Disentangled Graph Contrastive Learning for Review-based Recommendation

Yuyang Ren
Shanghai Jiao Tong University
renyuyang@sjtu.edu.cn

Haonan Zhang
Shanghai Jiao Tong University
zhanghaonan@sjtu.edu.cn

Qi Li
Shanghai Jiao Tong University
liqilcn@sjtu.edu.cn

Luoyi Fu
Shanghai Jiao Tong University
yiluofu@sjtu.edu.cn

Jiaxin Ding
Shanghai Jiao Tong University
jiaxinding@sjtu.edu.cn

Xinde Cao
Shanghai Jiao Tong University
xdcaosjtu@outlook.com

Xinbing Wang
Shanghai Jiao Tong University
xwang8@sjtu.edu.cn

Chenghu Zhou
Institute of Geographical Sciences
and Natural Resources Research,
Chinese Academy of Sciences
zhouch@lreis.ac.cn

IJCAI 2023
Code: None

Reported by liang li

Motivation

Details：

- However, these methods usually model user-item interactions in a holistic manner and neglect the entanglement of the latent factors behind them, e.g., price, quality, or appearance, resulting in suboptimal representations and reducing interpretability.

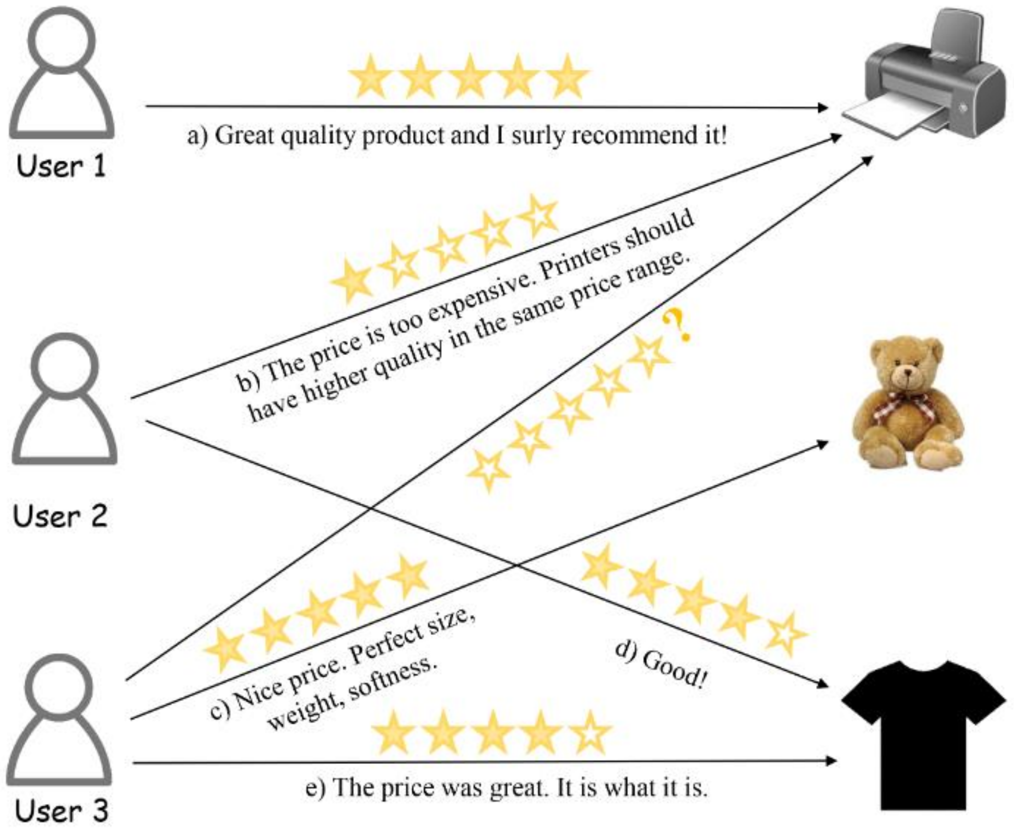


Figure 1: An example of user-item rating graph.

Problem Statement

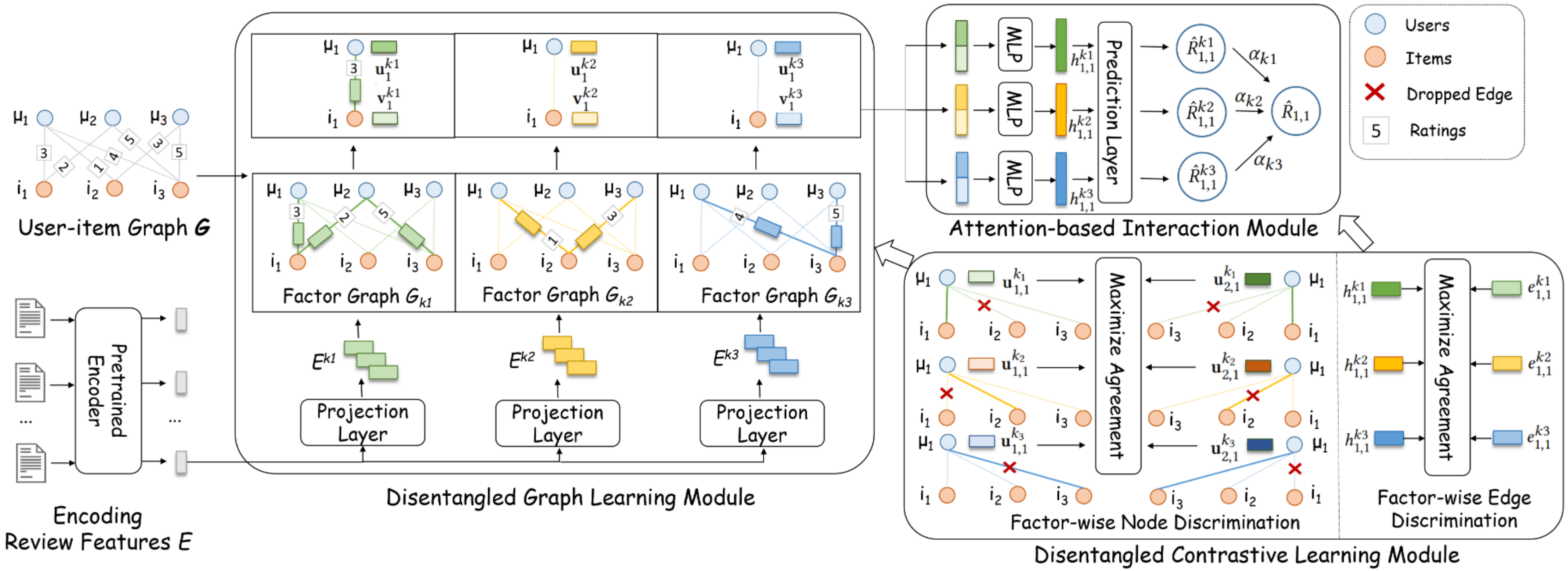


Figure 2: Overview of DGCLR. For clarity, we show the pipeline to generate the rating prediction for one user-item interaction.

$$R \in \mathbb{R}^{M\times N}$$

$$E \in \mathbb{R}^{M\times N\times d}$$

$$\mathcal{E} = (R, E)$$

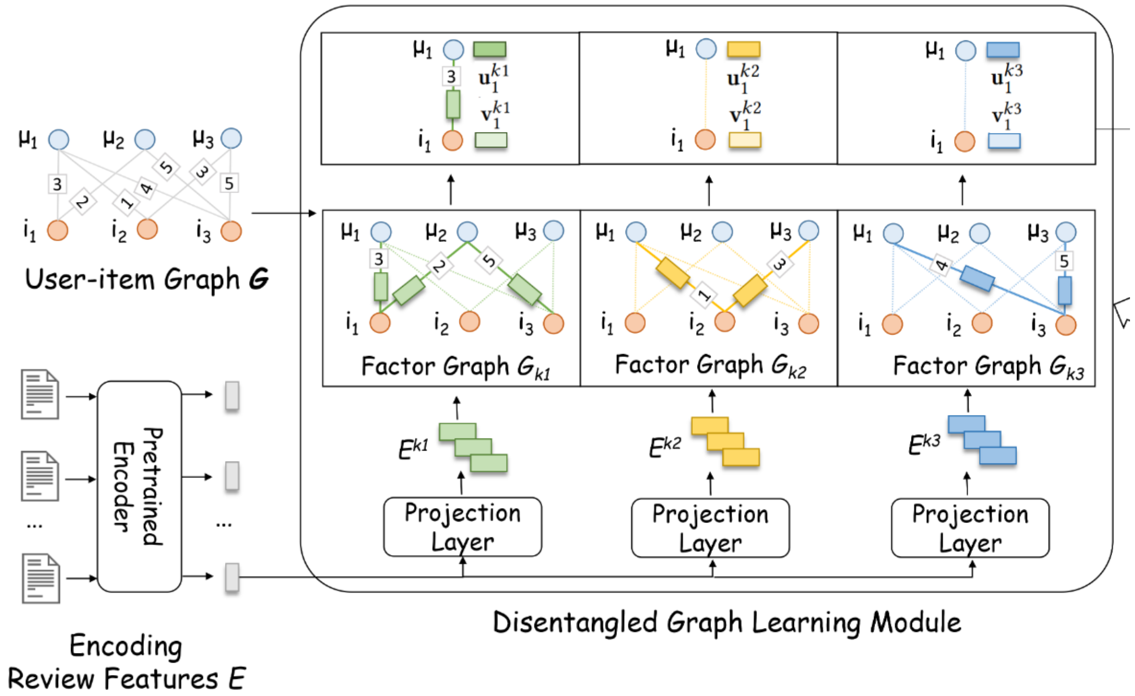
$$G = (\mathcal{U} \cup \mathcal{I}, \mathcal{E})$$

$$\mathrm{u}_i^{(0)} = (\mathrm{u}_i^{1,(0)}, \mathrm{u}_i^{2,(0)}, \ldots, \mathrm{u}_i^{K,(0)}) \quad (1) \qquad \mathrm{u}_i^{k,(0)} \in \mathbb{R}^{\frac{d}{K}}$$

$$\mathrm{v}_j^{(0)} = (\mathrm{v}_j^{1,(0)}, \mathrm{v}_j^{2,(0)}, \ldots, \mathrm{v}_j^{K,(0)})$$

$$\mathrm{e}_{i,j}^k = \sigma\left(\mathrm{W}_k^{\top}\mathrm{e}_{i,j} + \mathrm{b}_k\right) \quad (2)$$

Method



$$\mathrm{se}_{i,j}^{k}=\frac{\exp\left(\phi\left(\mathrm{e}_{i,j}^{k},\mathrm{c}_{k}\right)/\tau\right)}{\sum_{k'=1}^{K}\exp\left(\phi\left(\mathrm{e}_{i,j}^{k'},\mathrm{c}_{k'}\right)/\tau\right)} \tag{3}$$

$$\mathrm{st}_{i,j}^{k,(l)}=\frac{\exp\left(\phi\left(\mathrm{u}_{i}^{k,(l-1)},\mathrm{v}_{j}^{k,(l-1)}\right)/\tau\right)}{\sum_{k'=1}^{K}\exp\left(\phi\left(\mathrm{u}_{i}^{k',(l-1)},\mathrm{v}_{j}^{k',(l-1)}\right)/\tau\right)} \tag{4}$$

$$\mathrm{s}_{i,j}^{k,(l)}=\eta\,\mathrm{se}_{i,j}^{k}+(1-\eta)\,\mathrm{st}_{i,j}^{k,(l)} \tag{5}$$

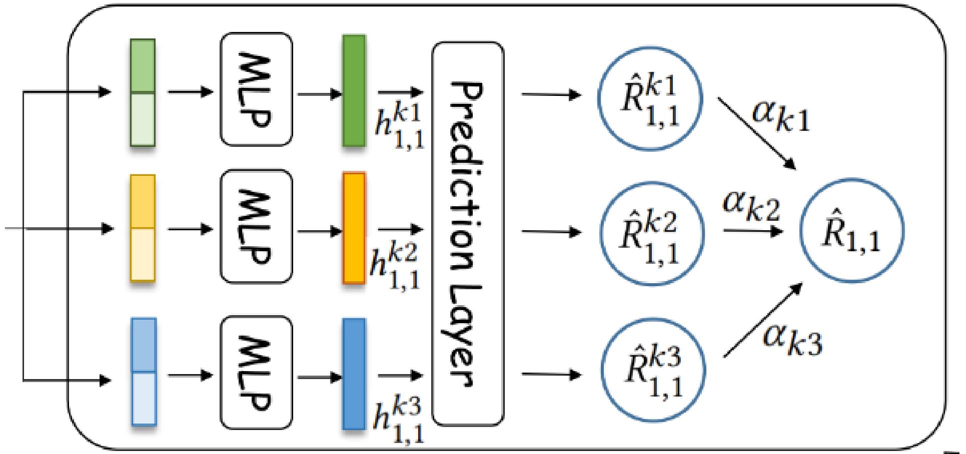
$$\mathrm{x}_{r;j\rightarrow i}^{k,(l)}=\frac{\mathrm{s}_{i,j}^{k,(l)}\left(\mathrm{e}_{ij}^{k}\cdot\mathrm{W}_{r}^{k,(l)}+\mathrm{v}_{j}^{k,(l-1)}\right)}{\sqrt{\left|\mathcal{D}_{j}^{k,(l)}\right|\left|\mathcal{D}_{i}^{k,(l)}\right|}}, \tag{6}$$

$$\mathcal{D}_{i}^{k,(l)}=\sum_{p\in\mathcal{N}(i)}\mathrm{s}_{i,p}^{k,(l)}\qquad\mathcal{D}_{j}^{k,(l)}=\sum_{p\in\mathcal{N}(j)}\mathrm{s}_{p,j}^{k,(l)}$$

$$\mathrm{u}_{i}^{k,(l)}=\mathrm{W}^{(l)}\sum_{r\in\mathcal{R}}\sum_{p\in\mathcal{N}_{i,r}}\mathrm{x}_{r;p\rightarrow i}^{k,(l)},\qquad\mathrm{v}_{j}^{k,(l)}=\mathrm{W}^{(l)}\sum_{r\in\mathcal{R}}\sum_{p\in\mathcal{N}_{j,r}}\mathrm{x}_{r;p\rightarrow j}^{k,(l)}$$

$$\mathrm{u}_{i}^{k}=\frac{1}{L}\sum_{l=1}^{L}\mathrm{u}_{i}^{k,(l)};\qquad\mathrm{v}_{j}^{k}=\frac{1}{L}\sum_{l=1}^{L}\mathrm{v}_{j}^{k,(l)} \tag{7}$$

Method



Attention-based Interaction Module

$$\mathrm{h}_{ij}^{k} = \mathrm{MLP}\left(\left[\mathrm{u}_i^k, \mathrm{v}_j^k\right]\right), \tag{8}$$

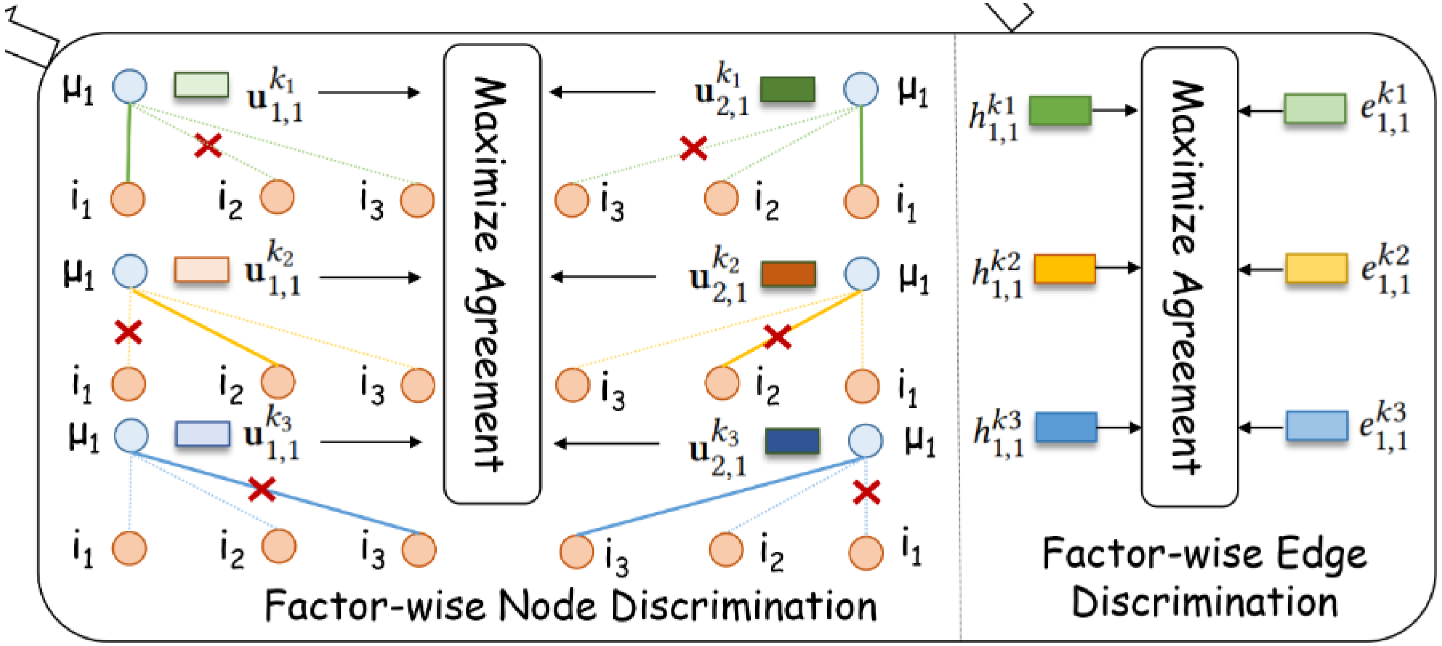
$$\hat{r}_{i,j}^{k} = \mathrm{w}^{\top}\mathrm{h}_{i,j}^{k} \tag{9}$$

$$a_k = \sigma\left(\mathrm{w}_r^{\top}\mathrm{h}_{i,j}^{k} + b_r\right)$$

$$\alpha_k = \frac{\exp\left(a_k/\tau\right)}{\sum_{k'=1}^{K}\exp\left(a_{k'}/\tau\right)} \tag{10}$$

$$\hat{r}_{i,j} = \sum_{k=1}^{K}\alpha_k\hat{r}_{i,j}^{k}$$

Method



Disentangled Contrastive Learning Module

$$\mathcal{L}_{fnd}^{user} = -\mathbb{E}_{\mathcal{K}\times\mathcal{U}}\left[\log D\left(\mathrm{u}_{1,i}^{k}, \mathrm{u}_{2,i}^{k}\right)\right] + \mathbb{E}_{\mathcal{K}\times\mathcal{U}\times\mathcal{U}'}\left[\log D\left(\mathrm{u}_{1,i}^{k}, \mathrm{u}_{2,i'}^{k}\right)\right] \quad (11)$$

$$D(\mathrm{a}, \mathrm{b}) = \sigma\left(\mathrm{a}^{\top}\mathrm{W}\mathrm{b}\right) \qquad \mathcal{L}_{fnd} = \mathcal{L}_{fnd}^{user} + \mathcal{L}_{fnd}^{item}$$

$$\mathcal{L}_{fed} = -\mathbb{E}_{\mathcal{K}\times\mathcal{E}}\left[\log D\left(\mathrm{h}_{i,j}^{k}, \mathrm{e}_{i,j}^{k}\right)\right] + \mathbb{E}_{\mathcal{K}\times\mathcal{E}\times\mathcal{E}'}\left[\log D\left(\mathrm{h}_{i,j}^{k}, \mathrm{e}_{i',j'}^{k}\right)\right] \quad (12)$$

$$\mathcal{L}_{\text{sup}} = \frac{1}{|\mathcal{T}|}\sum_{(i,j)\in\mathcal{T}}\left(\hat{r}_{ij} - r_{ij}\right)^2, \quad (13)$$

$$\mathcal{L} = \mathcal{L}_{\text{sup}} + \lambda_1\mathcal{L}_{fnd} + \lambda_2\mathcal{L}_{fed} \quad (14)$$

Experiments

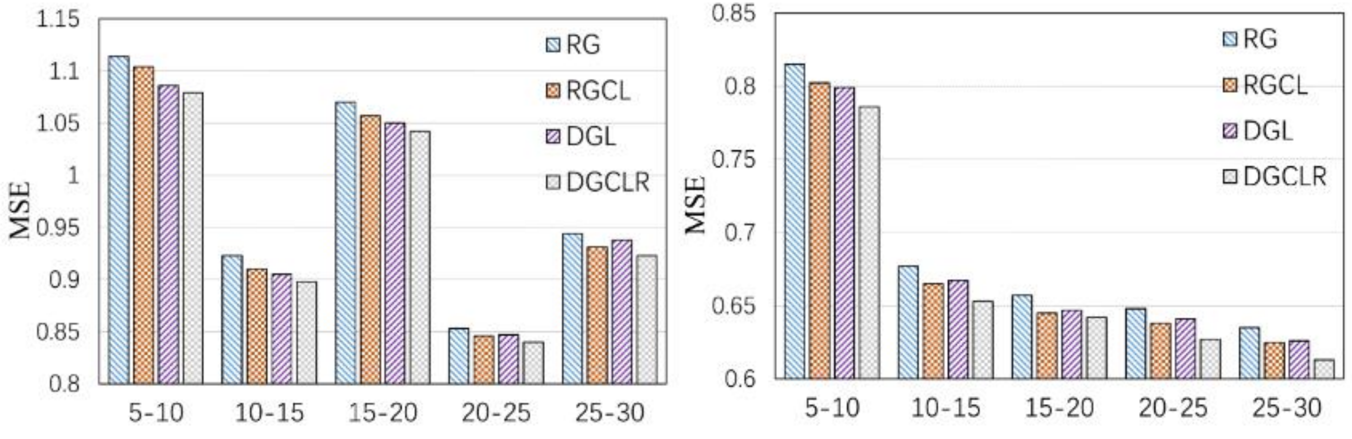
Table 1: Statistics of datasets.

Datasets	Toys	Clothing	Office	Kitchen	Tools
#Users	19,412	4,905	39,387	66,519	16,638
#Items	11,924	2,420	23,033	28,237	10,217
#Reviews	167,597	53,228	278,677	551,682	134,476
Density	0.072%	0.448%	0.031%	0.029%	0.079%

Table 2: Comparison results on the six datasets in terms of MSE. The best and second-best results are highlighted with boldface and underlined. All the results are reported as the mean value across 5 random runs.

Datasets	SVD	NCF	DeepCoNN	TransNet	DRRNN	NARRE	DAML	DGCF	RMG	RG	RGCL	DGCLR	Improv.
Toys	0.8082	0.8075	0.8026	0.7982	0.7884	0.7961	0.7940	0.7943	0.7901	0.7853	<u>0.7771</u>	0.7717	0.7%
Clothing	1.1161	1.1094	1.1184	1.1141	1.1035	1.1064	1.1065	1.1002	1.1064	1.1024	<u>1.0858</u>	1.0573	2.6%
Office	0.7438	0.7459	0.7426	0.7419	0.7306	0.7408	0.7358	0.7345	0.7348	0.7293	<u>0.7228</u>	0.7146	1.1%
Kitchen	1.1011	1.0946	1.0914	1.0879	1.0769	1.0835	1.0814	1.0798	1.0783	1.0754	<u>1.0732</u>	1.0658	0.7%
Tools	0.9412	0.9385	0.9356	0.9348	0.9249	0.9304	0.9295	0.9301	0.9288	0.9253	<u>0.9241</u>	0.9145	1.0%

Experiments



(a) Clothing (b) Office

Figure 3: Performance *w.r.t* interaction degrees.

Table 3: Ablation studies on the DGL and AI modules.

Datasets	Toys	Clothing	Office
RG	0.7853	1.1024	0.7293
Variant 1	0.7857	1.0987	0.7287
Variant 2	0.7801	1.0793	0.7231
Variant 3	0.7841	1.0871	0.7266
DGL	0.7793	1.0728	0.7222
DGL+AI	0.7776	1.0691	0.7210

Experiments

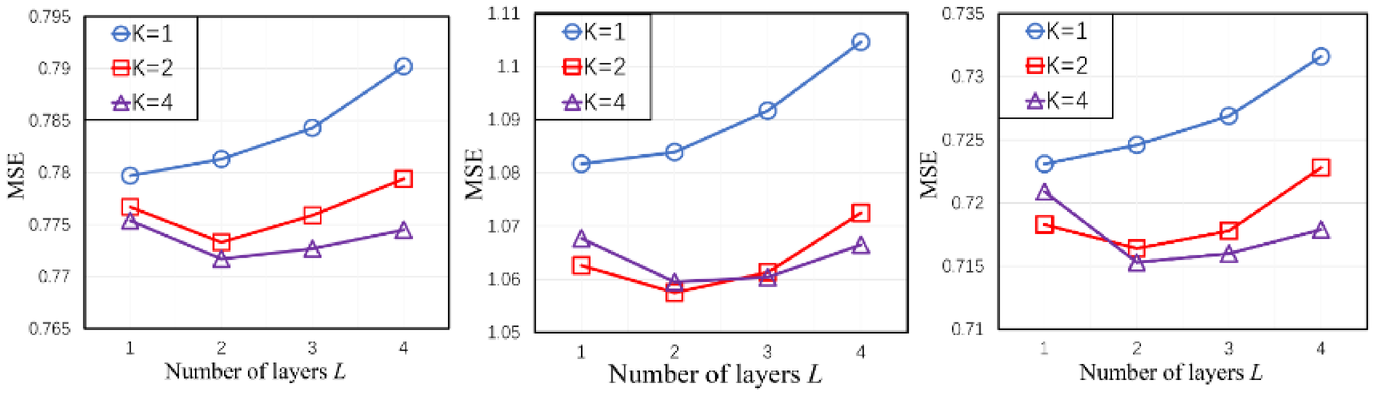
Table 4: Ablation studies on the DCL module.

Datasets	Toys	Clothing	Office
DGL+AI+ND	0.7762	1.0634	0.7188
DGL+AI+FND	0.7743	1.0586	0.7165
DGL+AI+ED	0.7755	1.0641	0.7184
DGL+AI+FED	0.7732	1.0588	0.7173
DGCLR	0.7717	1.0573	0.7146

Table 5: Impact of latent factor number on DGCLR.

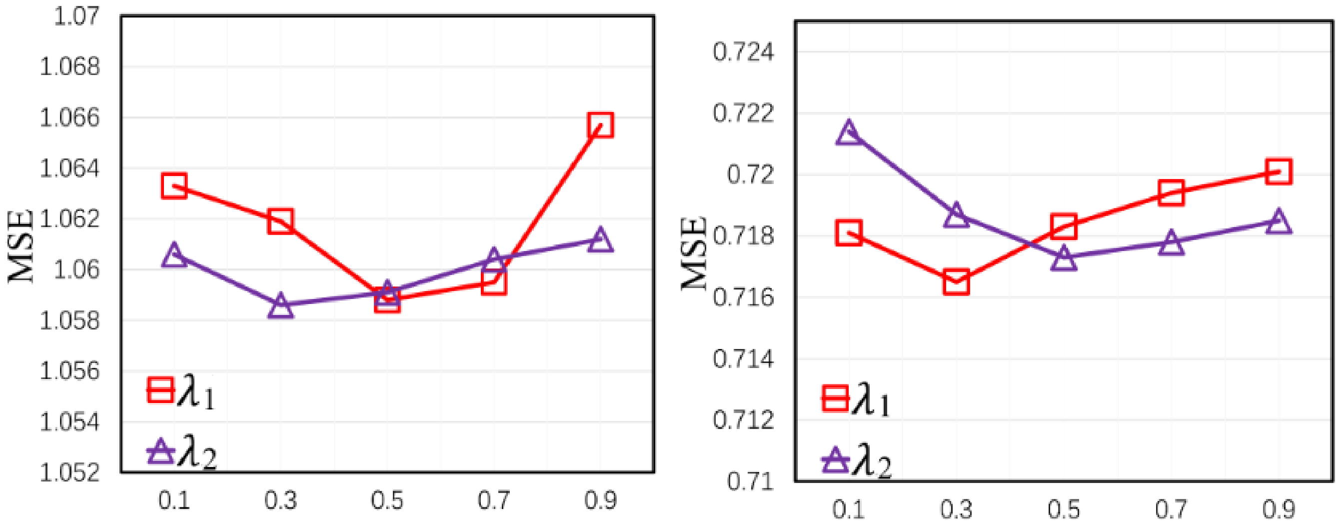
Datasets	Toys	Clothing	Office
$K = 1$	0.7797	1.0817	0.7231
$K = 2$	0.7723	1.0575	0.7164
$K = 4$	0.7717	1.0595	0.7146
$K = 8$	0.7772	1.0639	0.7217

Experiments



(a) Toys (b) Clothing (c) Office

Figure 4: Impact of layer number L on DGCLR.



(a) Clothing (b) Office

Figure 5: Impact of λ_1 and λ_2 on DGCLR.

Experiments

Table 6: Examples of reviews corresponding to each latent factor on Office. The key information is highlighted with red.

Factor k_1	$r=1$	$s_{i,j}^{k_1,L}=0.547$	Although i love the pastel colors, this item is wasteful. Unfortunately, I 'll never use the note tabs.
	$r=3$	$s_{i,j}^{k_1,L}=0.538$	This product is okay, but i had a difficult time getting it to stay open. i don't think it would be very beneficial in my business.
	$r=5$	$s_{i,j}^{k_1,L}=0.615$	the range is good and the clarity can not be beat in my opinion. the options are just what i needed for my purposes.
Factor k_2	$r=1$	$s_{i,j}^{k_2,L}=0.551$	I had previously given this a five star review, but after two months the stapler jammed shut and would not open.
	$r=3$	$s_{i,j}^{k_2,L}=0.587$	Print quality seems to be OK, but there 's no way to tell the printer whether you are using plain paper of glossy paper. Plain paper prints look washed out, premium paper prints look good.
	$r=5$	$s_{i,j}^{k_2,L}=0.513$	It's solidly made and stands up to regular use pretty darn well. The result is crisp laser printing on a home office budget.
Factor k_3	$r=1$	$s_{i,j}^{k_3,L}=0.637$	My rating reflects my dissatisfaction with this vendors deceptive advertising.
	$r=3$	$s_{i,j}^{k_3,L}=0.526$	This product almost delivers on its promises one. But the individual packets of labels easily detached from the main package.
	$r=5$	$s_{i,j}^{k_3,L}=0.581$	Making photo prints uses a lot of ink. This helps address that problem. Same quality prints as standard capacity cartridge.
Factor k_4	$r=1$	$s_{i,j}^{k_4,L}=0.579$	The ink is very inexpensive but with the quality of the system so cheaply made the inexpensive ink is hardly worth the cost of having to buy a new system in less than two years.
	$r=3$	$s_{i,j}^{k_4,L}=0.612$	For a relatively inexpensive laminator, this does an OK job. But the lack of guides on this unit is a real problem.
	$r=5$	$s_{i,j}^{k_4,L}=0.547$	I bought this because of the price and to my surprise it is fantastic. I will buy this again over any other more expensive ones.

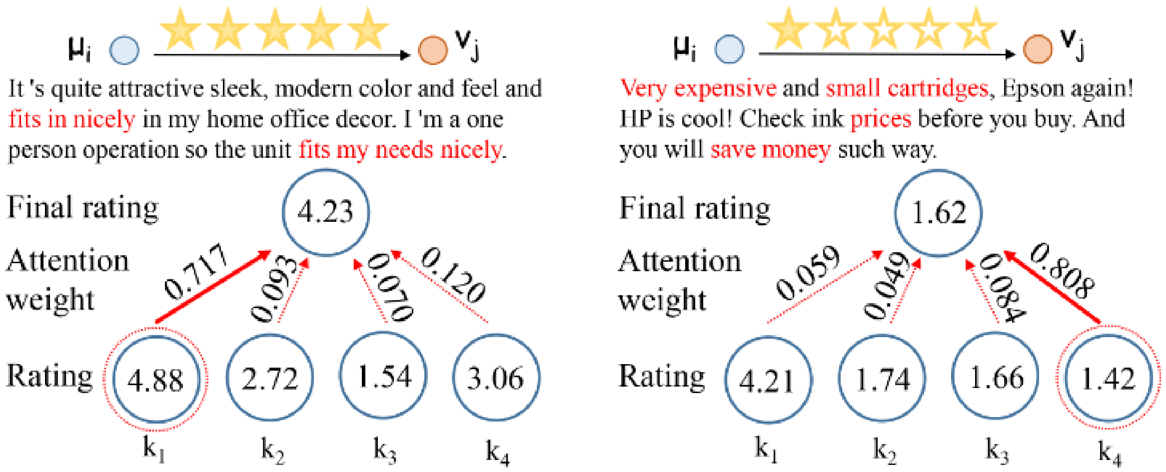


Figure 6: Examples of rating predictions in DGCLR.

Thanks