Decomposed Collaborative Filtering: Modeling Explicit and Implicit Factors For Recommender Systems

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Outline

- Introduction
- Method
- Experiment
- Conclusion

Matrix Factorization

	i_1	i_2	i_3
u_1	1.4	X	1.1
u_2	X	0.3	X
u_3	0.4	0.3	X
u_4	1.4	X	1.2

	f_1	f_2
u_1	0.8	0.6
u_2	0.9	0.1
u_3	0.1	0.3
u_4	0.9	0.5

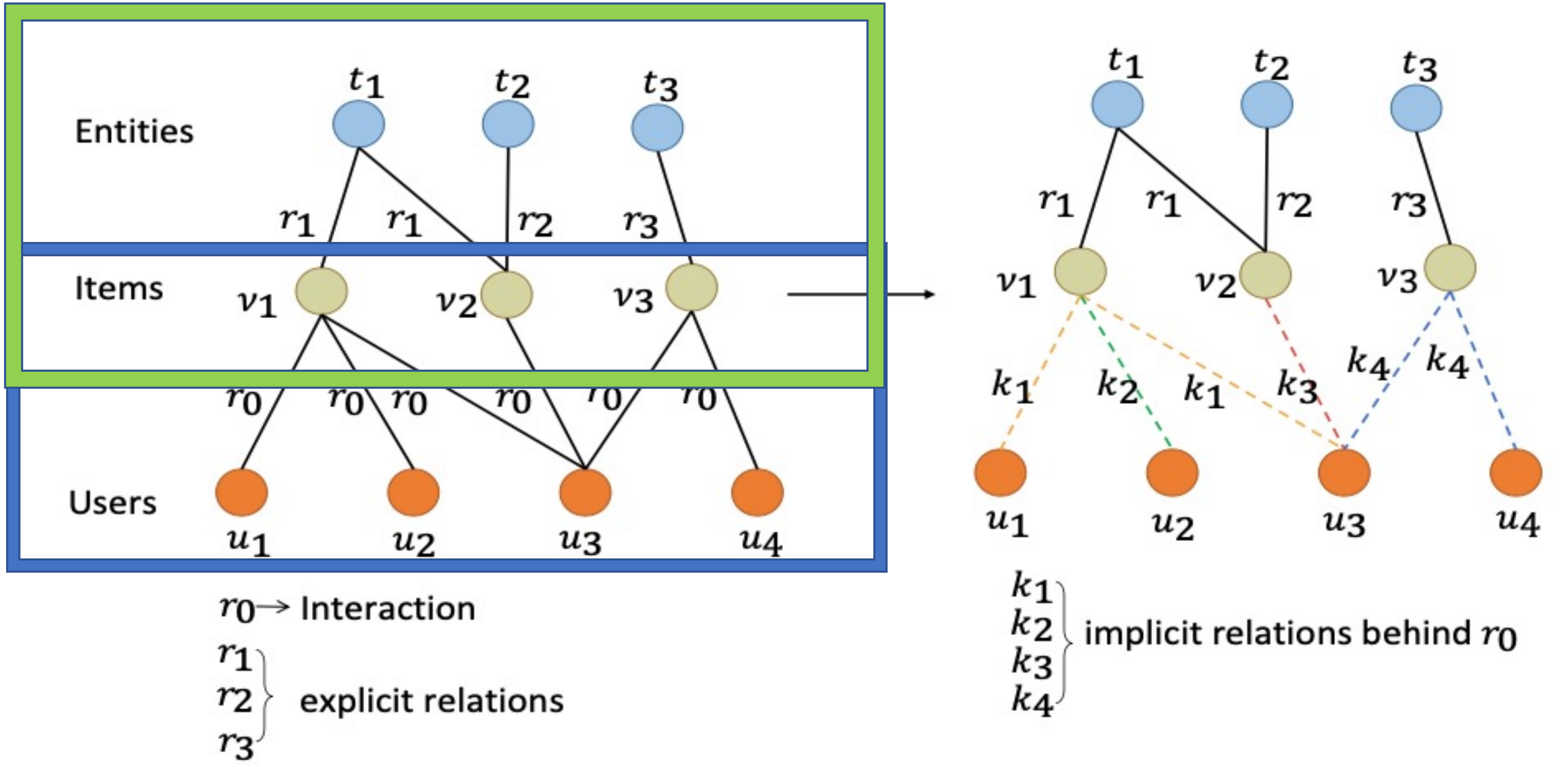
X

	i_1	i_2	i_3
f_1	1.0	0.2	1.0
f_2	1.0	1.0	0.5

only model the implicit factors

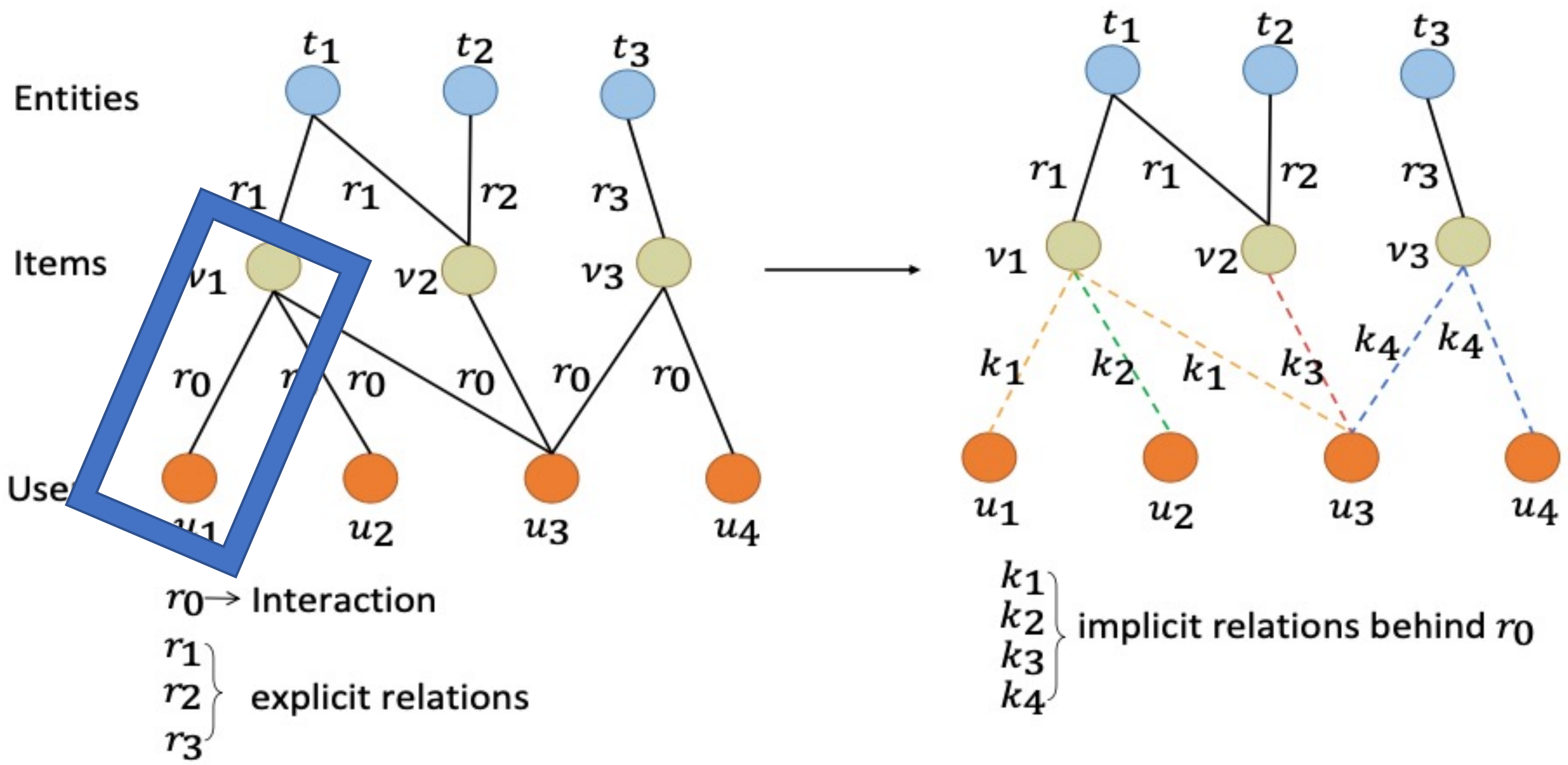
Collaborative Relation-aware Graph

Relationship between items and side information



Interaction of users and items

Input/Output



Output : predict the probability that user u will interact item v

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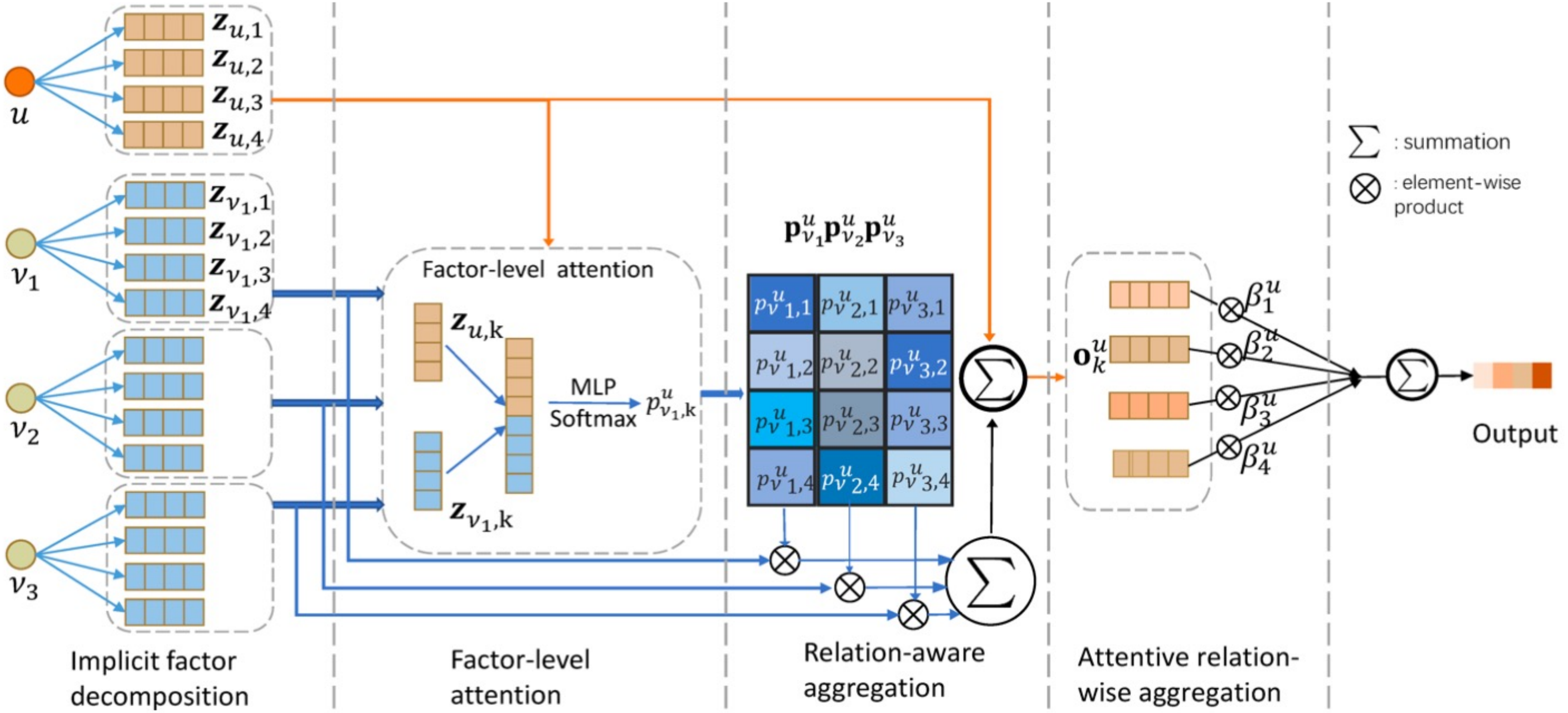
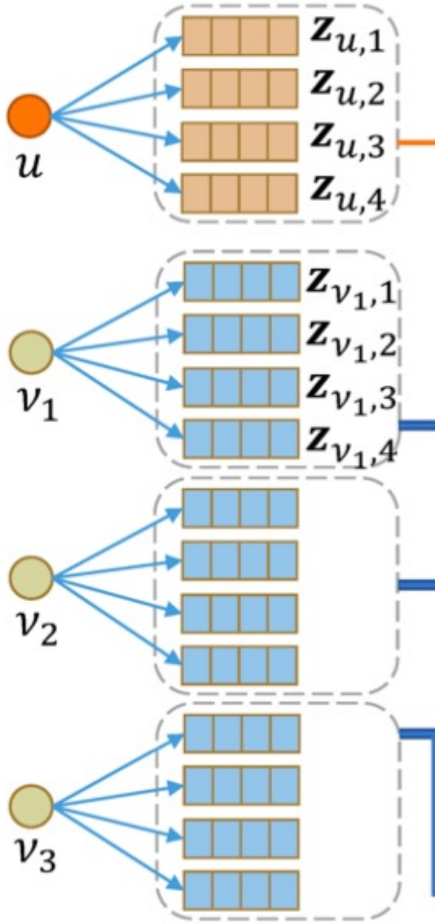
Decomposed Graph Convolutional Network (DGCN)



Implicit Factors Decomposition



Implicit factor decomposition

$$\mathcal{N}_u = \{i | y_{ui} = 1\}$$ user u and his interacted items set

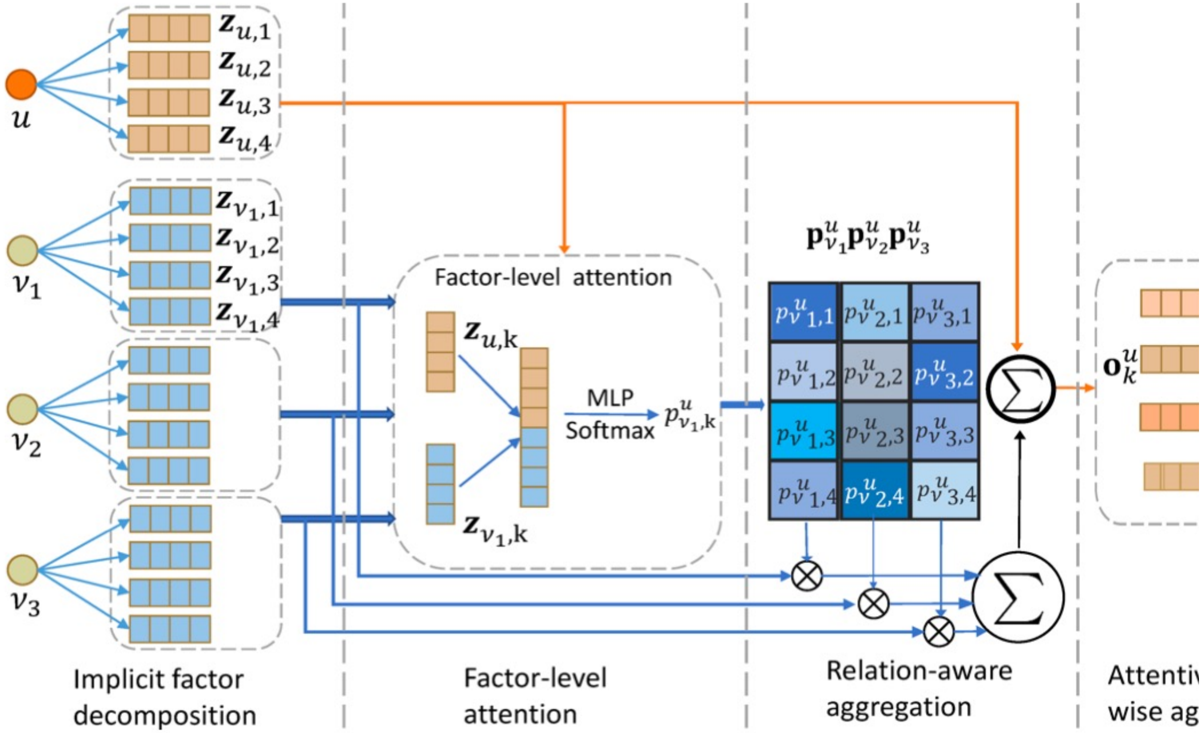
$$\mathbf{e}_u \in \mathbb{R}^d \text{ and } \{\mathbf{e}_i \in \mathbb{R}^d | i \in \mathcal{N}_u\}$$

$$\mathbf{z}_{u,k} = \sigma\left(\mathbf{W}_k^\top \mathbf{e}_u + \mathbf{b}_k\right), k = 1, 2, .., K,$$

$$\mathbf{z}_{i,k} = \sigma\left(\mathbf{W}_k^\top \mathbf{e}_i + \mathbf{b}_k\right), k = 1, 2, .., K.$$

$$\underset{4\times 4}{\overset{W_k^T}{[\quad\quad]}}\ \underset{4\times 1}{\overset{e_u}{[\ ]}} + \underset{4\times 1}{\overset{bias}{[\ ]}} = \underset{4\times 1}{\overset{z_{u,k}}{[\ ]}}$$

Factor-level attention network



$$\mathbf{p}_i^u = [p_{i,1}^u,\ p_{i,2}^u,\ p_{i,3}^u,\ \dots,\ p_{i,K}^u]$$

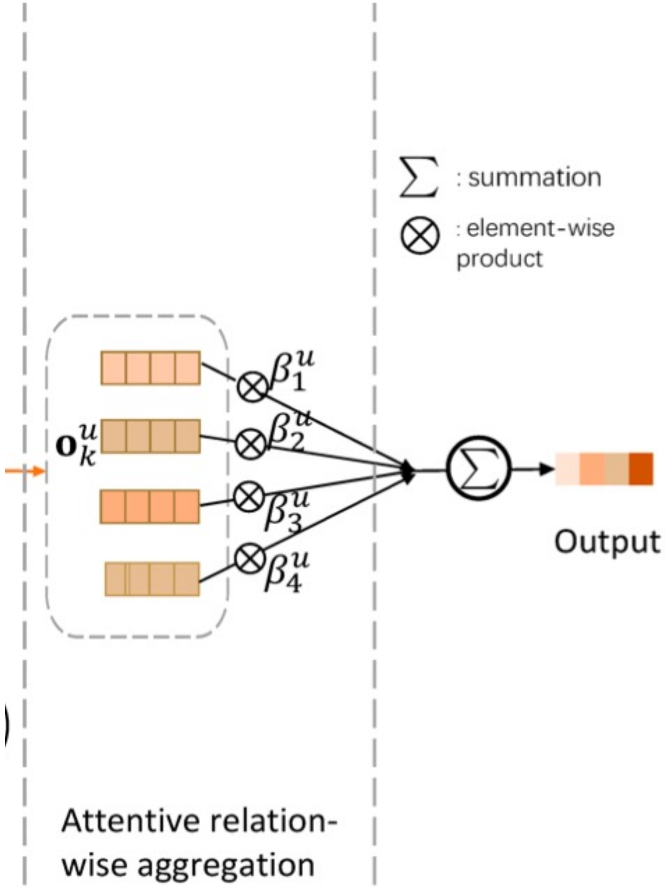
$$\tilde{p}_{i,k}^u = ReLU(\mathbf{W}_p^\top[\mathbf{z}_{i,k}, \mathbf{z}_{u,k}] + b_p),$$

$$p_{i,k}^u = \frac{\exp(\tilde{p}_{i,k}^u)}{\sum_{k'=1}^K \exp(\tilde{p}_{i,k'}^u)}, \forall i \in \mathcal{N}_u,$$

$p_{i,k}^u$ the probability i,k
that factor k is the reason why user u interacts item i

$$\mathbf{o}_k^u = ReLU(\mathbf{z}_{u,k} + \sum_{i \in \mathcal{N}_u} p_{i,k}^u \mathbf{z}_{i,k}), k = 1, 2, .., K$$

Attentive implicit relation-wise aggregation



$$\tilde{\beta}_k^u = \mathbf{ReLU}(\mathbf{W}\mathbf{o}_k^u + b),$$

$$\beta_k^u = \frac{exp(\tilde{\beta}_k^u)}{\sum_{k' \in \mathcal{R}^-} exp(\tilde{\beta}_{k'}^u)}.$$

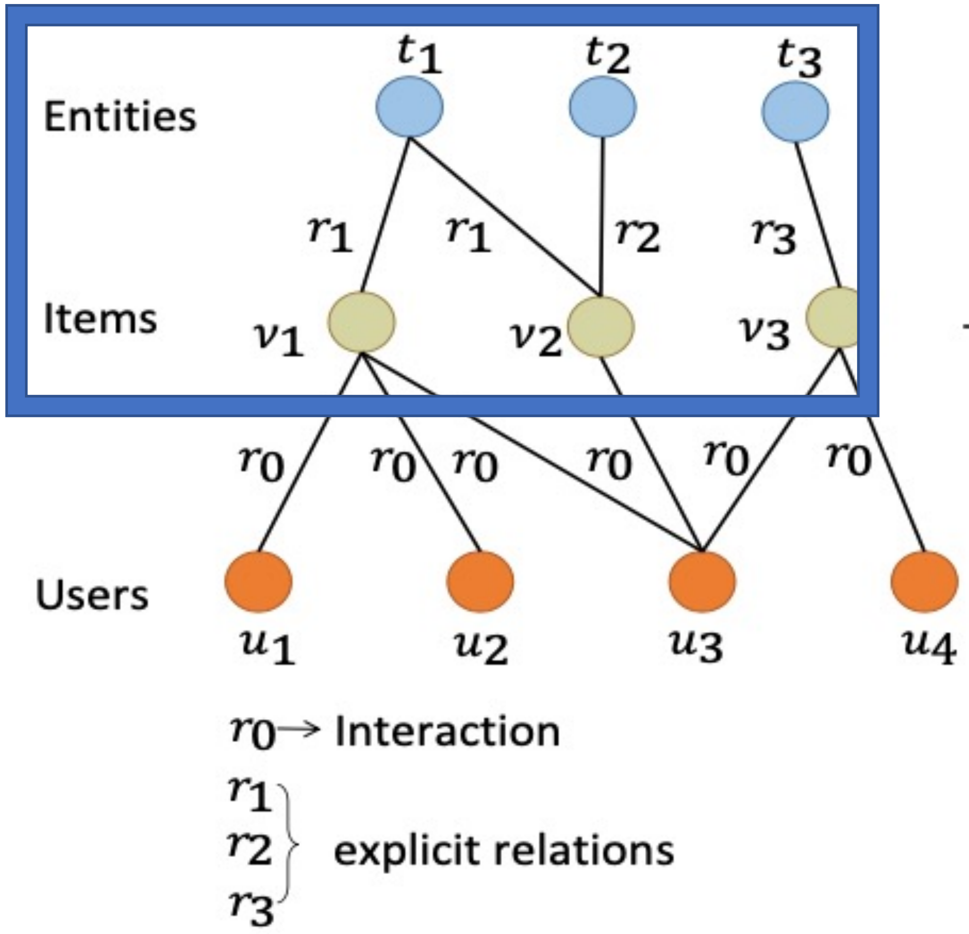
$$\mathbf{e}'_u = \sigma\Big(\sum_{k \in \mathcal{R}^-} \beta_k^u \mathbf{o}_k^u\Big).$$

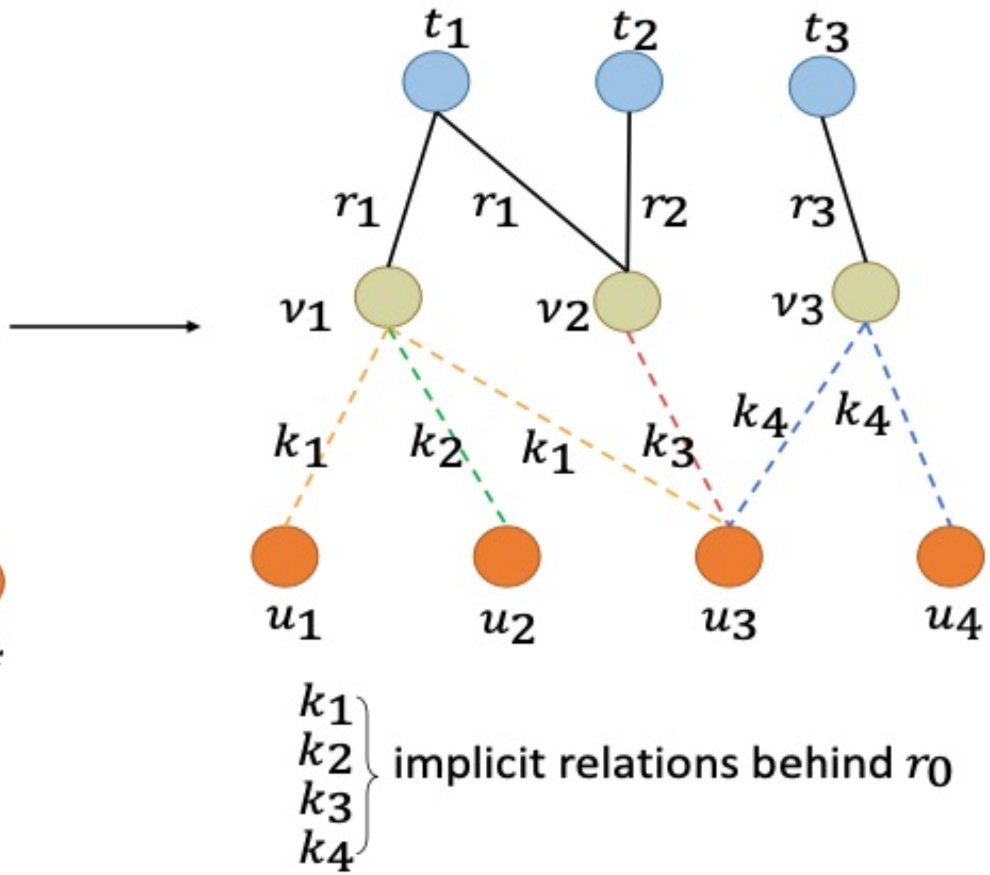
Disagreement regularization

$$\mathcal{L}_{dr\_cos} = \sum_{x \in \mathcal{U} \cup \mathcal{V}} \sum_{k_1=1}^{K} \sum_{k_2=k_1+1}^{K} \frac{\mathbf{o}_{k_1}^{x} \odot \mathbf{o}_{k_2}^{x}}{||\mathbf{o}_{k_1}^{x}|| \cdot ||\mathbf{o}_{k_2}^{x}||},$$

$$\mathcal{L}_{dr\_inner} = \sum_{x \in \mathcal{U} \cup \mathcal{V}} \sum_{k_1=1}^{K} \sum_{k_2=k_1+1}^{K} \left\| \mathbf{o}_{k_1}^{x} \odot \mathbf{o}_{k_2}^{x} \right\|_2 .$$

Explicit Relation Modeling





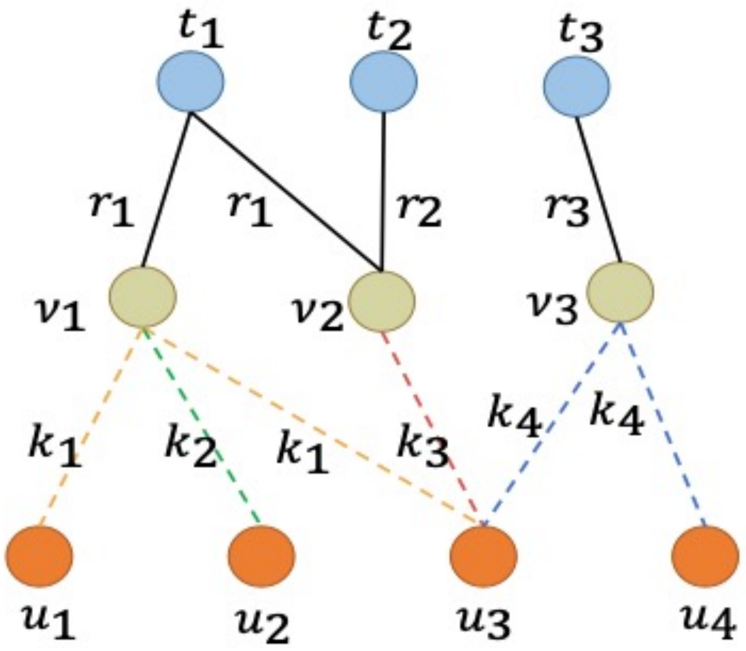
Explicit Relation Modeling

$$\tilde{\pi}(u, r, t) = \mathbf{e}_u^\top(\mathbf{e}_r + \mathbf{e}_t).$$

$$\pi(u, r, t) = \frac{\exp(\tilde{\pi}(u, r, t))}{\sum_{(r', t') \in \mathcal{N}_h^+} \exp(\tilde{\pi}(u, r', t'))}.$$

$$\mathbf{e}_{\mathcal{N}_h^+} = \sum_{(r', t') \in \mathcal{N}_h^+} \pi(u, r', t')\mathbf{e}_{t'}.$$

$$\mathbf{e}'_v = \sigma(\mathbf{W}_{agg}(\mathbf{e}_h + \mathbf{e}_{\mathcal{N}_h^+}) + f(\mathbf{e}_h, \{\mathbf{e}_t | t \in \mathcal{N}_h^-\})),$$



High-order Connectivity Modeling

$$\mathbf{e}_h^{(l)} = \sigma\Big(\sum_{k \in \mathcal{R}^+ \cup \mathcal{R}^-} \gamma_k^{(l)}\Big(\sum_{j \in \mathcal{N}_h^k} \alpha_{j,k}^{(l)} \mathbf{W}_k^{(l)} \mathbf{e}_j^{(l-1)} + \mathbf{W}_k^{(l)} \mathbf{e}_h^{(l-1)}\Big)\Big),$$

Model learning

$$\mathbf{u} = \mathbf{e}_u^{(0)} + \mathbf{e}_u^{(1)} + \ldots + \mathbf{e}_u^{(L)}, \mathbf{v} = \mathbf{e}_v^{(0)} + \mathbf{e}_v^{(1)} + \ldots + \mathbf{e}_v^{(L)},$$

$$\hat{y}_{uv} = \sigma(\mathbf{u}^{\mathrm{T}}\mathbf{v})$$

$$\begin{aligned}\mathcal{L} =& \mathcal{L}_{rs} + \lambda_1 \mathcal{L}_{dr\_inner} + \lambda_2 \mathcal{L}_{reg} \\ =& \sum_{u \in \mathcal{U}, v \in \mathcal{V}} \mathcal{J}(\hat{y}_{uv}, y_{uv}) \\ &+ \frac{\lambda_1}{2} \sum_{x \in \mathcal{U} \cup \mathcal{V}} \left\| \Big(\sum_{k=1}^{K} \mathbf{o}_k^x \Big)^2 - \sum_{k=1}^{K} (\mathbf{o}_k^x)^2 \right\|_2 + \lambda_2 \left\| \Theta \right\|_2\end{aligned}$$

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Dataset

	Movie	Book	Music
# users	138159	17860	1872
# items	16954	14967	3846
# interactions	13501622	139746	42346
# entities	102569	77903	9366
# explicit relations	32	25	60
# KG triples	499474	151500	15518

Experiment

Table 2: The results of Recall@N in top-N recommendation. Boldface denotes best baseline, and * denotes the significan *p*-value < 0.01 compared with the best baseline.

Methods	MovieLens-20M			Book-Crossing			Last.FM		
	Recall@5	Recall@10	Recall@20	Recall@5	Recall@10	Recall@20	Recall@5	Recall@10	Recall@20
MF	0.0879	0.1433	0.1843	0.0442	0.0568	0.0736	0.0718	0.1236	0.1766
CKE	0.0764	0.1303	0.1721	0.0452	0.0575	0.0733	0.0768	0.1346	0.2034
RippleNet	0.0878	0.1324	0.1798	0.0546	0.0711	0.0837	0.0732	0.1199	0.1501
KGCN	**0.0901**	0.1425	0.1995	**0.0631**	**0.0792**	0.0847	0.0735	0.1289	0.1826
PinSage	0.0893	**0.1492**	0.2124	0.0549	0.0751	0.0780	0.0816	0.1453	0.2113
NGCF	0.0842	0.1439	**0.2149**	0.0588	0.0734	0.0837	**0.0896**	**0.1459**	**0.2142**
DisenGCN	0.0832	0.1389	0.2116	0.0572	0.0704	**0.0874**	0.0893	0.1419	0.2114
DCF	**0.0927***	**0.1572***	**0.2295***	**0.0745***	**0.0927***	**0.1018***	**0.0975***	**0.1536***	**0.2230***
% improve.	2.89%	5.36%	6.79%	18.07%	17.05%	19.57%	8.81%	5.28%	4.11%

Experiment

Table 3: The results of NDCG@N in top-N recommendation. Boldface denotes best baseline, and * denotes the significance *p*-value < 0.01 compared with the best baseline.

Methods	MovieLens-20M			Book-Crossing			Last.FM		
	NDCG@5	NDCG@10	NDCG@20	NDCG@5	NDCG@10	NDCG@20	NDCG@5	NDCG@10	NDCG@20
MF	0.0895	0.1179	0.1279	0.0375	0.0465	0.0579	0.0602	0.0763	0.0807
CKE	0.0812	0.1016	0.1195	0.0402	0.0447	0.0494	0.0612	0.0801	0.0977
RippleNet	0.0905	0.1115	0.1212	0.0478	0.0535	0.0578	0.0621	0.0798	0.0819
KGCN	0.0936	0.1126	0.1373	**0.0584**	**0.0627**	**0.0654**	0.0619	0.0832	0.1013
PinSage	**0.0917**	**0.1310**	**0.1586**	0.0516	0.0587	0.0599	0.0688	0.0951	0.1103
NGCF	0.0904	0.1249	0.1568	0.0535	0.0592	0.0616	0.0711	**0.0991**	**0.1232**
DisenGCN	0.0786	0.1096	0.1475	0.0453	0.0499	0.0642	**0.0759**	0.0947	0.1198
DCF	**0.0992***	**0.1341***	**0.1690***	**0.0682***	**0.0749***	**0.0790***	**0.0789***	**0.1028***	**0.1289***
% improve.	8.18%	2.37%	6.56%	16.78%	19.46%	20.80%	10.97%	3.73%	4.62%

Experiment

Table 4: The results of AUC in CTR prediction.

	MovieLens-20M	Book-Crossing	Last.FM
MF	0.961(-2.1%)	0.692(-6.7%)	0.809(-2.5%)
CKE	0.925(-6.1%)	0.678(-8.8%)	0.802(-3.4%)
RippleNet	0.972(-0.9%)	0.715(-3.2%)	0.787(-5.3%)
KGCN	0.978(-0.3%)	0.735(-0.4%)	0.798(-3.9%)
PinSage	0.980(-0.1%)	0.719(-2.6%)	0.808(-2.6%)
NGCF	0.979(-0.2%)	0.717(-2.9%)	0.817(-1.5%)
DisenGCN	0.980(-0.1%)	0.717(-2.9%)	0.816(-1.6%)
DCF	**0.981**	**0.738**	**0.829**

Experiment

Table 5: Recall@20 results of different number of implicit relations for three datasets.

K	1	2	3	4	5	6
Movie	0.1985	0.2063	0.2245	**0.2295**	0.2146	0.2132
Book	0.0896	0.1031	0.0977	**0.1074**	0.1024	0.1018
Music	0.201	0.2036	0.2098	**0.2210**	0.2079	0.2068

Impact of number of fine-grained implicit relations

Experiment

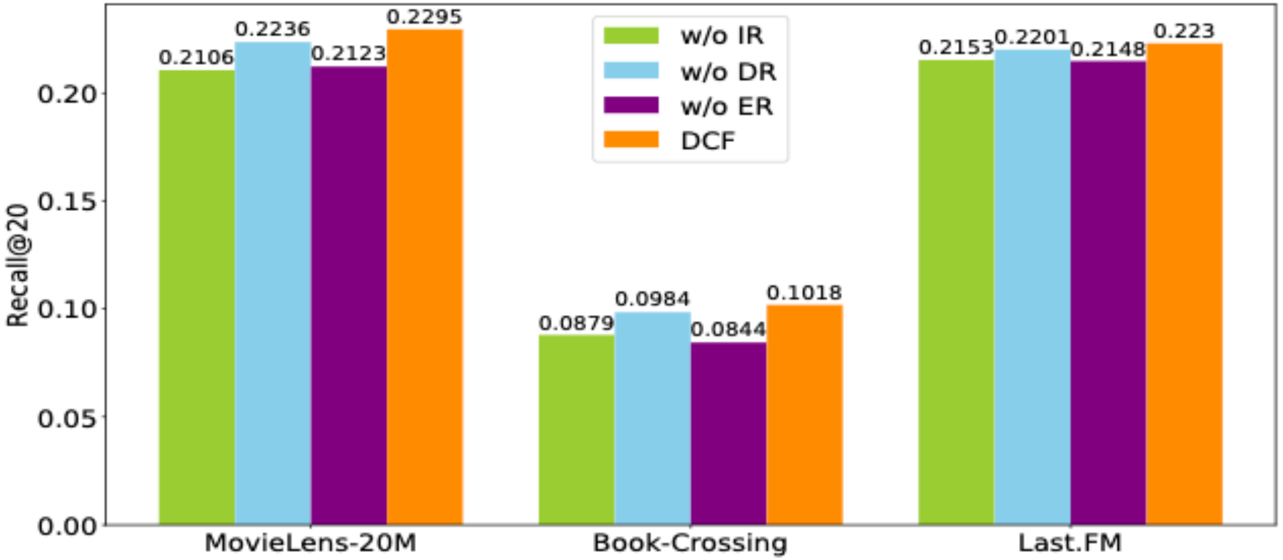
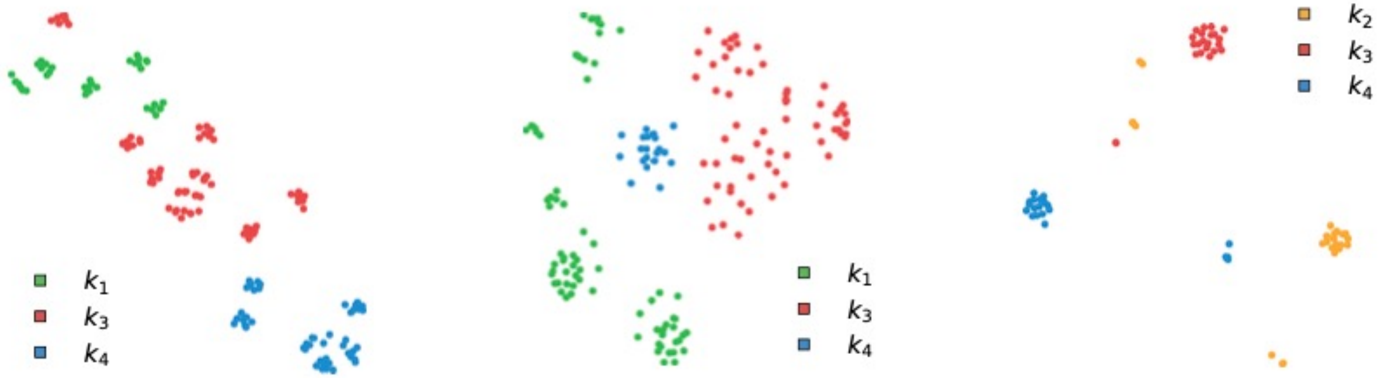


Figure 4: Performance comparison of three different variants of DCF.

Experiment



(a) u_{14916} (b) u_{5499} (c) u_{13497}

Figure 5: Interacted item embedding visualization using t-SNE of three users on Book-Crossing dataset. Items that are interacted by the user due to the same fine-grained implicit factor k_i tend to cluster together.

Experiment

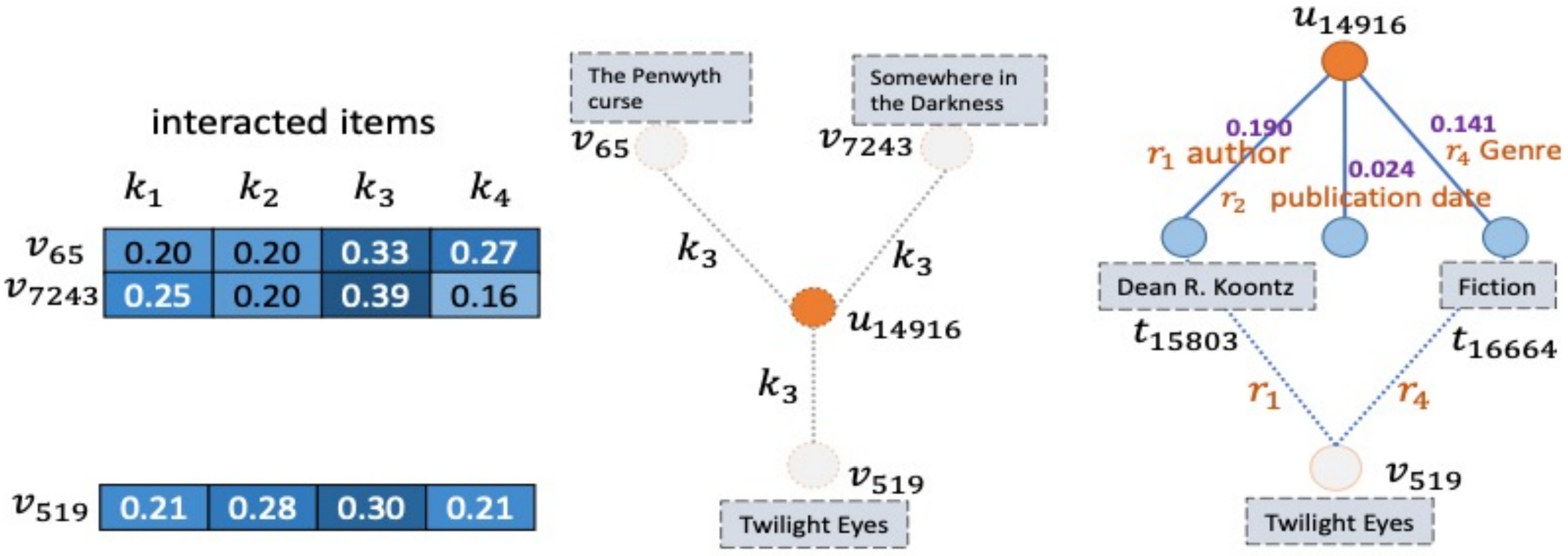


Figure 6: Real example from Book-Crossing dataset. Left figure is the factor-level attention weight of interacted items and recommended item, center figure reveals the relationship from implicit perspective, and right figure indicates their association from explicit perspective.

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Conclusion

- propose Decomposed Graph Convolutional Network (DGCN)
  - decomposes users and items into multiple factor-level representations
  - utilizes factor-level attention and attentive relation aggregation to model implicit factors behind collaborative signals in fine-grained level

- To capture explicit factors, they devise a user-specific relation aggregator to aggregate the most import entities