Dual Side Deep Context-aware Modulation for Social Recommendation

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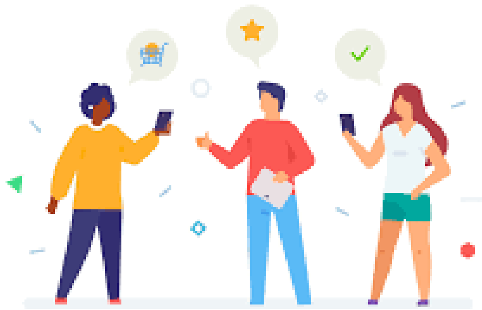
Problem

Recommendation

Social Networks



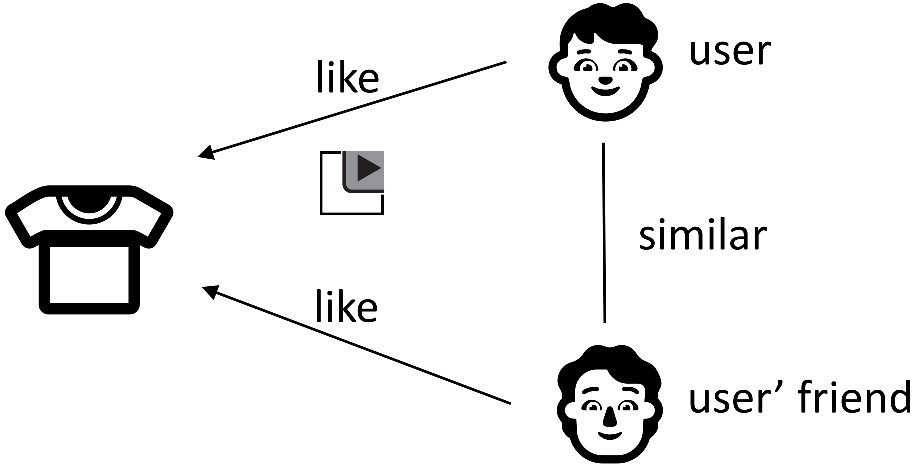
Social Recommendation

Related Works

Social Regularization

(Hao Ma, WSDM'11)

Assume that users who have social relations may have similar preference and design social regularization to restrain the user's embedding learning.



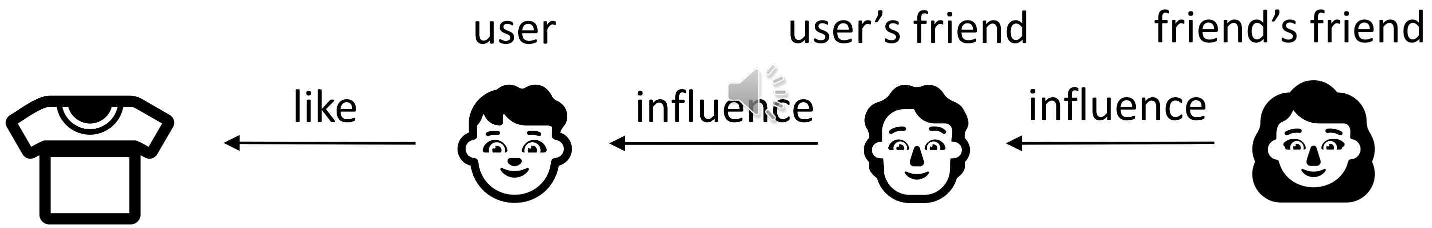
Limitation: only consider local social neighbors' information and neglect the helpful information from distant neighbors.

Related Works

High-order Social Influence

(Le Wu, TKDE'21)

Assume that connected people would influence each other based on social influence theory and aggregate their influence to enhance current user's preference.

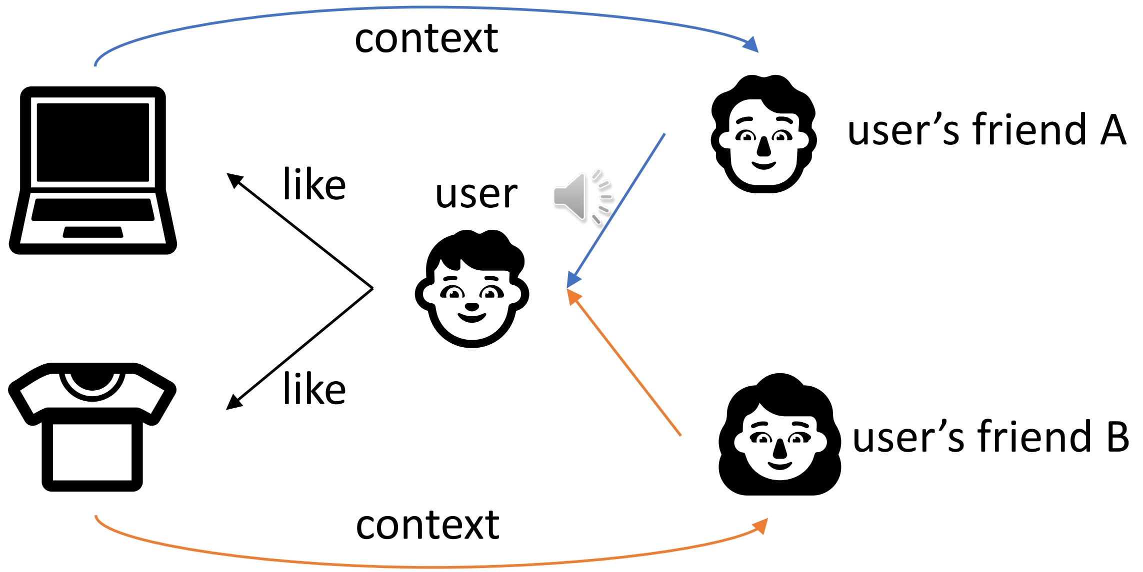


Limitation: model the friends' influence without considering the specific recommendation context.

Related Works

Context-aware Social Influence
(Chong Chen, WSDM’19)

Assume that friends’ influence strength may be different when it comes to different candidate items and consider the candidate as specific context to model the friends’ influence.

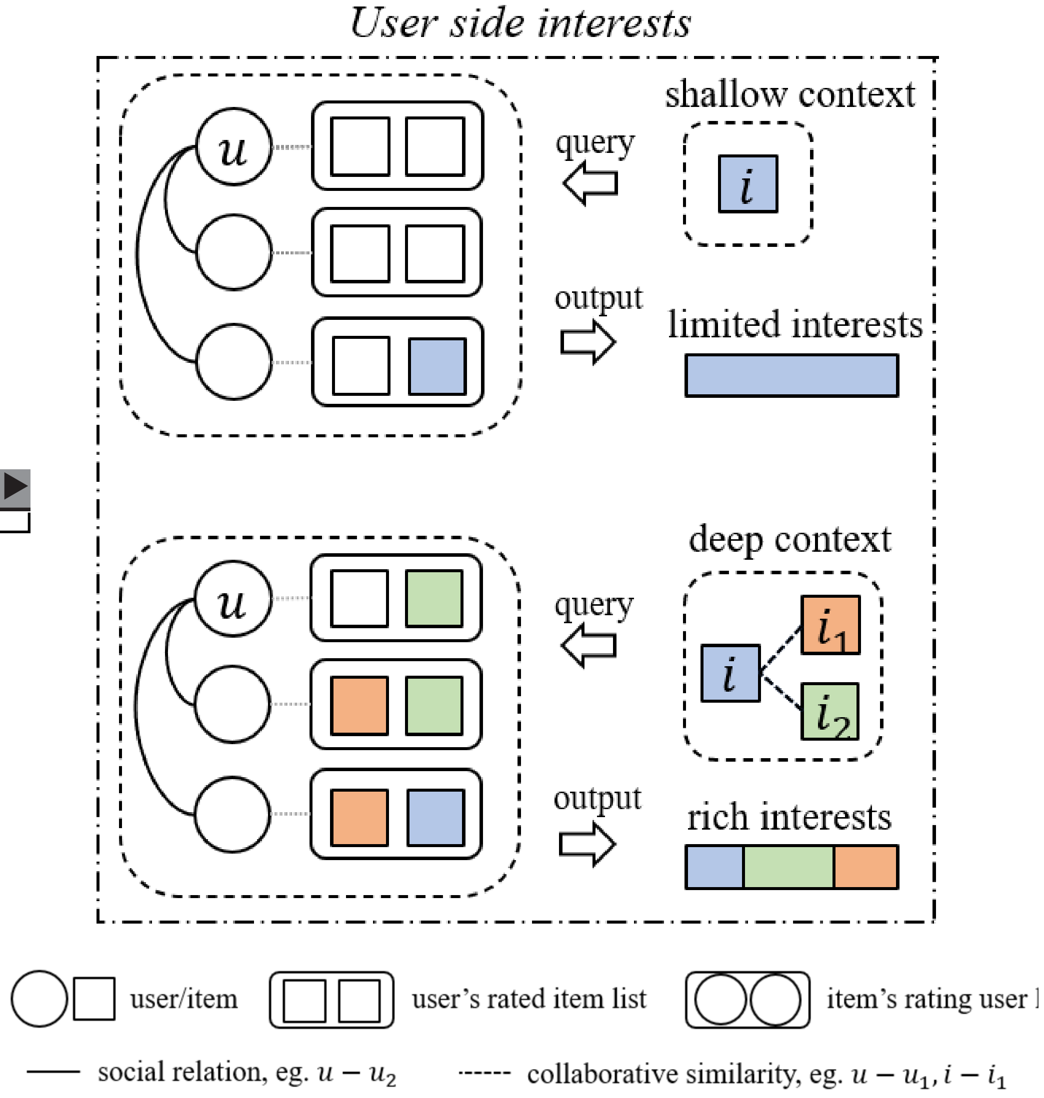


Limitation: only considering the candidate item as a (shallow) context leads to interest information biased to some extend.

Motivation

Deep context of user and friends' interest:

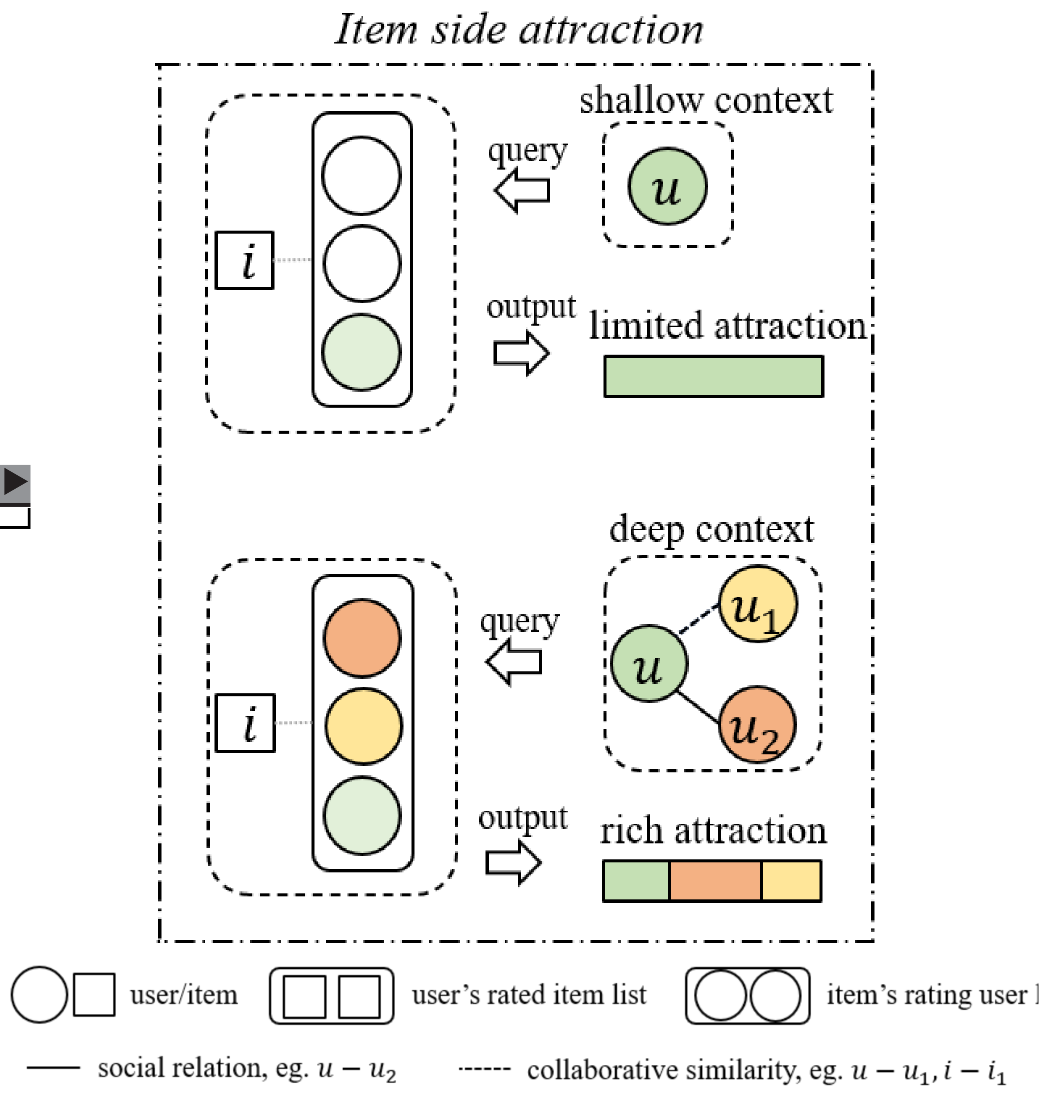
candidate item and it's similar items.



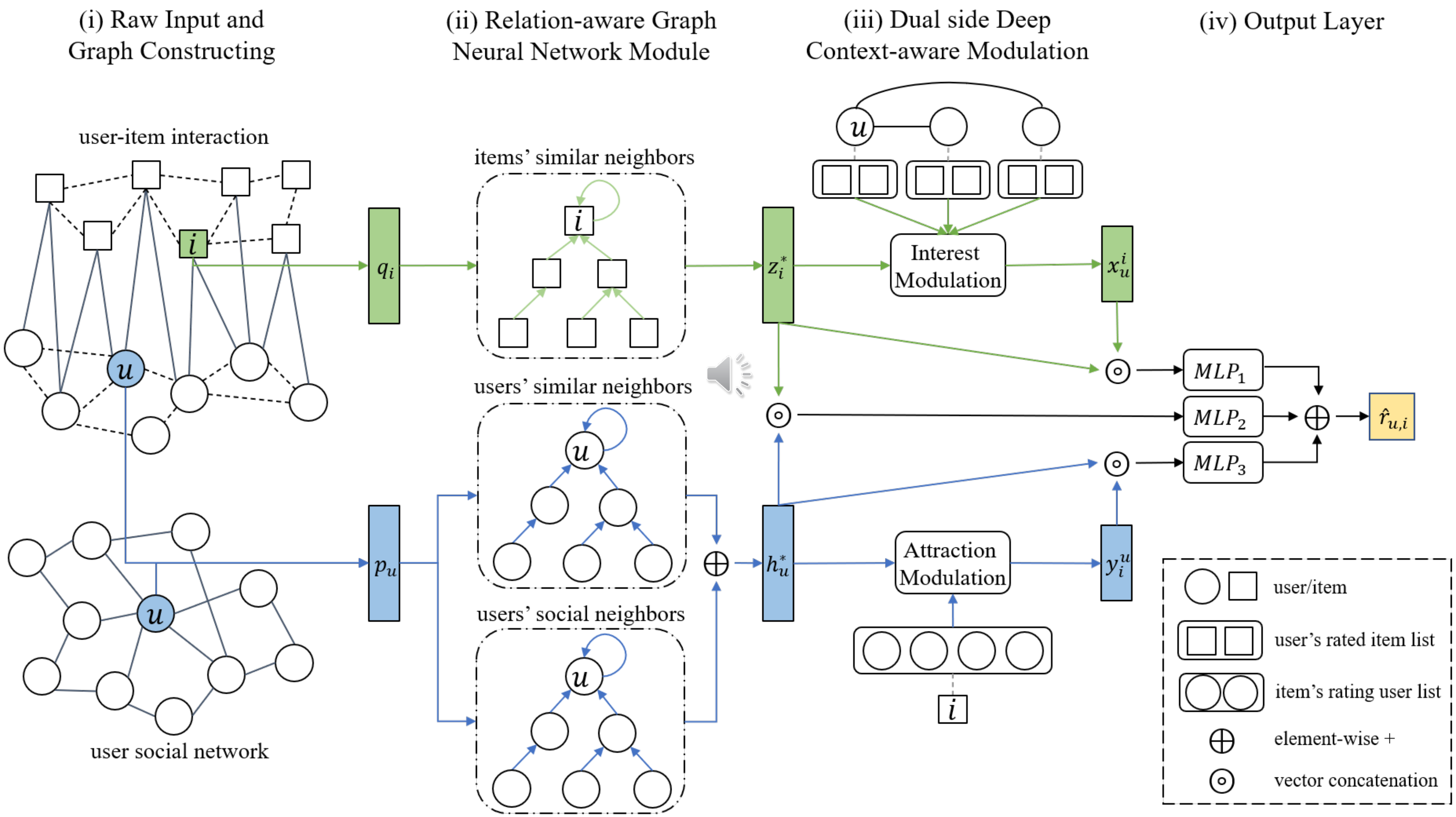
Motivation

Deep context of item attraction:

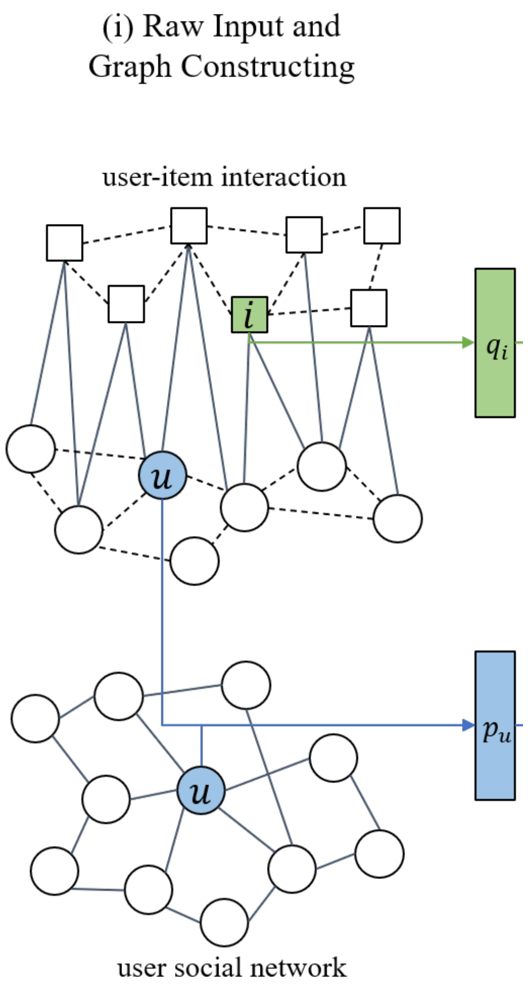
target user, her friends and her similar users.



Our Model: DICER



Raw Input and Graph Constructing



Raw Input:

user-user social network G_U^S

user-item interaction network $\mathbf{R}$

Graph Constructing:

user-user collaborative similarity network G_U^R

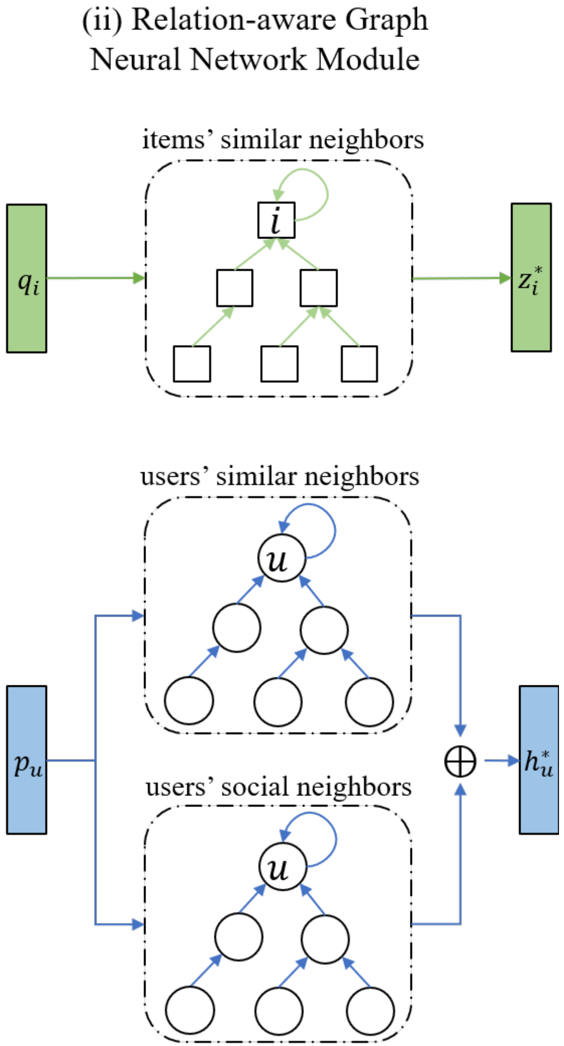
item-item collaborative similarity network G_I^R

Collaborative Similarity :

similarity strength $sim_{u,v} = \frac{|R_I(u) \cap R_I(v)|}{\sqrt{|R_I(u)| \cdot |R_I(v)|}}$

user u is similar to v if $sim_{u,v} > \eta$

High-order Relation Exploitation



Aggregate item-item collaborative similar neighbors

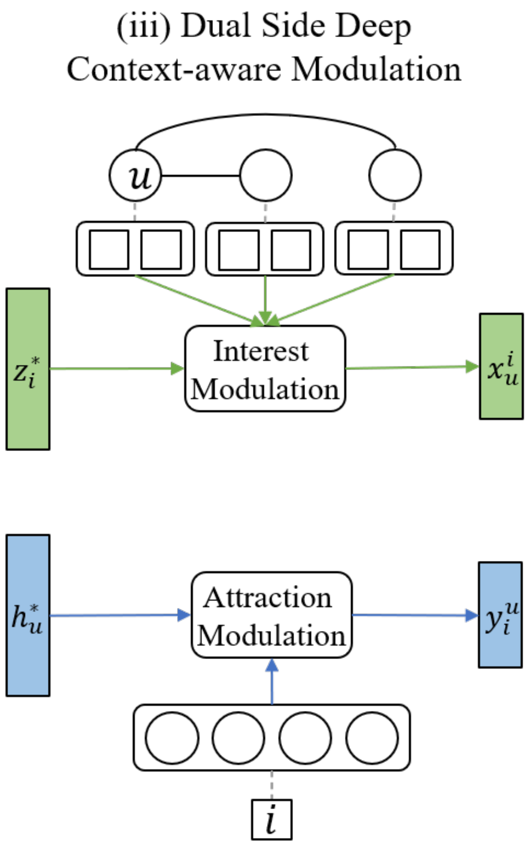
$$z_i^{l+1} = AGG_I^R\left(z_i^l,\ z_j^l, \forall j \in N_I(i)\right) = \sigma\left(\sum_{j \in N_I(i)} \left(W_1^I z_i^l + W_2^I (z_i^l \odot z_j^l)\right)\right)$$

Aggregate user-user collaborative similar neighbors

$$h_u^{R,l+1} = AGG_U^R\left(h_u^{R,l},\ h_v^{R,l}, \forall v \in N_U(u)\right) = \sigma\left(\sum_{v \in N_U(u)} \left(W_1^U h_f^{R,l} + W_2^U (h_u^{R,l} \odot h_v^{R,l})\right)\right)$$

Formulas of user social neighbors are similar

Deep Context-aware Modulation



Deep context-aware user interest modulation

$$m_u^i = f_I\left(z_i^\star,\ z_j^\star, \forall j \in R_I(u)\right) \qquad m_u^i = MP_{j\in R_I(u)}(\{z_{j,d}^\star \odot z_{i,d}^\star\}), \forall d = 1, ..., D$$

$$\alpha_{u,f}^* = (m_u^i)^\top \cdot (m_f^i) \qquad \alpha_{u,f} = \frac{exp(\alpha_{u,f}^*)}{\sum_{f\in F_U(u)} exp(\alpha_{u,f}^*)}$$

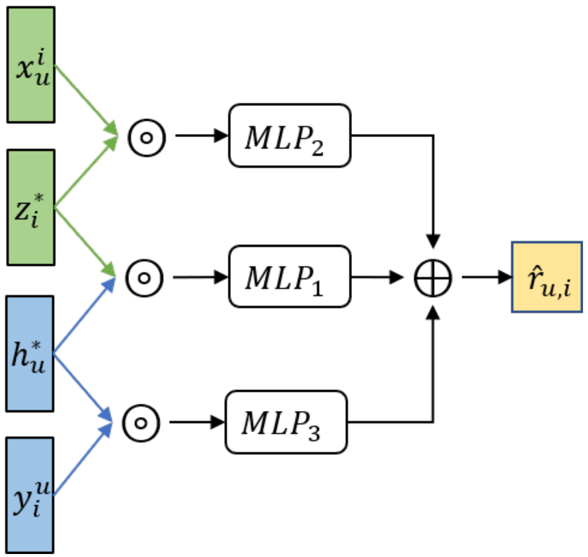
$$x_u^i = m_u^i + \sum_{f\in F_U(u)} \alpha_{u,f}\, m_f^i$$

Deep context-aware item attraction modulation

$$y_i^u = f_U\left(h_u^\star,\ h_v^\star, \forall v \in R_U(i)\right) \qquad y_i^u = MP_{v\in R_U(i)}(\{h_{v,d}^\star \odot h_{u,d}^\star\}), \forall d = 1, ..., D$$

Output Layer

(iv) Output Layer



Predict based on user-item matching perspective

$$r_{ui}^{O} = MLP_1(h_u^{\star}, z_i^{\star})$$

Predict based on user interest and item attraction perspectives

user interest: $$r_{ui}^{U} = MLP_2(x_u^{i}, z_i^{\star})$$

item attraction: $$r_{ui}^{I} = MLP_3(y_i^{u}, h_u^{\star})$$

$$\hat{r}_{u,i} = \lambda_1 r_{ui}^{O} + \lambda_2 r_{ui}^{U} + \lambda_3 r_{ui}^{I}$$

Experiments

Datasets

Ciao

Epinions

Two public datasets

Table 2: Statistics of the datasets

Dataset	*Ciao*	*Epinion*
Num. of Users	7,375	20,608
Num. of Items	106,797	23,585
Num. of Ratings	282,650	454,002
Num. of Relations	111,781	351,486
Rating Density	0.0359%	0.0934%
Relation Density	0.2055%	0.0828%

Experiments

Evaluation Protocol

Data partition

For Ciao, sequentially 80% for training, 10% for validating and 10% for testing

For Epinions, sequentially 80% for training, 10% for validating and 10% for testing

Evaluation metrics

For two datasets, *Recall@K* and *NDCG@K* for rank performance. $K = \{5, 10, 15\}$

Implementation

Python with PyTorch + Tesla v100 GPU with 32G memory

Experiments

Main Competitive Methods

Social recommendation	TrustMF	Trust matrix factorization – TPAMI’17
	TrustSVD	MF and incorporates friends’ embedding – AAAI’15
Deep learning based recommendation	NCF	Deep learning based recommendation– WWW’17
	NGCF	Graph based recommendation– SIGIR’19
Deep learning based social recommendation	SAMN	Attention Mechanism– WSDM’19
	DiffNet++	Graph Neural Network– TKDE’20

Experiments

Comparison of the Methods

Models	Social Domain		Item Domain		User Interest		Item Attraction		DL
	S	HS	I	HI	SC	DC	SC	DC	
TrustMF	√	\	√	\	\	\	\	\	\
TrustSVD	√	\	√	[illegible]	√	\	\	\	\
NCF	\	\	√	\	\	\	\	\	√
NGCF	\	\	√	√	\	\	\	\	√
SAMN	√	\	√	\	√	\	\	\	√
DiffNet++	√	√	√	√	\	\	\	\	√
DICER	√	√	√	√	√	√	√	√	√

"S" denotes the social information and "HS" denotes the high-order social information;
"I" denotes the item information and "HI" denotes the high-order item information;
"SC" denotes shallow context-aware and "DC" denotes deep context-aware;
"DL" denote deep learning based methods.

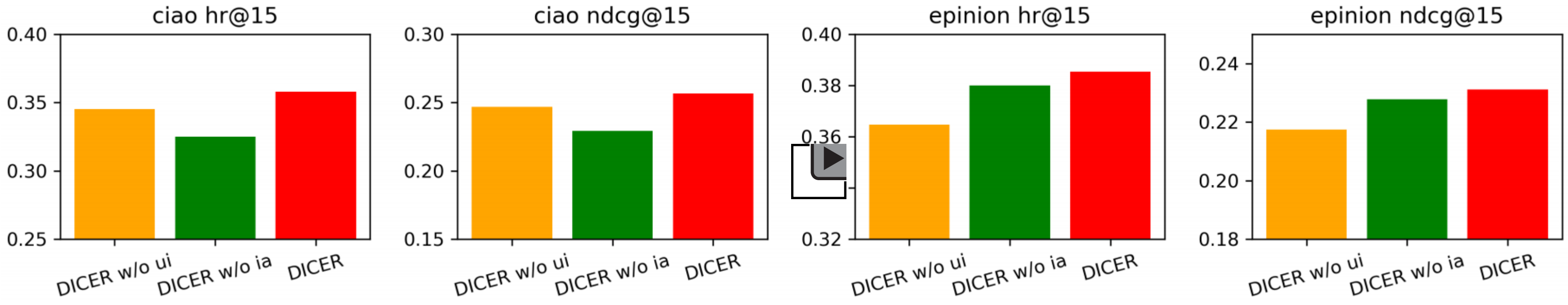
Experiments

Table1: Comparisons of different methods on two datasets. The last column “RI” indicates the relative improvement of DICER over the corresponding baseline on average.

Ciao	Recall@5	Recall@10	Recall@15	NDCG@5	NDCG@10	NDCG@15	RI
BPR	0.1782	0.2143	0.2469	0.1618	0.1720	0.1814	+42.84%
FM	0.1852	0.2269	0.2613	0.1638	0.1760	0.1861	+37.83%
TrustMF	0.2151	0.2631	0.3027	0.1916	0.2062	0.2179	+18.28%
TrustSVD	0.2159	0.2698	0.3117	0.1884	0.2056	0.2179	+17.53%
NCF	0.1840	0.2268	0.2609	0.1644	0.1773	0.1873	+37.62%
NGCF	0.2330	0.2821	0.3185	0.2063	0.2212	0.2319	+10.53%
SAMN	0.2322	0.2836	0.3245	0.2030	0.2205	0.2332	+10.40%
DiffNet++	0.2330	0.2844	0.3259	0.2063	0.2226	0.2351	+9.59%
DICER	**0.2554**	**0.3151**	**0.3579**	**0.2243**	**0.2437**	**0.2565**	
Epinion	**Recall@5**	**Recall@10**	**Recall@15**	**NDCG@5**	**NDCG@10**	**NDCG@15**	**RI**
BPR	0.1616	0.2264	0.2716	0.1253	0.1484	0.1622	+44.06%
FM	0.1592	0.2273	0.2763	0.1233	0.1476	0.1627	+44.38%
TrustMF	0.1816	0.2602	0.3163	0.1374	0.1651	0.1821	+27.75%
TrustSVD	0.1927	0.2623	0.3090	0.1466	0.1712	0.1852	+24.31%
NCF	0.1834	0.2624	0.3187	0.1397	0.1675	0.1844	+26.28%
NGCF	0.2099	0.2918	0.3488	0.1618	0.1908	0.2080	+11.80%
SAMN	0.2206	0.3055	0.3625	0.1697	0.1996	0.2170	+6.89%
DiffNet++	0.2298	0.3183	0.3786	0.1742	0.2055	0.2236	+3.21%
DICER	**0.2370**	**0.3269**	**0.3854**	**0.1818**	**0.2134**	**0.2312**	

Experiments

Figure1: Effect of dual side information on Ciao and Epinion datasets.



w/o ui: removed user interest; w/o ia: removed item attraction.

Experiments

Table2: Effect of deep context and modulation on Ciao.

Models	recall@5	recall@10	recall@15	ndcg@5	ndcg@10	ndcg@15
DICER-α	0.2307	0.2842	0.3302	0.2030	0.2193	0.2327
DICER-β	0.2340	0.2928	0.3380	0.2066	0.2251	0.2388
DICER-μ	0.2401	0.2945	0.3357	0.2108	0.2289	0.2401
DICER-$\alpha\&\beta\&\mu$	0.2187	0.2733	0.3169	0.1918	0.2093	0.2222
DICER-$attn$	0.2150	0.2688	0.3097	0.1875	0.2054	0.2179
DICER	**0.2554**	**0.3151**	**0.3579**	**0.2243**	**0.2437**	**0.2565**

-α: removed item's collaborative similarity; -β: removed user's collaborative similarity;

-μ: removed user's social relation; -$attn$: replace modulation function with a attention mechanism.

Conclusions

Our contributions can be summarized as follows

i) **General Aspects**: model user interest and item attraction under deep context.

i) **Novel Methodologies**: GNN + context–aware modulation

ii) **Multifaceted Experiments**: comparison + ablation study + parameter sensitivity

Available sources

Paper & Codes: https://arxiv.org/abs/2103.08976

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