Candidate–aware Graph Contrastive Learning for Recommendation

Wei He*
Guohao Sun*
2212483@mail.dhu.edu.cn
ghsun@dhu.edu.cn
Donghua University

Jinhu Lu
Donghua University
1209126@mail.dhu.edu.cn

Xiu Susie Fang†
Donghua University
xiu.fang@dhu.edu.cn

https://github.com/WeiHeCnSH/CGCL-Pytorch-master

（SIGIR-2023)

gesis
Leibniz-Institut
für Sozialwissenschaften

Reported by Ke Gan

1. Introduction
2. Approach
3. Experiments

Introduction

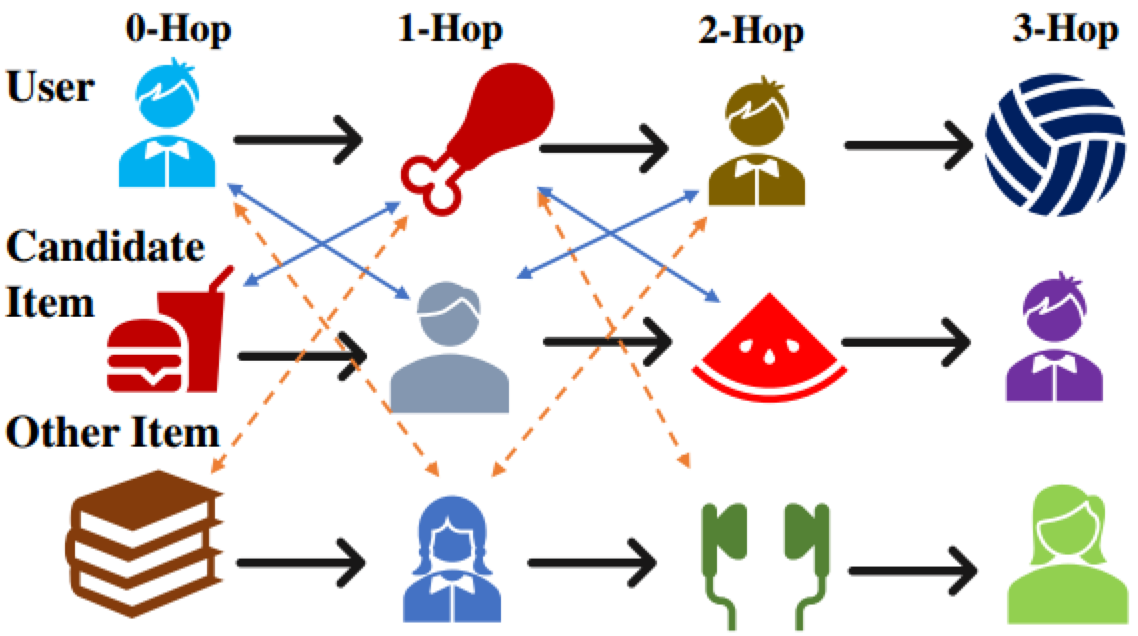
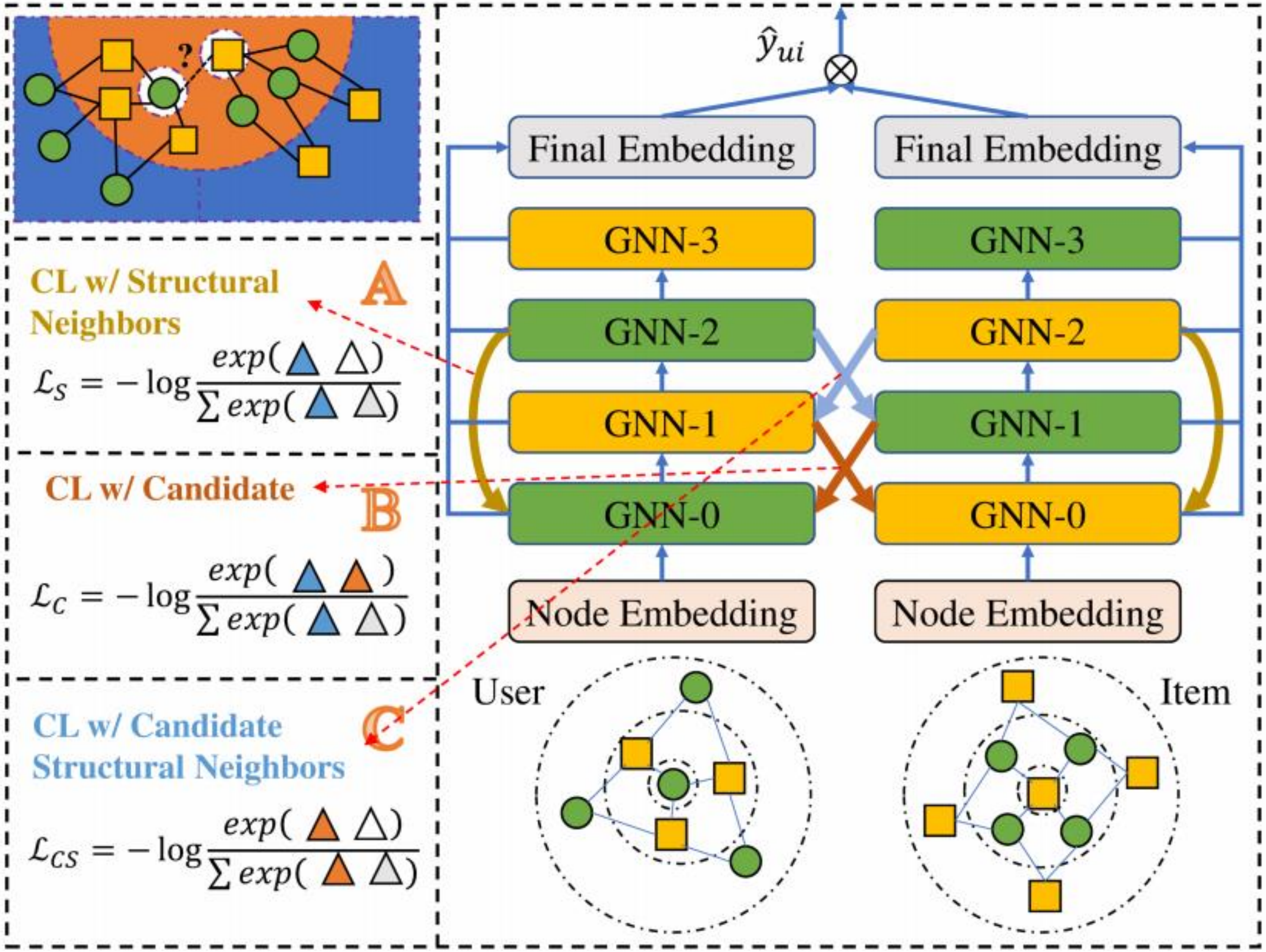


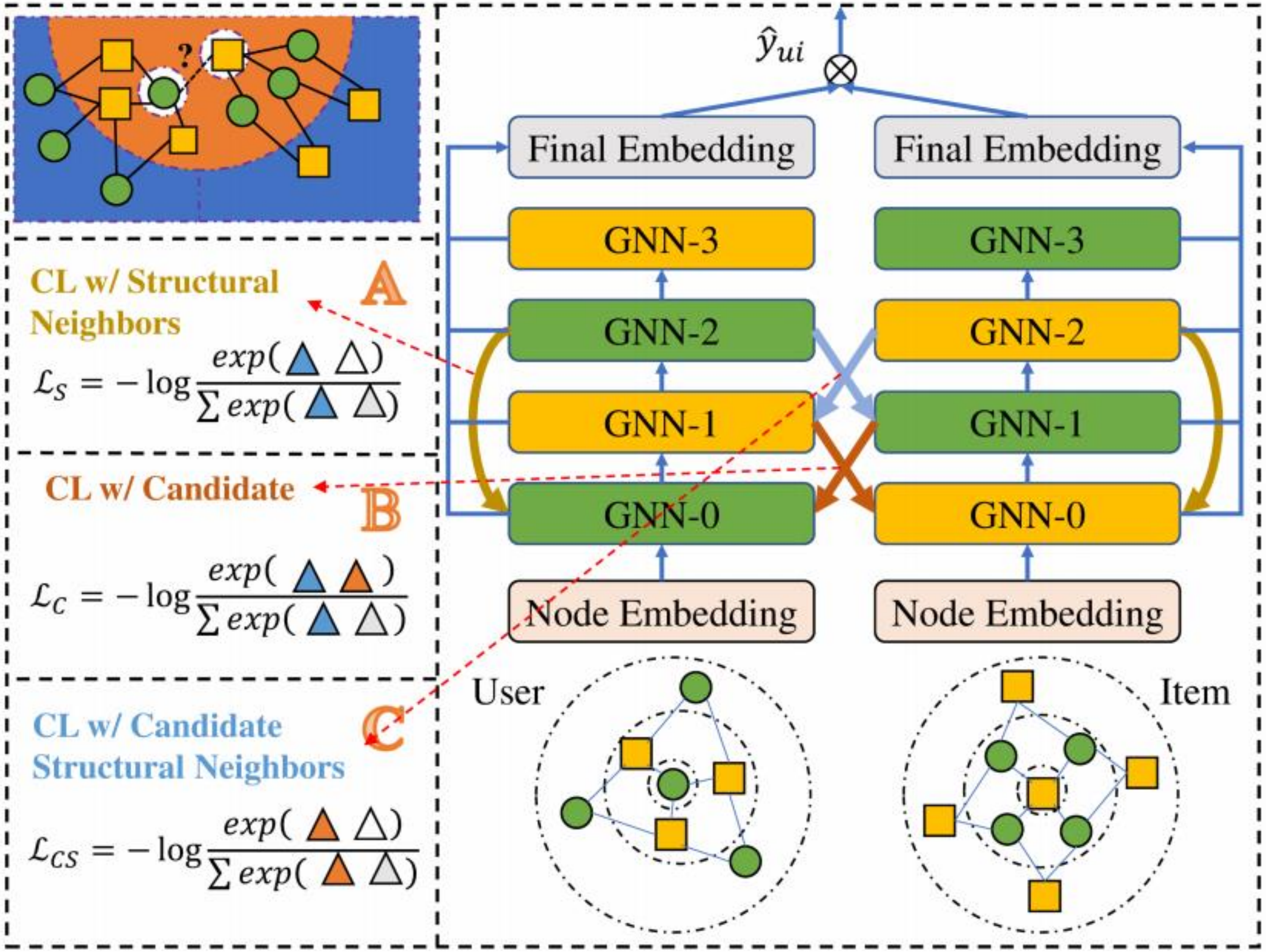
Figure 1: Illustration of the relationship between the user and the candidate item at different layers, where the blue line indicates the distance that needs to be pulled in the embedding space and vice versa in orange.

drumstick should be close to cola and watermelon and away from books and headphones in the embedding space because drumsticks, cola, and watermelon belong to the same class of the food

Approach


$\hat{y}_{ui}$
Final Embedding
Final Embedding
GNN-3
GNN-3
GNN-2
GNN-2
GNN-1
GNN-1
GNN-0
GNN-0
Node Embedding
Node Embedding
User
Item
?
CL w/ Structural Neighbors
A
$\mathcal{L}_S = -\log \frac{exp(\ )}{\sum exp(\ )}$
CL w/ Candidate
B
$\mathcal{L}_C = -\log \frac{exp(\ )}{\sum exp(\ )}$
CL w/ Candidate Structural Neighbors
C
$\mathcal{L}_{CS} = -\log \frac{exp(\ )}{\sum exp(\ )}$

Approach



$$e_u^{(0)} = lookup\,(u)\,, \quad e_i^{(0)} = lookup\,(i)\,. \tag{1}$$

$$e_{u,N}^{(l)} = Agg\left(e_i^{(l-1)}, i \in N_u\right), \quad e_{i,N}^{(l)} = Agg\left(e_u^{(l-1)}, u \in N_i\right). \tag{2}$$

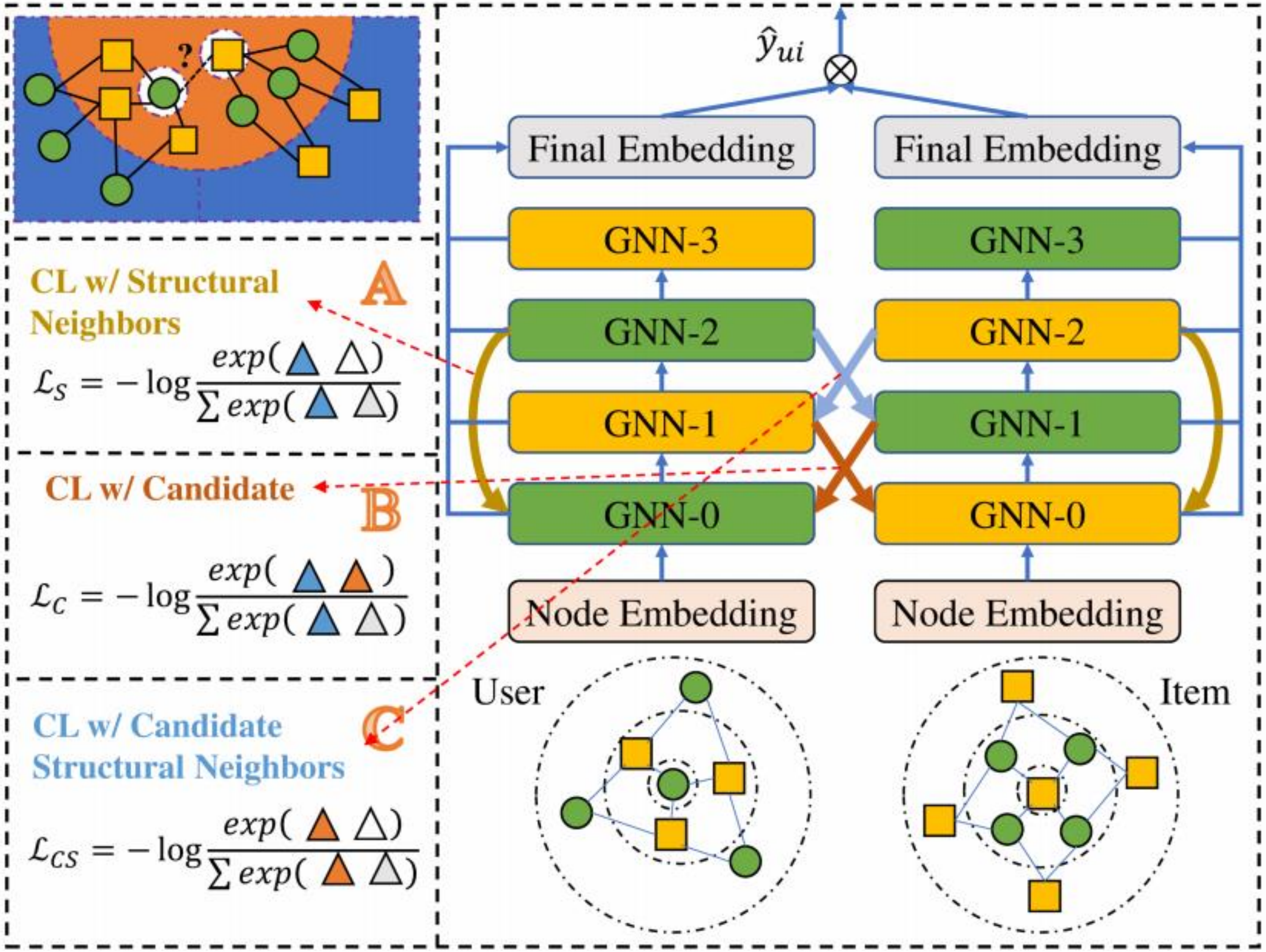
$$e_u^{(l)} = Prop\left(e_u^{(l-1)}, e_{u,N}^{(l)}\right), \quad e_i^{(l)} = Prop\left(e_i^{(l-1)}, e_{i,N}^{(l)}\right). \tag{3}$$

$$e_u = Readout\left(e_u^{(0)}, \cdots, e_u^{(L)}\right), \quad e_i = Readout\left(e_i^{(0)}, \cdots, e_i^{(L)}\right). \tag{4}$$

$$\hat{y}_{ui} = f\,(e_u, e_i)\,. \tag{5}$$

$$\mathcal{L}_{Rec} = g\,(y_{ui}, \hat{y}_{ui})\,. \tag{6}$$

Approach



$$e_{u,N}^{(l+1)} = \sum_{i \in N_u} \frac{1}{\sqrt{|N_u||N_i|}} e_i^{(l)}, \quad e_{i,N}^{(l+1)} = \sum_{u \in N_i} \frac{1}{\sqrt{|N_i||N_u|}} e_u^{(l)}. \tag{7}$$

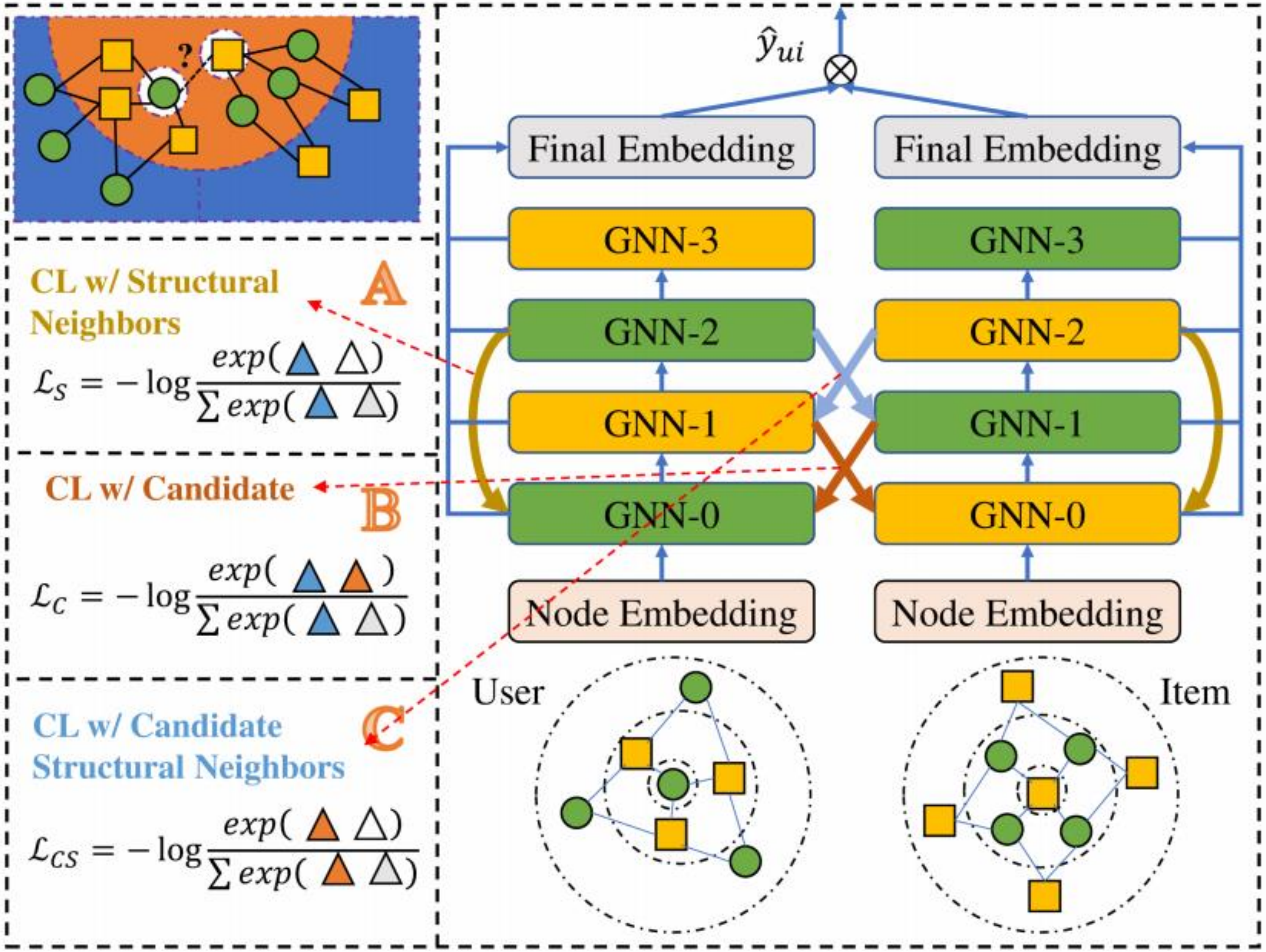
$$e_u^{(l+1)} = e_{u,N}^{(l+1)}, \quad e_i^{(l+1)} = e_{i,N}^{(l+1)}. \tag{8}$$

$$e_u = \frac{1}{L+1} \sum_{l=0}^{L} e_u^{(l)}, \quad e_i = \frac{1}{L+1} \sum_{l=0}^{L} e_i^{(l)}. \tag{9}$$

$$\hat{y}_{ui} = e_u^T e_i. \tag{10}$$

$$\mathcal{L}_{Rec} = \frac{1}{|O|} \sum_{(u,i,j) \in O} -\log \sigma\left(\hat{y}_{ui} - \hat{y}_{uj}\right). \tag{11}$$

Approach



Structural Neighbors

$$\mathcal{L}_S^U = \sum_{u\in\mathcal{U}} -\log \frac{\exp\left(sim\left(e_u^{(k)}, e_u^{(0)}\right)/\tau\right)}{\sum_{v\in\mathcal{U}} \exp\left(sim\left(e_u^{(k)}, e_v^{(0)}\right)/\tau\right)}. \tag{12}$$

$$\mathcal{L}_S^I = \sum_{i\in\mathcal{I}} -\log \frac{\exp\left(sim\left(e_i^{(k)}, e_i^{(0)}\right)/\tau\right)}{\sum_{j\in\mathcal{I}} \exp\left(sim\left(e_i^{(k)}, e_j^{(0)}\right)/\tau\right)}. \tag{13}$$

$$\mathcal{L}_S = \alpha\mathcal{L}_S^U + (1-\alpha)\,\mathcal{L}_S^I. \tag{14}$$

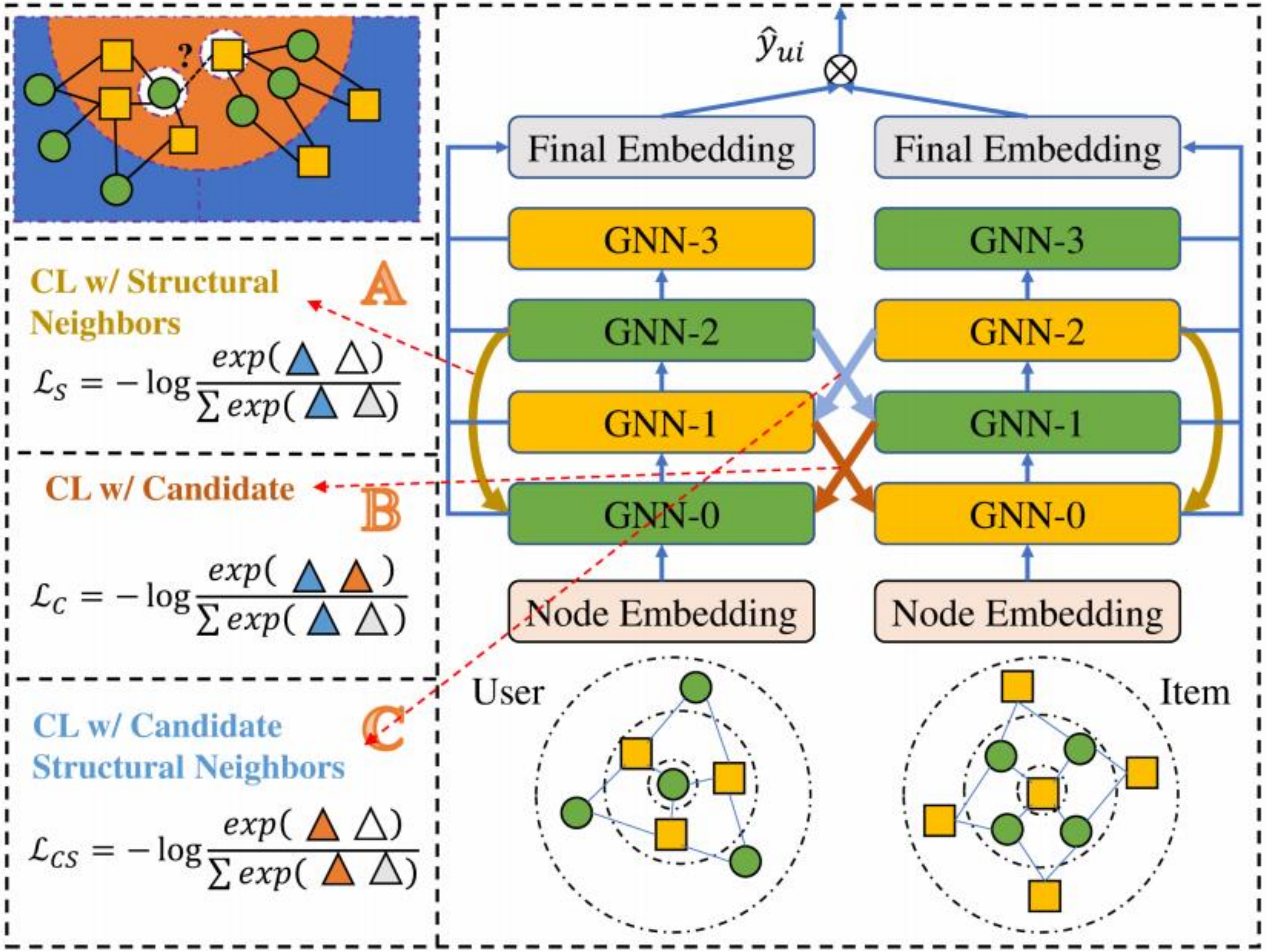
Candidate

$$\mathcal{L}_C^U = \sum_{i\in\mathcal{I}} -\log \frac{\exp\left(sim\left(e_i^{(k')}, e_u^{(0)}\right)/\tau\right)}{\sum_{v\in\mathcal{U}} \exp\left(sim\left(e_i^{(k')}, e_v^{(0)}\right)/\tau\right)}. \tag{15}$$

$$\mathcal{L}_C^I = \sum_{v\in\mathcal{U}} -\log \frac{\exp\left(sim\left(e_u^{(k')}, e_i^{(0)}\right)/\tau\right)}{\sum_{j\in\mathcal{I}} \exp\left(sim\left(e_u^{(k')}, e_j^{(0)}\right)/\tau\right)}. \tag{16}$$

$$\mathcal{L}_C = \alpha\mathcal{L}_C^U + (1-\alpha)\,\mathcal{L}_C^I. \tag{17}$$

Experiment



Candidate Structure Neighbors

$$\mathcal{L}_{CS}^{U} = \sum_{i\in\mathcal{I}} -\log \frac{\exp\left(sim\left(e_i^{(k)}, e_u^{(k')}\right)/\tau\right)}{\sum_{v\in\mathcal{U}} \exp\left(sim\left(e_i^{(k)}, e_v^{(k')}\right)/\tau\right)}. \tag{18}$$

$$\mathcal{L}_{CS}^{I} = \sum_{v\in\mathcal{U}} -\log \frac{\exp\left(sim\left(e_u^{(k)}, e_i^{(k')}\right)/\tau\right)}{\sum_{j\in\mathcal{I}} \exp\left(sim\left(e_u^{(k)}, e_j^{(k')}\right)/\tau\right)}. \tag{19}$$

$$\mathcal{L}_{CS} = \alpha\mathcal{L}_{CS}^{U} + (1-\alpha)\,\mathcal{L}_{CS}^{I}. \tag{20}$$

$$\mathcal{L}_{CGCL} = \mathcal{L}_{Rec} + \lambda_1\mathcal{L}_S + \lambda_2\mathcal{L}_C + \lambda_3\mathcal{L}_{CS} + \lambda_4\|\Theta\|_2^2. \tag{21}$$

Experiment

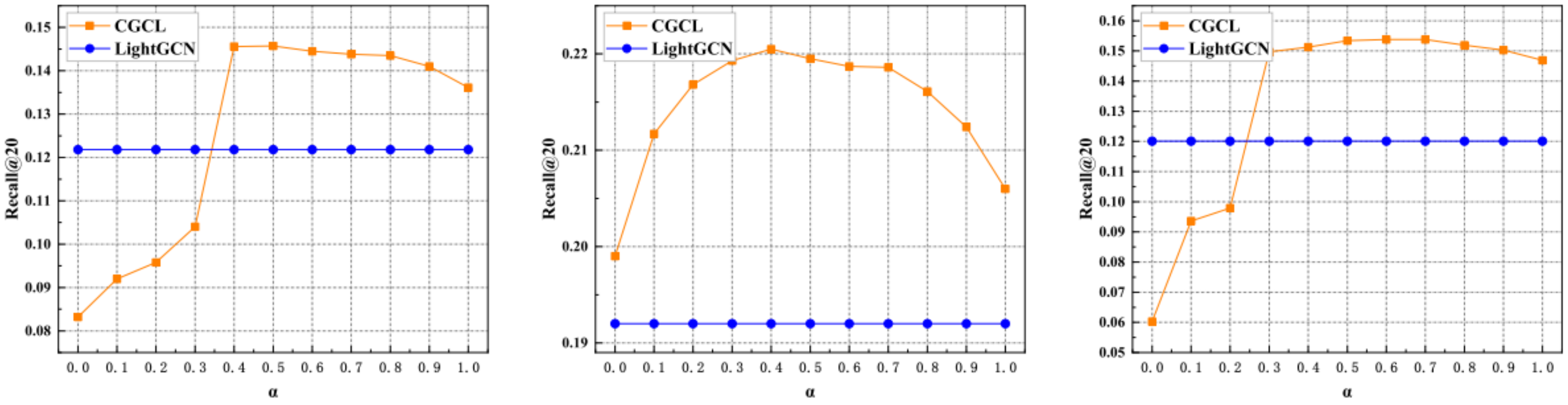
DataSet	Yelp				Gowalla				Amazon-Books			
Metric	Recall		NDCG		Recall		NDCG		Recall		NDCG	
Method	20	50	20	50	20	50	20	50	20	50	20	50
NeuMF	0.0572	0.1457	0.0328	0.0510	0.1167	0.2255	0.0753	0.0969	0.0530	0.1216	0.0339	0.0486
DMF	0.0660	0.1253	0.0353	0.0507	0.1025	0.1706	0.0591	0.0759	0.0542	0.1007	0.0293	0.0414
GCMC	0.0908	0.1690	0.0494	0.0696	0.1472	0.2410	0.0810	0.1038	0.0868	0.1553	0.0481	0.0658
NGCF	0.0953	0.1764	0.0519	0.0729	0.1576	0.2546	0.0893	0.1130	0.0902	0.1598	0.0495	0.0676
LightGCN	0.1218	0.2123	0.0690	0.0741	0.1920	0.2988	0.1133	0.1192	0.1201	0.2002	0.0691	0.0737
SGL-ED	0.1335	0.2177	0.0808	0.1028	0.2153	0.3277	0.1281	0.1558	0.1418	0.2172	0.0866	0.1065
SimpleX	0.1221	0.2044	0.0728	0.0941	0.1555	0.2601	0.0784	0.1040	0.1339	0.2143	0.0790	0.1001
NCL	0.1394	0.2258	0.0816	0.1044	0.2147	0.3299	0.1260	0.1543	0.1389	0.2209	0.0818	0.1034
CGCL	**0.1457**	**0.2404**	**0.0849**	**0.1097**	**0.2205**	**0.3391**	**0.1292**	**0.1583**	**0.1538**	**0.2400**	**0.0920**	**0.1147**
Imp (%).	4.52	6.47	4.04	5.08	2.42	2.79	0.86	1.60	8.46	8.65	6.24	7.70

Table 2: The overall performance comparison of the proposed CGCL model with the state-of-the-art DNN-, GNN-, and GCL-based baselines. The optimal value is bolded and the suboptimal value is underlined.

Experiment

DataSets	#Users	#Items	#Interactions	#Density
Yelp	45,478	30,709	1,777,765	0.00127
Gowalla	29,859	40,989	1,027,464	0.00084
Books	58,145	58,052	2,517,437	0.00075

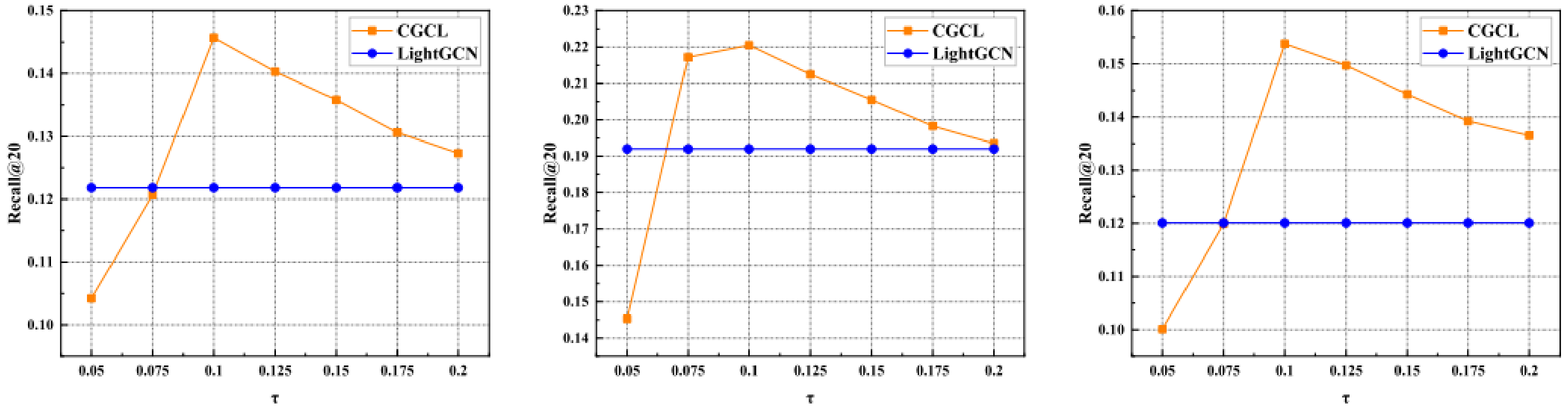
Table 1: Statistics of the datasets



(a) Yelp. (b) Gowalla. (c) Amazon-Books.

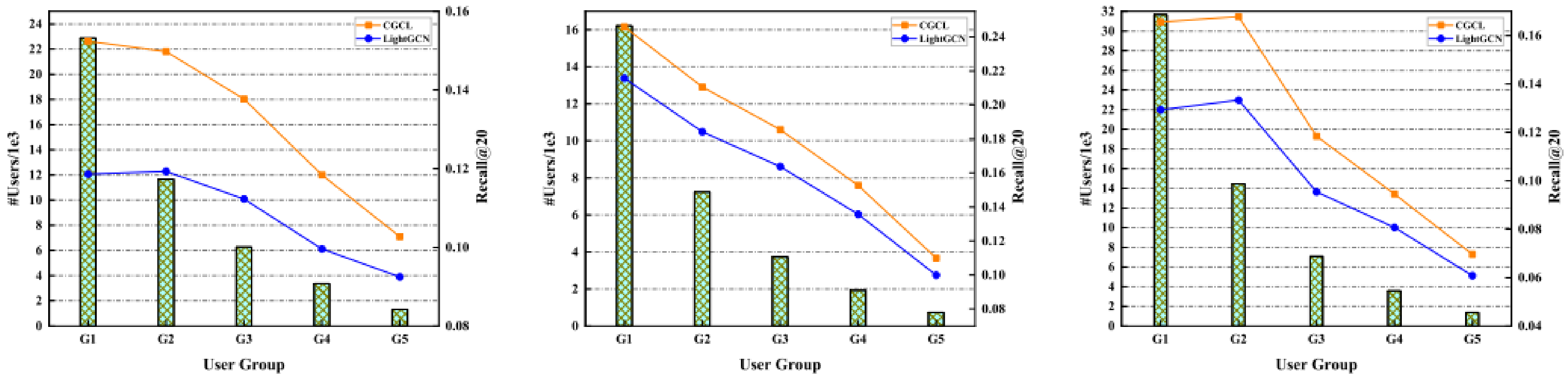
Figure 3: Performance Comparison w.r.t. Different Balance Coefficient α.

Experiment



(a) Yelp. (b) Gowalla. (c) Amazon-Books.

Figure 4: Performance Comparison w.r.t. Different Temperature τ.



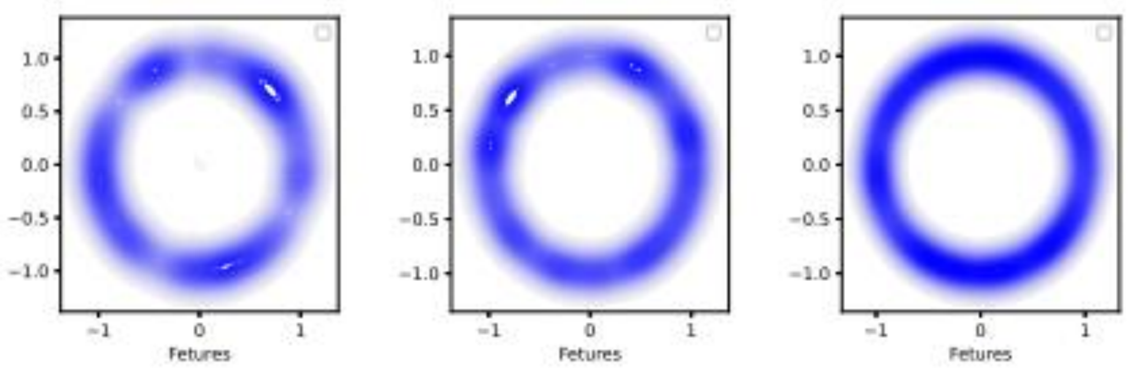
(a) Yelp. (b) Gowalla. (c) Amazon-Books.

DataSet	Yelp		Gowalla		Amazon-Books	
Metric	R@20	N@20	R@20	N@20	R@20	N@20
LightGCN	0.1218	0.069	0.1942	0.1123	0.1201	0.0691
O s	0.1328	0.0761	0.2028	0.1191	0.1236	0.0712
O c	0.1342	0.0768	0.2061	0.1195	0.1343	0.0780
O cs	0.1331	0.0755	0.2058	0.1202	0.1262	0.0729
W/o s	0.1327	0.0755	0.2056	0.1177	0.1259	0.0727
W/o c	0.1412	0.0824	0.2025	0.1184	0.1521	0.0910
W/o cs	0.1447	0.0846	0.2197	0.1291	0.1534	0.0908
All	0.1457	0.0849	0.2205	0.1292	0.1538	0.0920

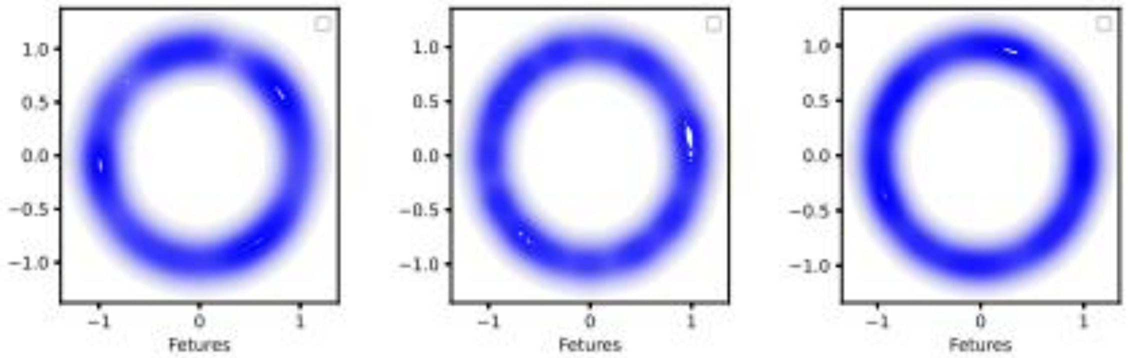
Table 3: Ablation Experimental

DataSet	Yelp		Gowalla		Amazon-Books	
Metric	R@20	N@20	R@20	N@20	R@20	N@20
NGCF	0.0953	0.0519	0.1576	0.0893	0.0902	0.0495
+CGCL	0.1084	0.0609	0.1812	0.1048	0.1259	0.0731
Imp(%).	13.75	17.34	14.97	17.36	39.58	47.68
LightGCN	0.1218	0.0690	0.1942	0.1123	0.1201	0.0691
+CGCL	0.1457	0.0849	0.2205	0.1292	0.1538	0.0920
Imp(%).	19.62	23.04	13.54	15.05	27.73	32.56

Table 4: Performance comparison w.r.t. different backbones.



(a) LightGCN in Yelp. (b) LightGCN in Gowalla. (c) LightGCN in Books.



(d) CGCL in Yelp. (e) CGCL in Gowalla. (f) CGCL in Books.

Figure 7: Feature distribution of item representations learn from the datasets in $\mathbb{R}^2$ (The darker the color, the more items fall within that area).

Thank you!