Multi-Behavior Recommendation with Cascading Graph Convolution Networks

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code: https://github.com/SS-00-SS/MBCGCN.

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Reported by Minqin Li

Introduction

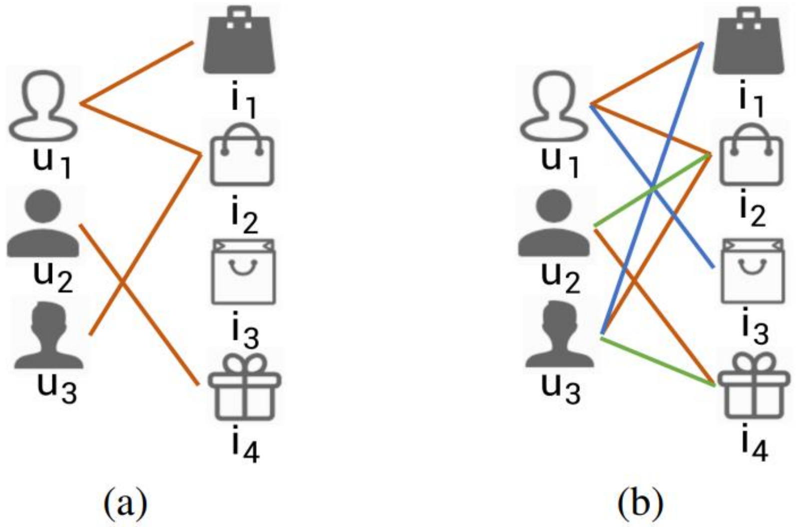

Figure 1: Examples of single-behavior and multi-behavior in e-commerce scene. (a) is *single-behavior* and (b) is *multi-behavior*. The **red** line indicates *purchase* behavior, the **blue** line indicates *click* behavior, and the **green** line indicates *add to cart* behavior.

Method

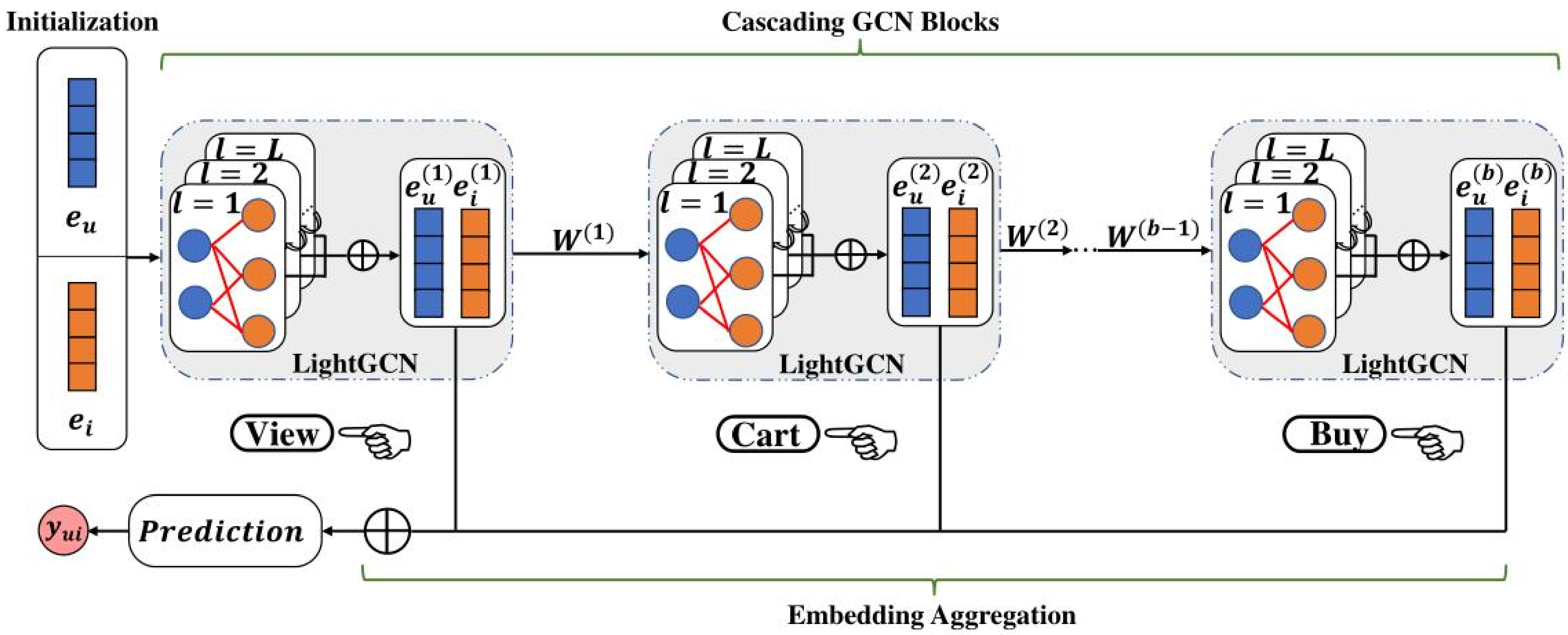

Figure 1: Overview of our MB-CGCN model.

Method

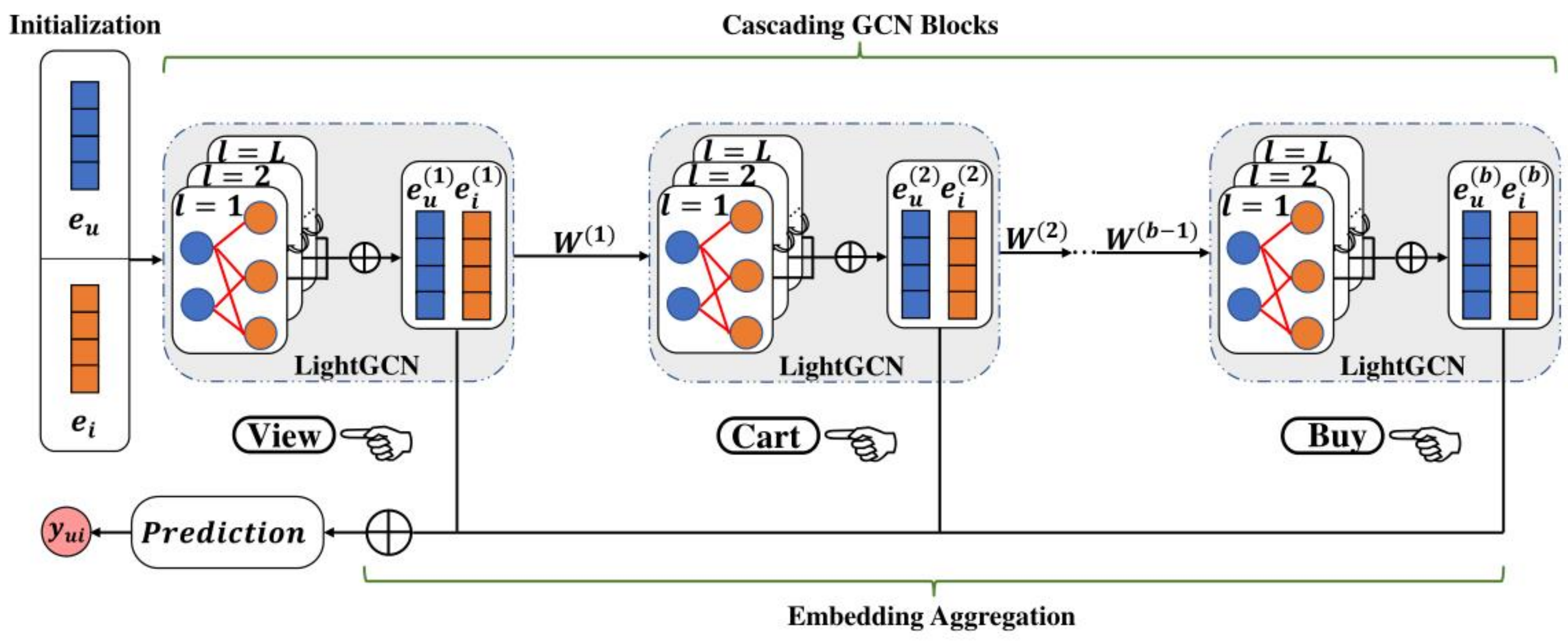

Figure 1: Overview of our MB-CGCN model.

$$y_{u,i}^{b} = \begin{cases} 1, & \text{If } u \text{ has interacted with } i \text{ under behavior } b; \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

$$\boldsymbol{e}_{u_m}^{0} = \boldsymbol{P} \cdot \boldsymbol{ID}_m^U, \quad \boldsymbol{e}_{i_n}^{0} = \boldsymbol{Q} \cdot \boldsymbol{ID}_n^I \tag{2}$$

$$\boldsymbol{e}_{\boldsymbol{u}}^{(b,l+1)} = \sum_{i \in \mathcal{N}_u} \frac{1}{\sqrt{|\mathcal{N}_u|}\sqrt{|\mathcal{N}_i|}} \boldsymbol{e}_{\boldsymbol{i}}^{(b,l)} \tag{3}$$

$$\boldsymbol{e}_{\boldsymbol{i}}^{(b,l+1)} = \sum_{u \in \mathcal{N}_i} \frac{1}{\sqrt{|\mathcal{N}_i|}\sqrt{|\mathcal{N}_u|}} \boldsymbol{e}_{\boldsymbol{u}}^{(b,l)} \tag{4}$$

$$\boldsymbol{e}_{\boldsymbol{u}}^{(b)} = \sum_{l=0}^{L} \boldsymbol{e}_{u}^{(b,l)}, \quad \boldsymbol{e}_{\boldsymbol{i}}^{(b)} = \sum_{l=0}^{L} \boldsymbol{e}_{\boldsymbol{i}}^{(b,l)}. \tag{5}$$

Method

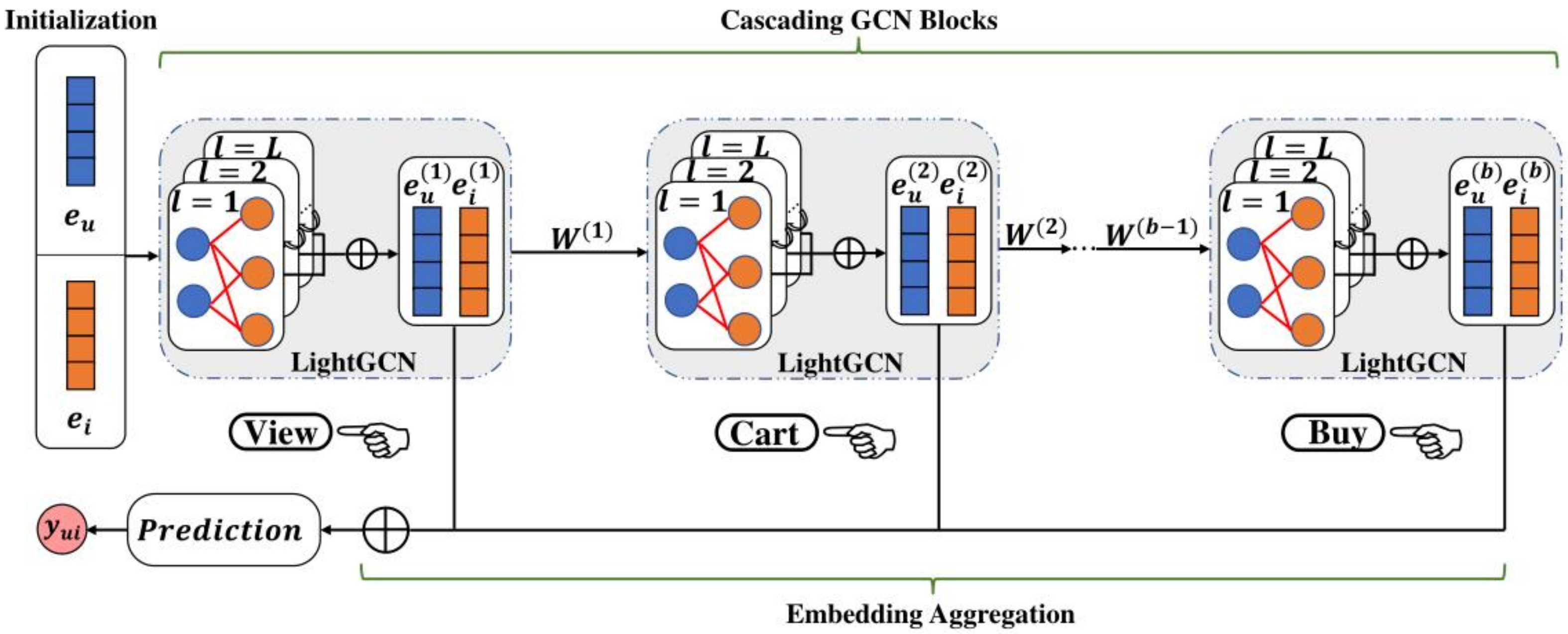

Figure 1: Overview of our MB-CGCN model.

$$e_u^{(b+1,0)} = W_u^b e_u^{(b)}, \quad e_i^{(b+1,0)} = W_i^b e_i^{(b)} \tag{6}$$

$$e_u = \sum_{b=1}^{B} e_u^{(b)}, \quad e_i = \sum_{b=1}^{B} e_i^{(b)} \tag{7}$$

$$\hat{y}_{ui} = e_u^T e_i \tag{8}$$

$$\mathcal{L} = \sum_{(u,i,j)\in O} -ln\sigma(y_{ui} - y_{uj}) + \lambda \|\Theta\|^2 \tag{9}$$

Experiments

Table 1: Statistics of the datasets used in our experiments.

Dataset	User#	Item#	Buy#	Cart#	View#
Beibei	21,716	7,997	304,576	642,622	2,412,586
Tmall	15,449	11,953	104,329	195,476	873,954

Experiments

Table 2: Overall performance comparison. Improv. denotes the relative improvements over the best baseline.

Dataset	Metric	Single behavior Methods			Multi behavior Methods						Improv.
		MF-BPR	NeuMF	LightGCN	RGCN	GNMR	NMTR	MBGCN	CRGCN	MB-CGCN	
Beibei	Recall@10	0.0191	0.0232	0.0391	0.0363	0.0413	0.0429	0.0470	0.0459	**0.0579**	23.2%
	NDCG@10	0.0049	0.0135	0.0209	0.0188	0.0221	0.0198	0.0259	0.0324	**0.0381**	17.6%
	Recall@20	0.0531	0.0736	0.0717	0.0684	0.0729	0.0776	0.0792	0.0891	**0.0972**	9.1%
	NDCG@20	0.0239	0.0290	0.0270	0.0274	0.0279	0.0296	0.0330	0.0348	**0.0404**	16.1%
	Recall@50	0.1014	0.1402	0.1347	0.1309	0.1391	0.1453	0.1493	0.1694	**0.1924**	13.6%
	NDCG@50	0.0330	0.0405	0.0366	0.0371	0.0374	0.0399	0.0447	0.0487	**0.0572**	17.5%
Tmall	Recall@10	0.0076	0.0236	0.0411	0.0215	0.0368	0.0282	0.0509	0.0855	**0.1233**	44.2%
	NDCG@10	0.0036	0.0128	0.0240	0.0104	0.0216	0.0137	0.0294	0.0439	**0.0677**	54.2%
	Recall@20	0.0244	0.0311	0.0546	0.0326	0.0608	0.0642	0.0691	0.1369	**0.2007**	46.6%
	NDCG@20	0.0155	0.0152	0.0266	0.0125	0.0263	0.0303	0.0350	0.0676	**0.0880**	30.2%
	Recall@50	0.0393	0.0494	0.0874	0.0411	0.0971	0.1034	0.1117	0.2325	**0.3322**	42.9%
	NDCG@50	0.0197	0.0193	0.0338	0.0160	0.0336	0.0383	0.0455	0.0866	**0.1134**	30.9%

Experiments

Table 3: Effects of the feature transformation in MB-CGCN. The reported performance is computed based on the top 20 results.($w/o.\ ft$ and $w.\ ft$ denote MB-CGCN with and without the feature transformation, respectively.

Method	Beibei		Tmall	
	Recall	NDCG	Recall	NDCG
w/o. ft	0.0892	0.0382	0.1994	0.0825
w. ft	**0.0972**	**0.0404**	**0.2007**	**0.0880**

Table 4: Effects of feature aggregation in MB-CGCN. The reported performance is computed based on the top 20 results.

Method	Beibei		Tmall	
	Recall	NDCG	Recall	NDCG
w/o. agg.	0.0556	0.0140	0.0698	0.0291
w. concat.	0.0758	0.0282	0.1648	0.0688
w. agg.	**0.0972**	**0.0404**	**0.2007**	**0.0880**

Experiments

Table 5: Effects of behavior number in MB-CGCN. The reported performance is computed based on the top 20 results.

Method	Beibei		Tmall	
	Recall	NDCG	Recall	NDCG
buy	0.0717	0.0270	0.0546	0.0266
cart>buy	0.0930	0.0389	0.1956	0.0851
view>cart>buy	**0.0972**	**0.0404**	**0.2007**	**0.0880**

Experiments

Table 6: Effects of layer numbers by setting the same layer numbers to all behaviors.

Method	Beibei		Tmall	
	Recall	NDCG	Recall	NDCG
1-Layer	0.0942	0.0328	0.1923	0.0864
2-Layer	0.0954	0.0359	0.1933	0.0867
3-Layer	**0.0961**	**0.0370**	**0.1967**	**0.0869**

Experiments

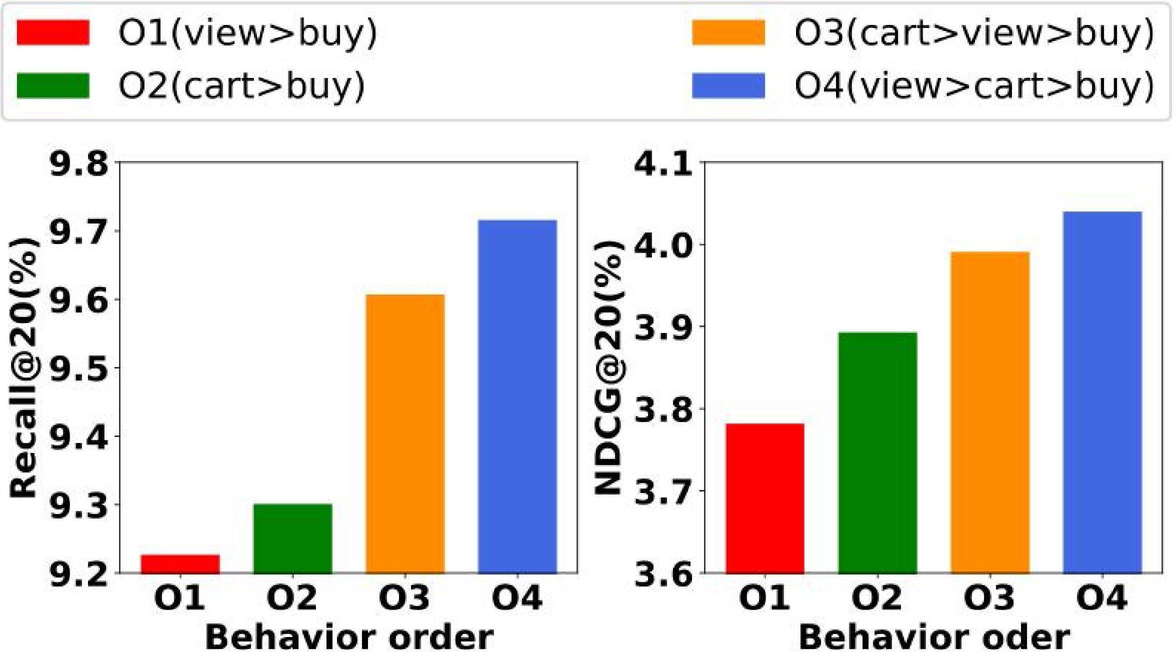

Figure 2: Effects of behavior order on Beibei.

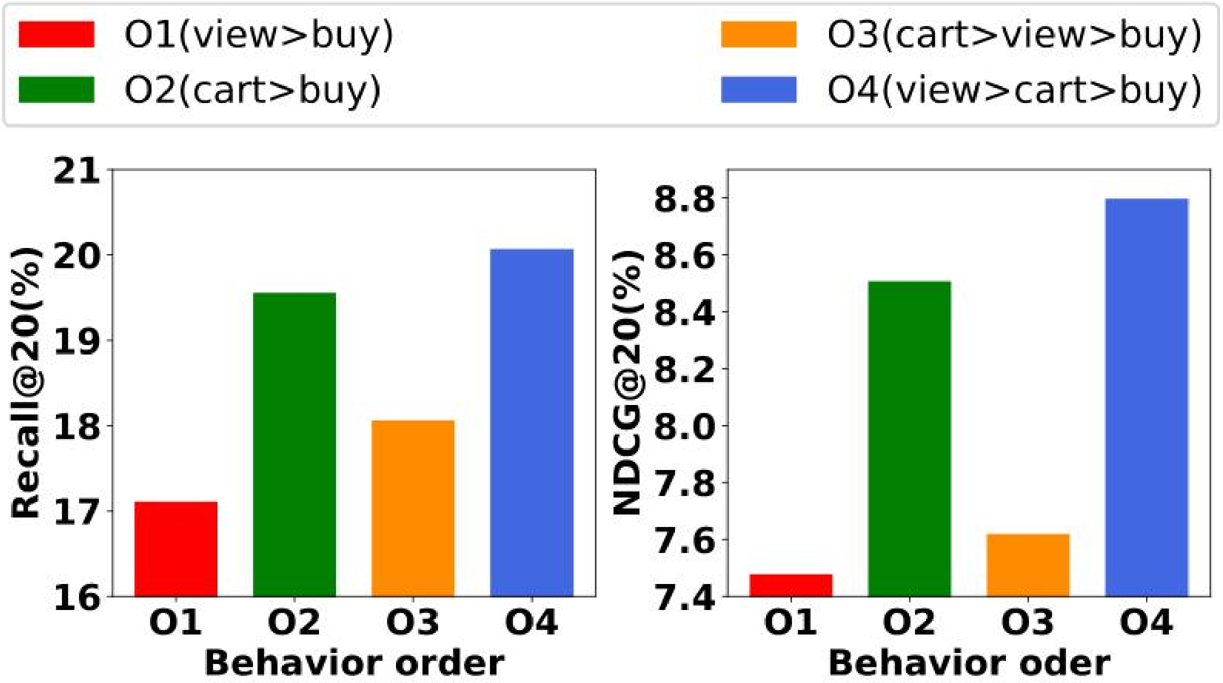

Figure 3: Effects of behavior order on Tmall.

Thanks