Heterogeneous Graph Contrastive Learning for Recommendation

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https://github.com/HKUDS/HGCL

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Reported by Ke Gan

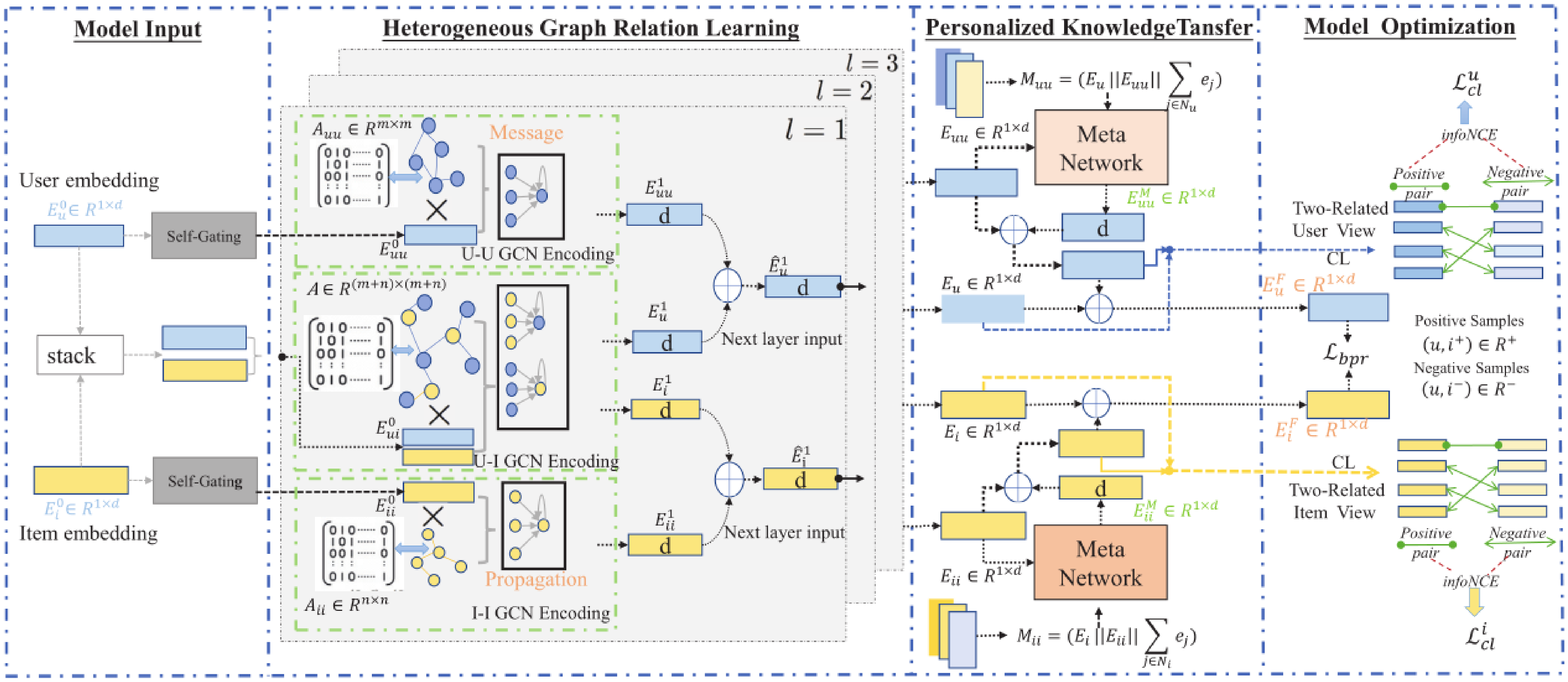
1. Introduction
2. Approach
3. Experiments

Introduction

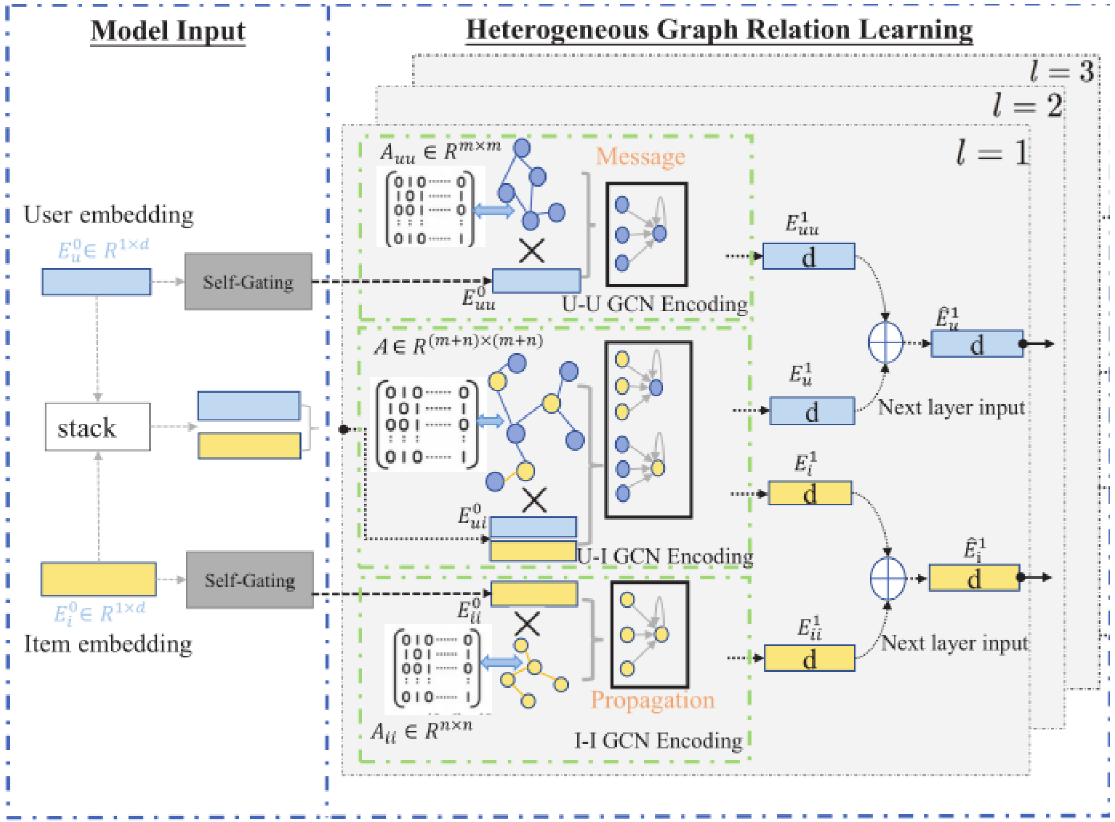
GNN-based collaborative filtering modelsmerely focus on homogeneous interaction relationships in user-item connection graphs

the limitation of sparse training labels may not generate quality user/item embeddings

Approach


Model Input
Heterogeneous Graph Relation Learning
Personalized KnowledgeTansfer
Model Optimization
User embedding
Self-Gating
stack
Item embedding
Message
U-U GCN Encoding
U-I GCN Encoding
I-I GCN Encoding
Propagation
Next layer input
Next layer input
l = 1
l = 2
l = 3
Meta Network
Meta Network
Two-Related User View
Two-Related Item View
CL
CL
infoNCE
infoNCE
Positive pair
Negative pair
Positive pair
Negative pair
Positive Samples
Negative Samples

Approach



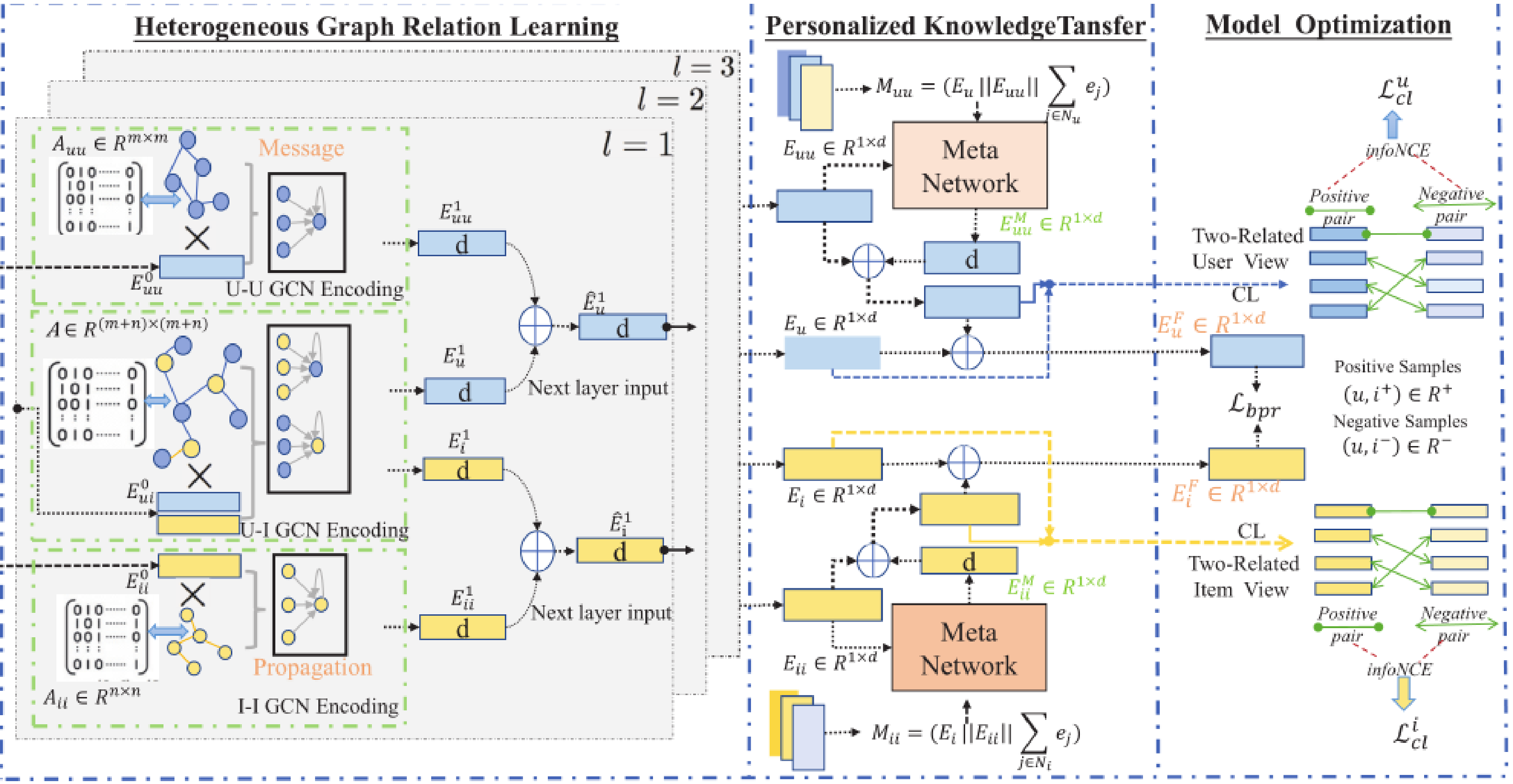
$$\mathbf{E}_{uu}^0 = \mathbf{E}_u^0 \odot \sigma(\mathbf{E}_u^0 \mathbf{W}_g + \mathbf{b}_g); \quad \mathbf{E}_{ii}^0 = \mathbf{E}_i^0 \odot \sigma(\mathbf{E}_i^0 \mathbf{W}_g + \mathbf{b}_g) \quad (1)$$

$$\mathbf{e}_u^{l+1} = \sum_{i \in \mathcal{N}_u} \frac{1}{\sqrt{|\mathcal{N}_u|}\sqrt{|\mathcal{N}_i|}} \mathbf{e}_i^l; \quad \mathbf{e}_i^{l+1} = \sum_{u \in \mathcal{N}_i} \frac{1}{\sqrt{|\mathcal{N}_i|}\sqrt{|\mathcal{N}_u|}} \mathbf{e}_u^l \quad (2)$$

$$\widehat{\mathbf{E}}_u^{l+1} = f(\mathbf{E}_u^{l+1}, \mathbf{E}_{uu}^{l+1}); \quad \widehat{\mathbf{E}}_i^{l+1} = f(\mathbf{E}_i^{l+1}, \mathbf{E}_{ii}^{l+1}) \quad (3)$$

$$\mathbf{E}_u = \mathbf{E}_u^0 + \sum_{l=1}^{L} \frac{\mathbf{E}_u^l}{||\mathbf{E}_u^l||}; \quad \mathbf{E}_i = \mathbf{E}_i^0 + \sum_{l=1}^{L} \frac{\mathbf{E}_i^l}{||\mathbf{E}_i^l||} \quad (4)$$

Approach



$$\mathbf{M}_{uu} = \mathbf{E}_u || \mathbf{E}_{uu} || \sum_{i \in \mathcal{N}_u} \mathbf{e}_i; \quad \mathbf{M}_{ii} = \mathbf{E}_i || \mathbf{E}_{ii} || \sum_{u \in \mathcal{N}_i} \mathbf{e}_u \qquad (5)$$

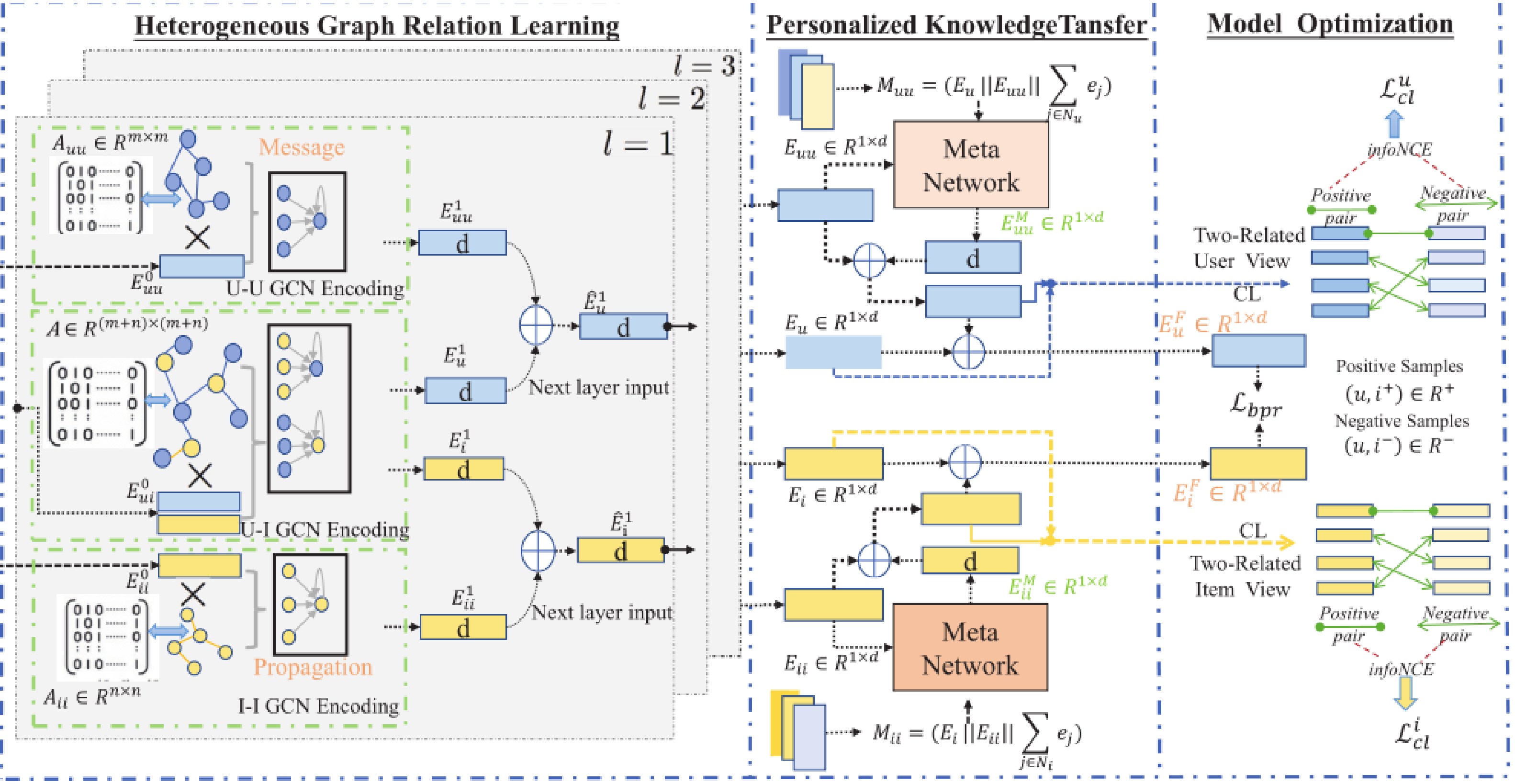
$$\begin{cases} f_{mlp}^1(\mathbf{M}_{uu}) \rightarrow \mathbf{W}_{uu}^{M1} \\ f_{mlp}^2(\mathbf{M}_{uu}) \rightarrow \mathbf{W}_{uu}^{M2} \end{cases} \qquad (6)$$

$$\mathbf{E}_{uu}^M = \sigma(\mathbf{W}_{uu}^{M1} \mathbf{W}_{uu}^{M2} \mathbf{E}_{uu}) \qquad (7)$$

$$\mathbf{E}_u^F = \alpha_u * \mathbf{E}_u + (1 - \alpha_u) * (\mathbf{E}_{uu} + \mathbf{E}_{uu}^M); \qquad (8)$$

$\mathbf{E}_i^F$ can be generated in a similar way.

Approach



$$\mathcal{L}_{cl}^u = \sum_{u\in\mathcal{V}_u} -\log \frac{\exp\left(s(\mathbf{e}_{uu}^M + \mathbf{e}_{uu}, \mathbf{e}_u)/\tau\right)}{\sum_{u'\in\mathcal{V}_u} \exp\left(s(\mathbf{e}_{uu}^M + \mathbf{e}_{uu}, \mathbf{e}'_u)/\tau\right)} \tag{9}$$

Analogously, we can obtain the InfoNCE loss $\mathcal{L}_{cl}^i$ of items aspect.

$$\mathcal{L}_{cl} = \alpha_1 * \mathcal{L}_{cl}^u + \alpha_2 * \mathcal{L}_{cl}^i,$$

$$\hat{y}_{u,i} = \mathbf{e}_u^{F\top} \mathbf{e}_i^F,$$

$$\mathcal{L}_{bpr} = \sum_{(u,i^+,i^-)\in O} -\ln(\mathrm{sigmoid}(\hat{y}_{u,i^+} - \hat{y}_{u,i^-})) + \lambda\|\Theta\|^2 \tag{10}$$

$$\mathcal{L} = \mathcal{L}_{bpr} + \beta * \mathcal{L}_{cl} \tag{11}$$

Experiment

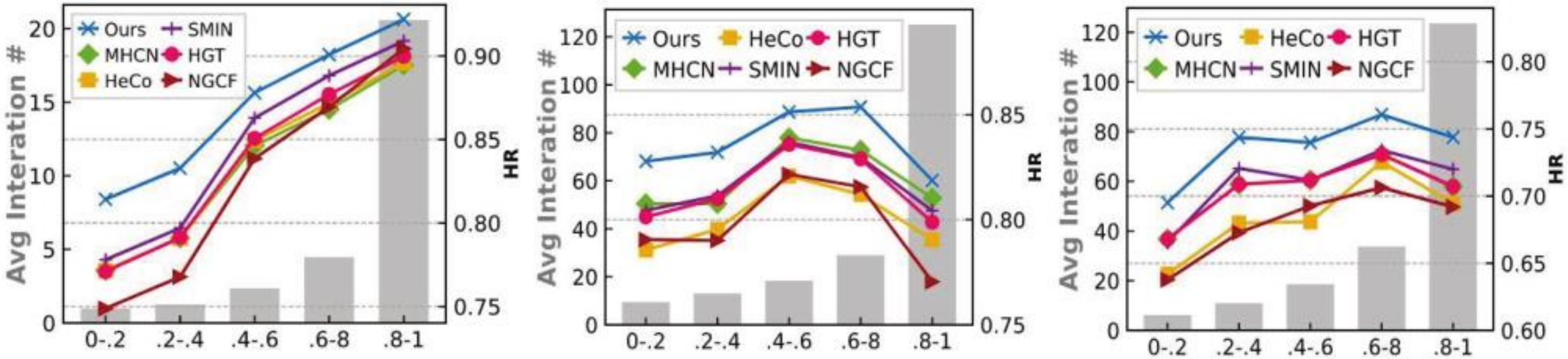
Table 1: Performance comparison of all methods on different datasets in terms of *NDCG* and *HR*.

Data	Metric	SAMN	DGRec	ETANN	NGCF	KGAT	MKR	GraphRec	DANSER	HERec	MCRec	HAN	HeCo	HGT	MHCN	SMIN	**HGCL**
Ciao	H@10	0.6576	0.6653	0.6738	0.6945	0.6601	0.6793	0.6825	0.6730	0.6800	0.6772	0.6589	0.6867	0.6939	0.7053	0.7108	**0.7376**
	N@10	0.4561	0.4953	0.4665	0.4894	0.4512	0.4589	0.4730	0.4521	0.4712	0.4708	0.4469	0.4867	0.4869	0.4928	0.5012	**0.5261**
Epinions	H@10	0.7592	0.7603	0.7650	0.7984	0.7510	0.7647	0.7723	0.7714	0.7642	0.7630	0.7505	0.7998	0.8150	0.8201	0.8179	**0.8367**
	N@10	0.5614	0.5668	0.5663	0.5945	0.5578	0.5669	0.5751	0.5741	0.5495	0.5326	0.5275	0.5910	0.6126	0.6158	0.6137	**0.6413**
Yelp	H@10	0.7910	0.7950	0.8031	0.8265	0.7881	0.8005	0.8098	0.8077	0.7928	0.7869	0.7731	0.8359	0.8364	0.8344	0.8478	**0.8712**
	N@10	0.5516	0.5593	0.5560	0.5854	0.5501	0.5635	0.5679	0.5692	0.5612	0.5590	0.5604	0.5847	0.5883	0.5799	0.5993	**0.6310**

Table 2: Statistics of experimented datasets

Dataset	User #	Item #	Interaction #	Sparsity
Ciao	6776	101415	265308	99.9614%
Epinions	15210	233929	630391	99.9823%
Yelp	161305	114852	957923	99.9948%

Experiment



(a) Yelp HR@10 (b) Epinions HR@10 (c) Ciao HR@10

Figure 2: Performance comparison with respect to different data sparsity degrees on three datasets.

Table 3: Ablation study on key components of HGCL

Data	Ciao		Epinions		Yelp	
Metric	HR	NDCG	HR	NDCG	HR	NDCG
w/o-cl	0.7124	0.5015	0.8176	0.6166	0.8471	0.6030
w/o-meta	0.7215	0.5135	0.8247	0.6282	0.8585	0.6218
w/o-ii	0.7116	0.5055	0.8245	0.6317	0.8573	0.6188
w/o-uu	0.7149	0.5047	0.8285	0.6266	0.8533	0.6208
HGCL	**0.7376**	**0.5261**	**0.8367**	**0.6413**	**0.8712**	**0.6310**

of different methods, two widely-adopted metrics HR(Hit Ratio) and NDCG (Normalized Discounted Cumulative Gain) are used.

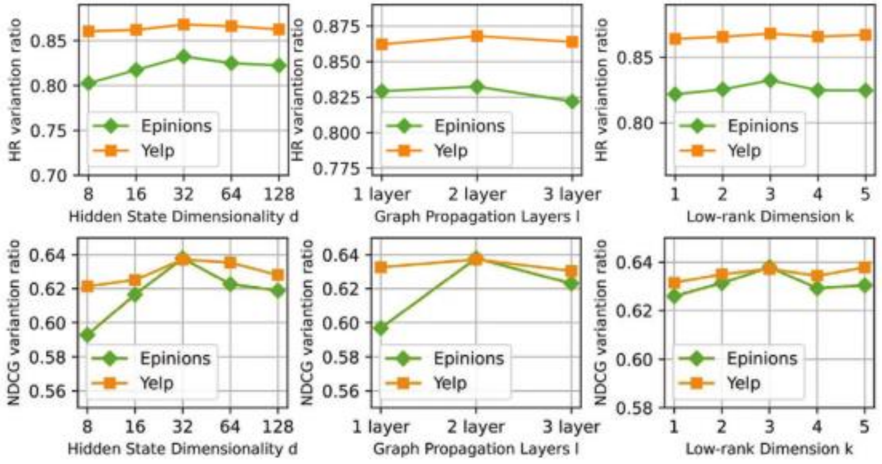


Figure 3: Hyperparameter study of the HGCL.

Experiment

User Cases from Ciao Dataset

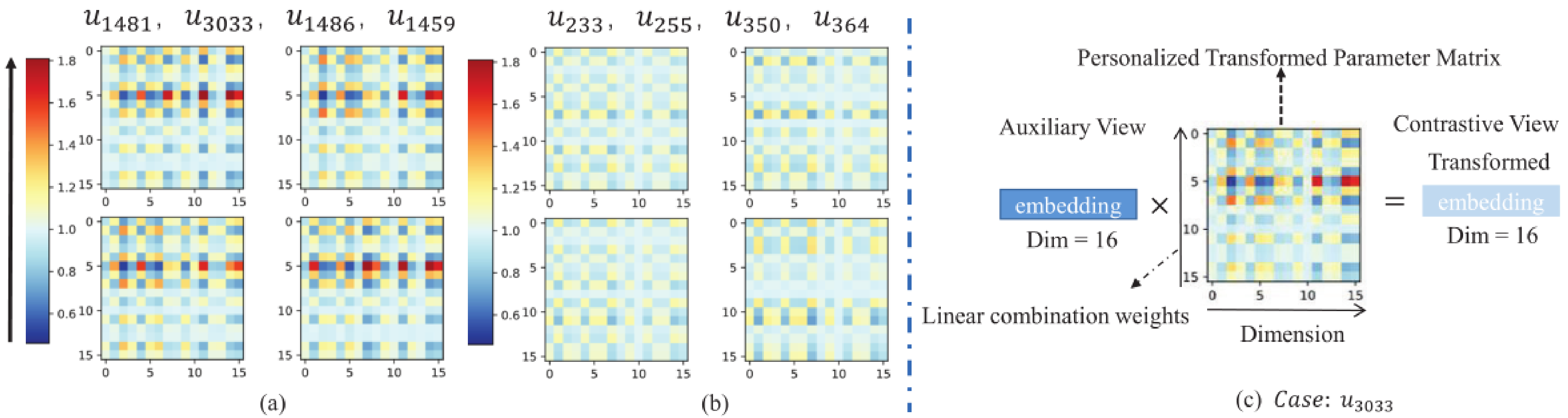


Figure 4: Case study on Ciao dataset to visualize the learned contrastive transformation matrices sampled from different users to reflect the diverse social influence. (a): Four users who are more likely to be influenced by their social relations; (b): Four users who are less likely to be influenced by their social relations. (c): The embeddings generated from auxiliary view will be transformed for representation contrasting for self-supervision augmentation of user-item interaction modeling.

Thank you!