengwo N@10	Mafengwo N@20	Weeplaces N@5	Weeplaces N@10	Weeplaces N@20	Steam N@5	Steam N@10	Steam N@20
Group Recommendation	**AGREE** (SIGIR'18)	0.0887	0.1051	0.1218	0.1132	0.1330	0.1501	0.0742	0.0937	0.1143
	ConsRec (WWW'23)	0.1519	0.1832	0.2069	0.1714	0.2037	0.2283	0.1034	0.1335	0.1604
Recommender Systems	**MF-BPR**	0.1293	0.1484	0.1631	0.1170	0.1358	0.1507	0.0771	0.0979	0.1190
	NGCF (SIGIR'19)	0.1440	0.1655	0.1820	0.1213	0.1417	0.1572	0.0862	0.1082	0.1311
	LightGCN (SIGIR'20)	0.1713	0.1922	0.2093	0.1225	0.1443	0.1619	0.1013	0.1274	0.1513
	SGL (SIGIR'21)	0.1718	0.1945	0.2099	0.1235	0.1448	0.1614	0.1018	0.1278	0.1520
	SimGCL (SIGIR'22)	0.1725	0.1926	0.2095	0.1233	0.1460	0.1626	0.1015	0.1273	0.1514
	DCCF (SIGIR'23)	0.1493	0.1691	0.1837	0.1256	0.1476	0.1659	0.1053	0.1314	0.1573
User-centric Group Discovery	**CFAG** (WSDM'23)	0.1552	0.1867	0.2111	0.1938	0.2264	0.2551	0.1035	0.1324	0.1584
	DiRec ours	**0.1908**	**0.2208**	**0.2455**	**0.2246**	**0.2565**	**0.2797**	**0.1086**	**0.1405**	**0.1669**

Table 5: Ablation Study on three datasets with NDCG (N) reported. "Social-" and "Interest-" refer to the variant that only utilizes social-intent and interest-intent, respectively. "w/o. HG" denotes the variant that replaces hypergraph modeling with bipartite graph modeling. And "w/o. UI Re." and "w/o. GI Aug." refer to variants that eliminate reweighting and augmentation, respectively.

Dataset	Mafengwo		Weeplaces		Steam	
Metric	N@10	N@20	N@10	N@20	N@10	N@20
Full	**0.2208**	**0.2455**	**0.2565**	**0.2797**	**0.1405**	**0.1669**
Social-	0.1954	0.2157	0.1593	0.1784	0.1373	0.1628
Interest-	0.1561	0.1900	0.2426	0.2671	0.1097	0.1391
w/o. HG	0.2110	0.2325	0.2490	0.2754	0.1253	0.1546
w/o. UI Re.	0.2208	0.2453	0.2558	0.2788	0.1398	0.1664
w/o. GI Aug.	0.2117	0.2393	0.2200	0.2417	0.1371	0.1639
w/o. SSL	0.2194	0.2430	0.2525	0.2752	0.1395	0.1651

Experiment

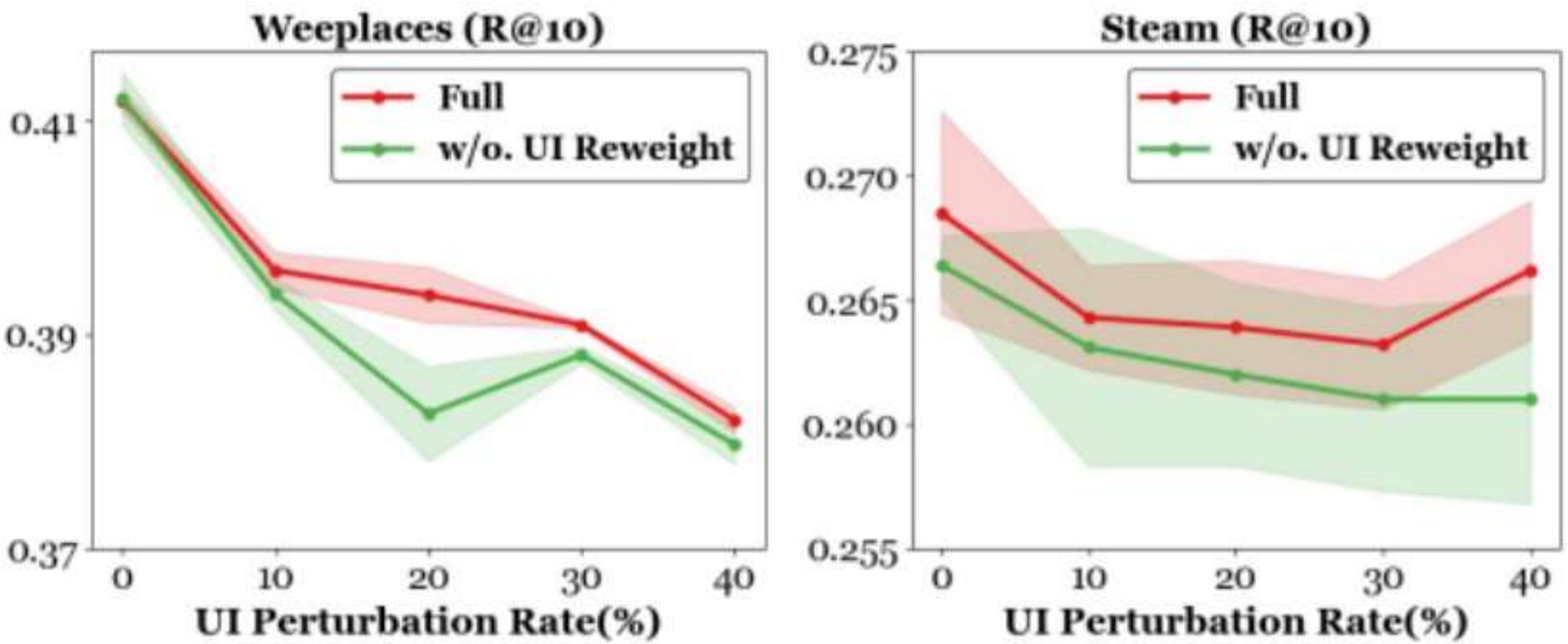


Figure 4: Performance comparison between DiRec and the variant the eliminates reweighting part under varying levels of user-item interaction perturbations.

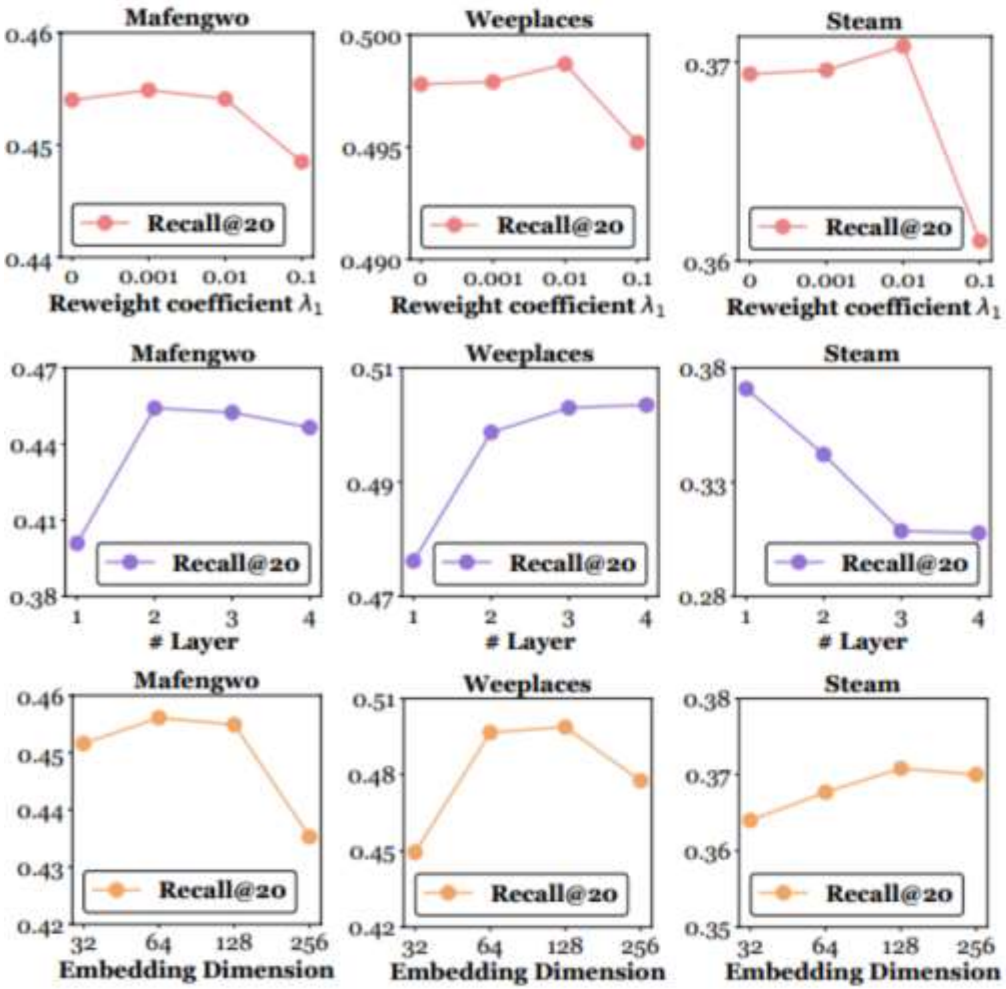


Figure 5: Parameters Study

Thank you!

Leibniz-Institut
für Sozialwissenschaften