Denoised Self-Augmented Learning for Social Recommendation

Tianle Wang, Lianghao Xia, Chao Huang*
University of Hong Kong, Hong Kong
louiswong.cs@connect.hku.hk, aka_xia@foxmail.com
chaohuang75@gmail.com

https://github.com/HKUDS/DSL

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Reported by Yuyang Lai

Introduction

In practical social recommendation scenarios, however, user-item interaction data is often very **sparse**.

The SSL-based augmentation is severely hindered by **noisy social relations** when enhancing the representation learning of complex user preferences.

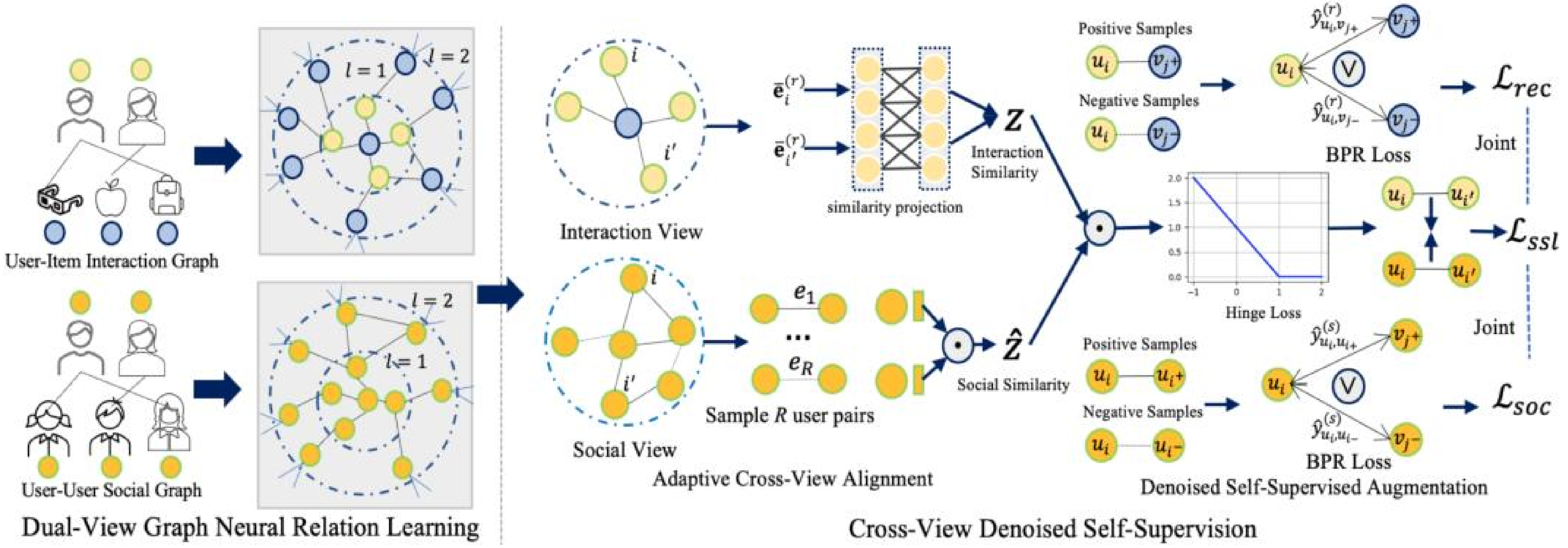
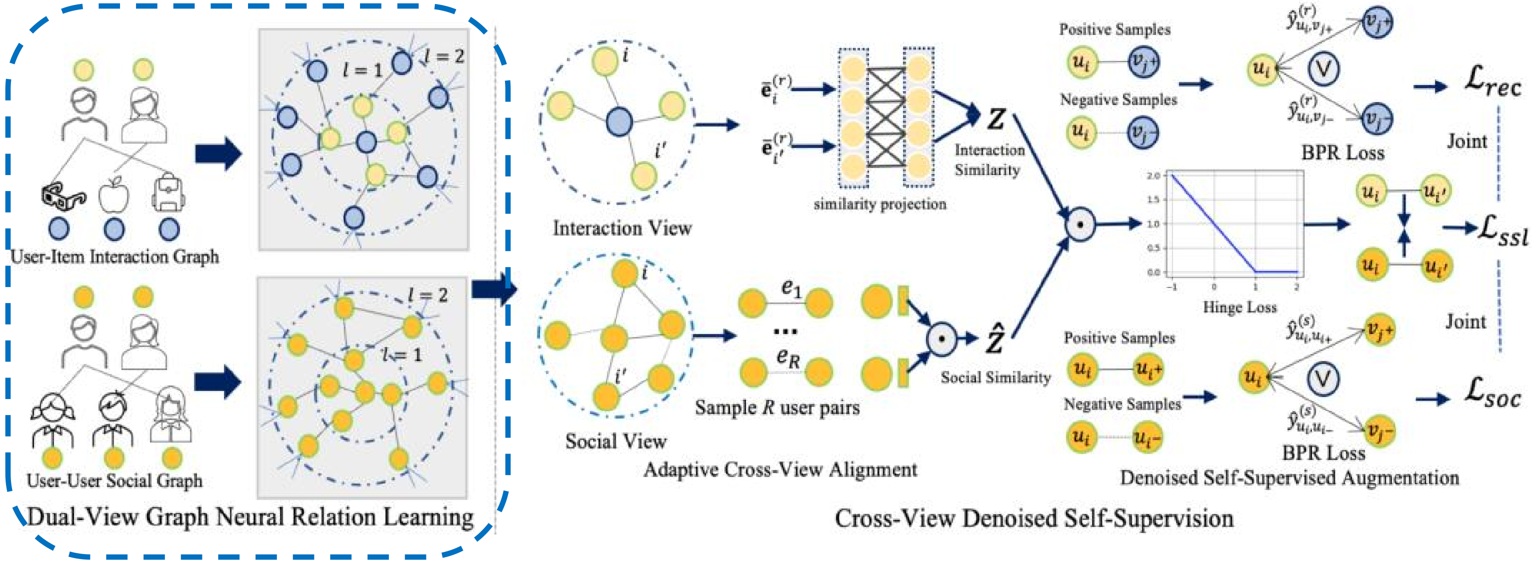


Figure 1: Overall framework of the proposed denoised self-augmented learning (DSL) model.

Method



$$\mathcal{U} = \{u_1, ..., u_I\} \qquad \mathcal{V} = \{v_1, ..., v_J\}$$

$$\mathcal{G}_r = \{\mathcal{U}, \mathcal{V}, \mathcal{E}_r\} \qquad \mathcal{G}_s = \{\mathcal{U}, \mathcal{E}_s\}$$

Dual-View Graph Neural Relation Learning

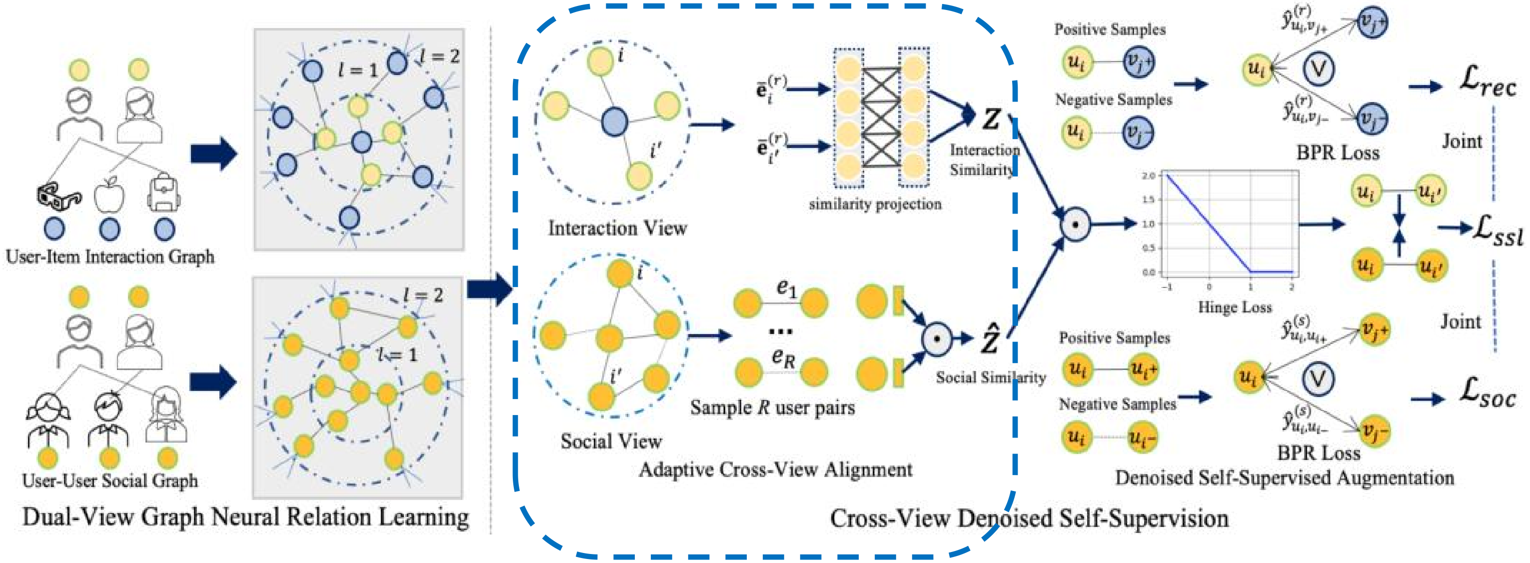
$$\mathbf{E}_r^{(l)} = (\mathcal{L}_r + \mathbf{I}) \cdot \mathbf{E}_r^{(l-1)} \tag{1}$$

$$\mathcal{L}_r = \mathbf{D}_r^{-\frac{1}{2}} \mathbf{A}_r \mathbf{D}_r^{-\frac{1}{2}}, \quad \mathbf{A}_r = \begin{bmatrix} \mathbf{0} & \mathbf{R} \\ \mathbf{R}^\top & \mathbf{0} \end{bmatrix} \tag{2}$$

$$\mathbf{E}_s^{(l)} = (\mathcal{L}_s + \mathbf{I}) \cdot \mathbf{E}_s^{(l-1)}, \quad \mathcal{L}_s = \mathbf{D}_s^{-\frac{1}{2}} \mathbf{S} \, \mathbf{D}_s^{-\frac{1}{2}} \tag{3}$$

$$\bar{\mathbf{E}}_r = \sum_{l=0}^{L} \mathbf{E}_r^{(l)}, \quad \bar{\mathbf{E}}_s = \sum_{l=0}^{L} \mathbf{E}_s^{(l)} \tag{4}$$

Method

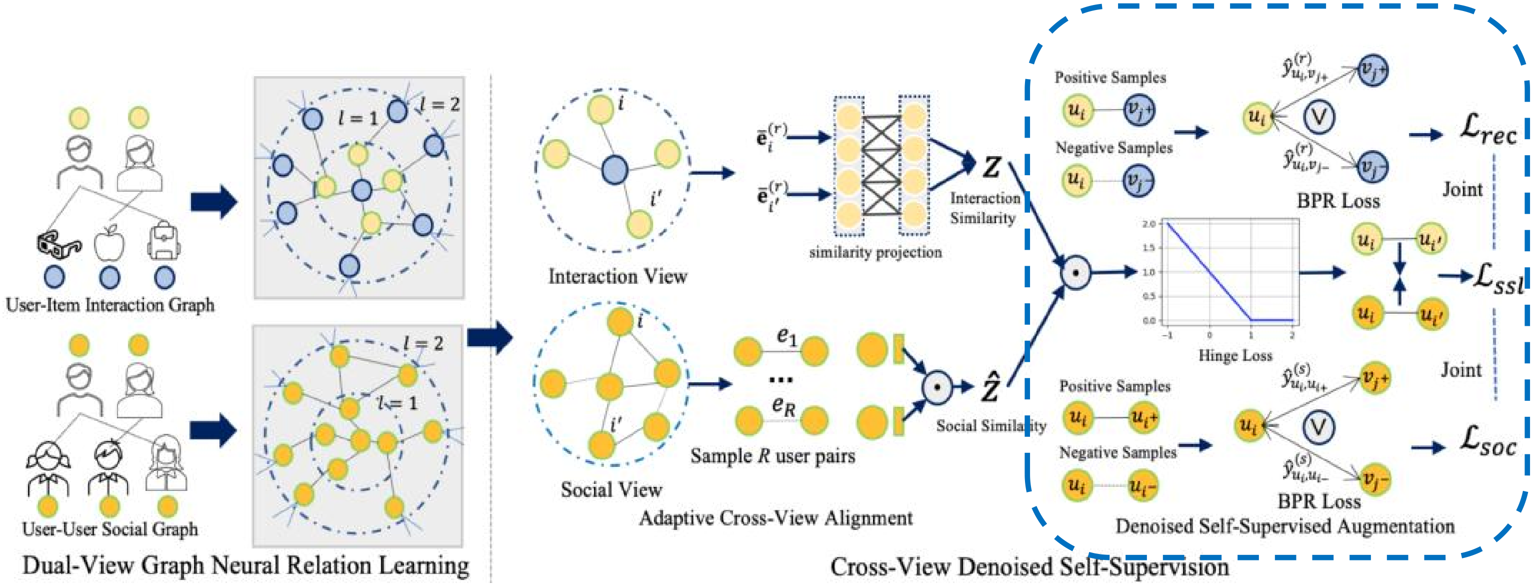


$$z_{i,i'} = [\bar{\mathbf{e}}_i^{(r)}; \bar{\mathbf{e}}_{i'}^{(r)}] \qquad \hat{z}_{i,i'} = [\bar{\mathbf{e}}_i^{(s)\top}; \bar{\mathbf{e}}_{i'}^{(s)}]$$

$$z_{i,i'} = \mathrm{sigm}(\mathbf{d}^\top \cdot \sigma(\mathbf{T} \cdot [\bar{\mathbf{e}}_i^{(r)}; \bar{\mathbf{e}}_{i'}^{(r)}] + \bar{\mathbf{e}}_i^{(r)} + \bar{\mathbf{e}}_{i'}^{(r)} + \mathbf{c})) \quad (5)$$

$$L_{ssl} = \sum_{(u_i, u_{i'})} \max(0, 1 - z_{i,i'} \hat{z}_{i,i'}) \quad (6)$$

Method



$$\hat{y}^{(r)}_{u_i,v_j} = \bar{\mathbf{e}}_i^{(r)\top}\bar{\mathbf{e}}_j^{(r)}; \quad \hat{y}^{(s)}_{u_i,u_{i'}} = \bar{\mathbf{e}}_i^{(s)\top}\bar{\mathbf{e}}_{i'}^{(s)} \tag{7}$$

$$L_{rec} = \sum_{(u_i,v_{j+},v_{j-})} -\ln \mathrm{sigm}(\hat{y}^{(r)}_{u_i,v_{j+}} - \hat{y}^{(r)}_{u_i,v_{j-}})$$
$$L_{soc} = \sum_{(u_i,u_{i+},u_{i-})} -\ln \mathrm{sigm}(\hat{y}^{(s)}_{u_i,u_{i+}} - \hat{y}^{(s)}_{u_i,u_{i-}}) \tag{8}$$

$$L = L_{rec} + \lambda_1 L_{soc} + \lambda_2 L_{ssl} + \lambda_3(\|\mathbf{E}_u\|_F^2 + \|\mathbf{E}_v\|_F^2) \tag{9}$$

$$\frac{\partial L_{cl}}{\partial \bar{\mathbf{e}}_i} = -\bar{\mathbf{e}}_{i+} + \sum_{u_{i-}} \bar{\mathbf{e}}_{i-} \frac{\exp \bar{\mathbf{e}}_i^\top \bar{\mathbf{e}}_{i-}}{\sum_{u_{i-}} \exp \bar{\mathbf{e}}_i^\top \bar{\mathbf{e}}_{i-}} \tag{10}$$

$$\frac{\partial L_{ssl}}{\partial \bar{\mathbf{e}}_i} = \sum_{u_{i'}} -z_{i,i'}\bar{\mathbf{e}}_{i'} \tag{11}$$

Experiments

Data	Ciao	Epinions	Yelp
# Users	6,672	11,111	161,305
# Items	98,875	190,774	114,852
# Interactions	198,181	247,591	1,118,645
Interaction Density	0.0300%	0.0117%	0.0060%
# Social Ties	109,503	203,989	2,142,242

Table 1: Statistical information of evaluated datasets.

Dataset	Metrics	PMF	TrustMF	DiffNet	DGRec	EATNN	NGCF+	MHCN	KCGN	SMIN	DSL	%Imp
Ciao	HR	0.4223	0.4492	0.5544	0.4658	0.4255	0.5629	0.5950	0.5785	0.5852	**0.6374**	26.0
	NDCG	0.2464	0.2520	0.3167	0.2401	0.2525	0.3429	0.3805	0.3552	0.3687	**0.4065**	37.2
Epinions	HR	0.1686	0.1769	0.2182	0.2055	0.1576	0.2969	0.3507	0.3122	0.3159	**0.3983**	76.9
	NDCG	0.0968	0.0842	0.1162	0.0908	0.0794	0.1582	0.1926	0.1721	0.1867	**0.2290**	96.2
Yelp	HR	0.7554	0.7791	0.8031	0.7950	0.8031	0.8265	0.8571	0.8484	0.8478	**0.8923**	10.1
	NDCG	0.5165	0.5424	0.5670	0.5593	0.5560	0.5854	0.6310	0.6028	0.5993	**0.6599**	15.5

Table 2: Recommendation performance of different methods. %Imp denotes relative improvements over all baselines on average.

Experiments

Data	Ciao		Epinions		Yelp	
Metrics	HR	NDCG	HR	NDCG	HR	NDCG
DSAL-d	0.615	0.399	0.354	0.207	0.887	0.658
DSAL-s	0.594	0.374	0.327	0.169	0.839	0.621
DSAL-c	0.603	0.388	0.336	0.199	0.889	**0.662**
DSAL	**0.637**	**0.406**	**0.398**	**0.229**	**0.892**	0.659

Table 3: Component-wise ablation study of DSL.

Metrics	PMF	TrustMF	DiffNet	DGRec	EATNN	NGCF+	MHCN	KCGN	SMIN	DSL	%Imp
HR@5	0.3032	0.3133	0.3963	0.3035	0.3259	0.4263	0.4762	0.4361	0.4565	**0.5007**	35.2
NDCG@5	0.2071	0.2073	0.2650	0.1872	0.2342	0.3020	0.3479	0.3094	0.3298	**0.3626**	43.0
HR@10	0.4223	0.4492	0.5544	0.4658	0.4255	0.5629	0.5950	0.5785	0.5852	**0.6374**	26.0
NDCG@10	0.2464	0.2520	0.3167	0.2401	0.2525	0.3429	0.3805	0.3552	0.3687	**0.4065**	37.2
HR@20	0.5565	0.6133	0.6973	0.6193	0.5309	0.7032	0.7418	0.7191	0.7000	**0.7683**	18.6
NDCG@20	0.2799	0.3020	0.3514	0.2746	0.2838	0.3675	0.4241	0.3844	0.3780	**0.4353**	31.6

Table 4: Ranking performance on Ciao dataset with varying Top-N values in terms of HR@N and NDCG@N

Experiments

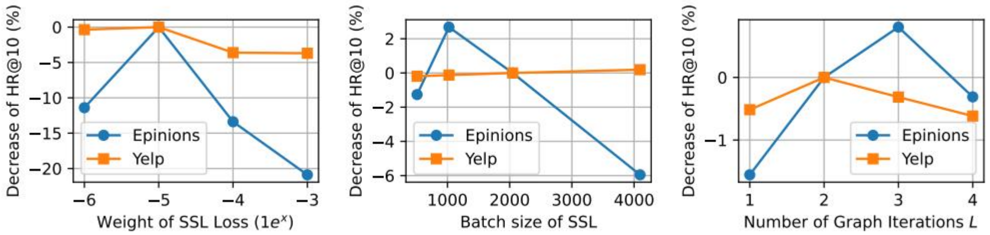


Figure 2: We conduct a hyperparameter study of the DSL with respect to i) SSL loss weight for regularization, ii) batch size for training, and iii) # of propagation layers for message passing.

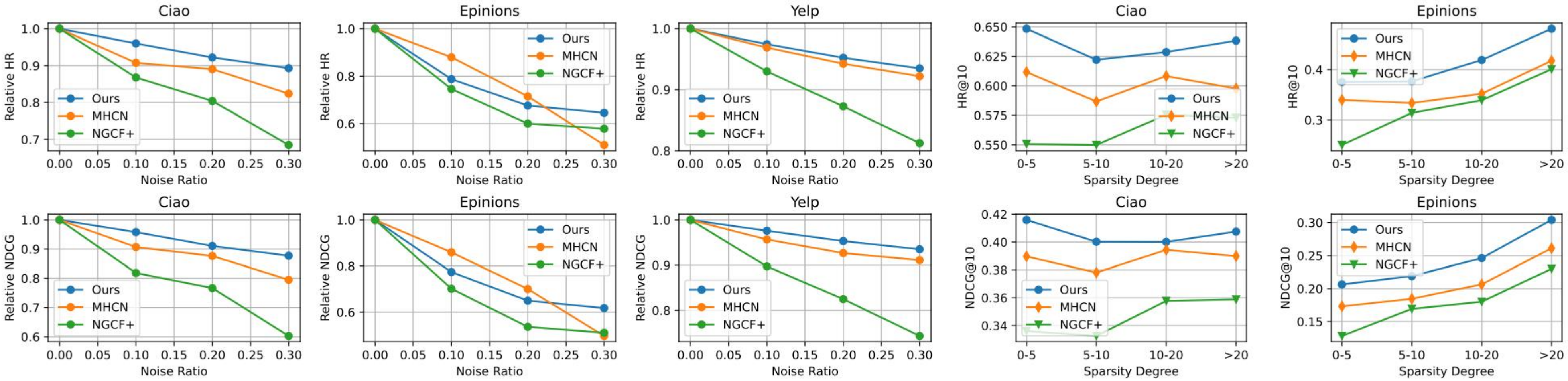


Figure 3: Model robustness study *w.r.t* data noise and data sparsity, in terms of HR@N and NDCG@N.

Experiments

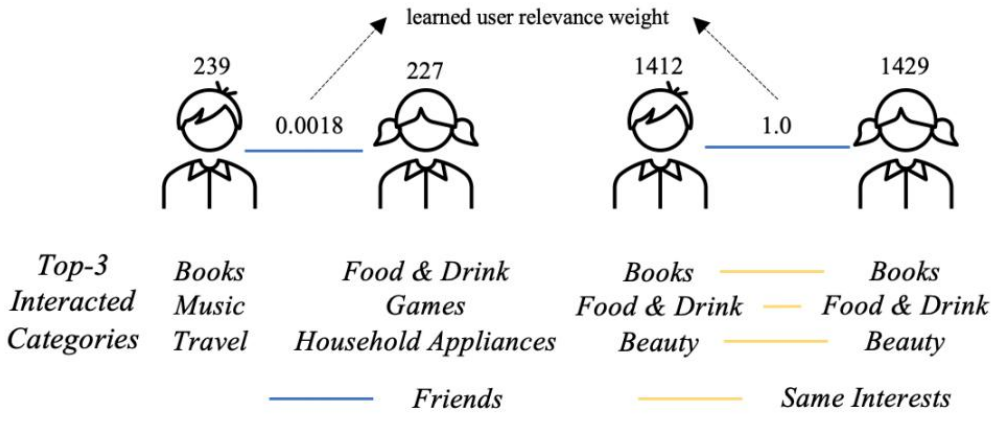


Figure 4: Case study on denoising social relations for modeling user-item interaction patterns with sampled socially-connected user pairs.

Data	DiffNet	NGCF+	MHCN	KCGN	SMIN	Our
Ciao	8.1	8.2	4.92	26.9	7.8	3.2
Epinions	39.1	16.3	9.34	49.4	19.7	6.1
Yelp	692.9	124.6	56.2	132.5	75.3	58.6

Table 5: Model computational cost measured by running time (s).

Thank you!