Revolutionizing Graph Aggregation: From Suppression to Amplification via BoostGCN

Jiaxin Wu[1], Chenglong Pang[2], Guangxiong Chen[1], Jie Zhao[1,*]

[1]Guangdong University of Technology [2]Donghua University

Presenter: Jiaxin Wu

NEURAL INFORMATION PROCESSING SYSTEMS

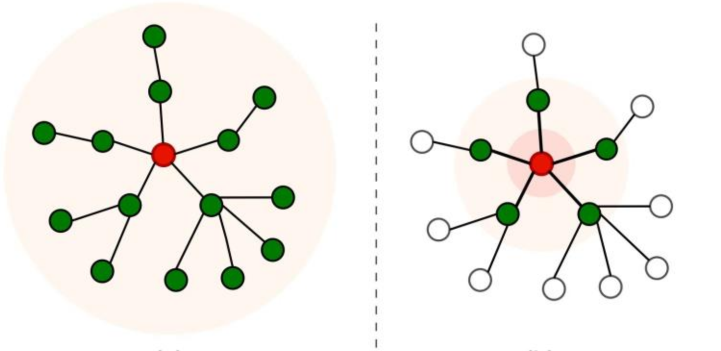
Problems

Datasets	Amazon-Book	
Metrics	Recall@20	NDCG@20
Laplacian-based	0.0411	0.0315
Mean-based	**0.0419**	**0.0320**
Improv.(%)	**+1.95%**	**+1.59%**

- ***Existing GCN models often utilize the graph Laplacian norm to suppress the propagation of information to enhance performance.***
- ***Suppression methods may dilute valuable interaction information and make the model slowly learn sparse interaction relationships from neighbors, which increases training time and negatively affects performance.***

Our Solution

Information Suppression Information Amplification



(a) (b)

- ✓ ***Our BoostGCN focuses on amplifying significant interactions with first-order neighbors.***
- ✓ ***BoostGCN has the following advantages:***

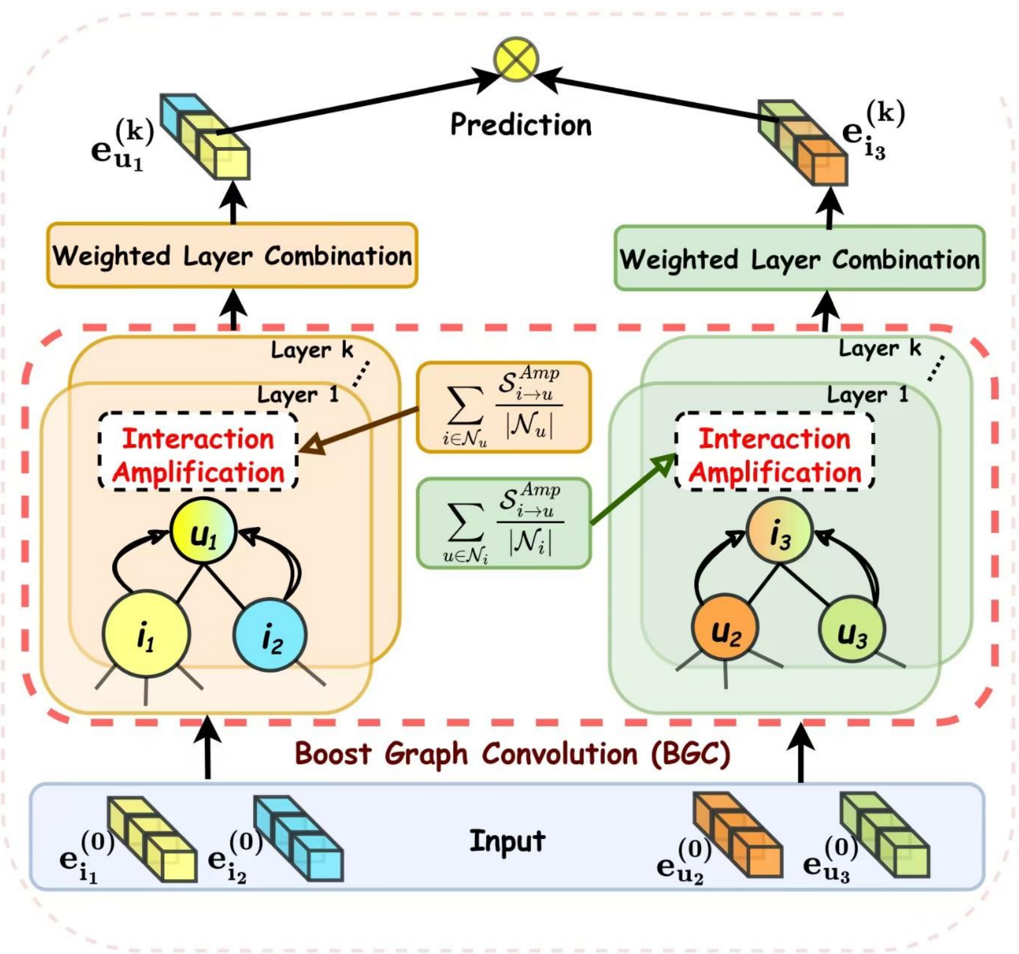
1.Great Performance

2.Low Training Time

3.Popularity Debiasing

4.Parameter Friendly

Method



BoostGCN (Ours)

$$e_i^{(k+1)} = \sum_{u \in N_i} \frac{log_\beta(|N_i|)+1}{|N_i|} e_u^{(k)};$$

$$e_u^{(k+1)} = \sum_{i \in N_u} \frac{log_\beta(|N_i|)+1}{|N_u|} e_i^{(k)};$$

$$log_\beta(|N_i|) + 1 \in (1, +\infty)$$

When $\beta \to +\infty$,

BoostGCN equals LightGCN

- ✓ *More interactions,*
- ✓ *More Importance,*
- ✓ *Amplifying More.*

LightGCN

$$e_i^{(k+1)} = \sum_{u \in N_i} \frac{1}{\sqrt{|N_i|}\sqrt{|N_u|}} e_u^{(k)};$$

$$e_u^{(k+1)} = \sum_{i \in N_u} \frac{1}{\sqrt{|N_i|}\sqrt{|N_u|}} e_i^{(k)};$$

- ✓ *More interactions,*
- ✓ *Less Importance,*
- ✓ *Suppressing More.*

NEURAL INFORMATION PROCESSING SYSTEMS

Recommendation Performance

Dataset	Metric	MF-BPR	MMGCN^{id}	NGCF	UltraGCN	IMP-GCN	NSE-GCN	LayerGCN	LightGCN	LTGNN	TransGNN	GAT	BoostGCN
100k	R@5	0.2636	0.2463	0.2318	0.2647	0.2864	0.2963	0.2851	0.2861	0.2833	0.2733	0.2879	**0.2982**
	N@5	0.6599	0.6181	0.6067	0.6575	0.7029	0.7209	0.6840	0.6971	0.6872	0.6630	0.6983	**0.7234**
	R@15	0.5289	0.4953	0.4929	0.5393	0.5611	0.5886	0.5563	0.5669	0.5612	0.5415	0.5703	**0.5908**
	N@15	0.6616	0.6190	0.6126	0.6662	0.7028	0.7301	0.6894	0.7044	0.6952	0.6708	0.7065	**0.7319**
1M	R@5	0.2165	0.2178	0.2081	0.2389	0.2424	0.2546	0.2599	0.2476	0.2370	0.2581	0.2537	**0.2641**
	N@5	0.7220	0.7183	0.7128	0.7554	0.7624	0.7863	0.7949	0.7770	0.7235	0.7881	0.7844	**0.8063**
	R@15	0.4609	0.4648	0.4545	0.5057	0.4965	0.5128	0.5251	0.5058	0.4770	0.5196	0.5106	**0.5316**
	N@15	0.7041	0.7011	0.6934	0.7464	0.7441	0.7651	0.7782	0.7571	0.7075	0.7707	0.7574	**0.7885**
Gowa.	R@5	0.1996	0.0706	0.1485	0.2288	0.2808	0.2946	0.2932	0.2521	0.2178	0.2913	0.2883	**0.2965**
	N@5	0.2836	0.1122	0.1892	0.3131	0.3733	0.3906	0.3890	0.3408	0.2893	0.3863	0.3828	**0.3937**
	R@15	0.3447	0.1400	0.3310	0.3851	0.4868	0.5123	0.5092	0.4476	0.3780	0.5055	0.5003	**0.5145**
	N@15	0.3125	0.1251	0.2506	0.3460	0.4235	0.4468	0.4444	0.3883	0.3298	0.4410	0.4365	**0.4489**
Yelp	R@5	0.1225	0.0826	0.0984	0.1435	0.1753	0.1677	0.1845	0.1545	0.1375	0.1640	0.1635	**0.2001**
	N@5	0.2225	0.1582	0.1747	0.2581	0.3110	0.2945	0.3238	0.2747	0.2416	0.2883	0.2874	**0.3517**
	R@15	0.2592	0.1900	0.2460	0.3021	0.3567	0.3478	0.3722	0.3213	0.2726	0.3253	0.3243	**0.3968**
	N@15	0.2498	0.1819	0.2186	0.2901	0.3455	0.3324	0.3611	0.3086	0.2658	0.3172	0.3162	**0.3869**

Dataset		100k		1M		Yelp		Gowa.	
#Layer	Model	R@5	N@5	R@5	N@5	R@5	N@5	R@5	N@5
1	LightGCN	0.2840	0.6937	0.2413	0.7647	0.1630	0.2895	0.2614	0.3517
	BoostGCN	**0.2946**	**0.7157**	**0.2607**	**0.7997**	**0.1824**	**0.3258**	**0.2746**	**0.3631**
	Improv.	**+3.73%**	**+3.17%**	**+8.04%**	**+4.58%**	**+11.90%**	**+12.54%**	**+5.05%**	**+3.24%**
2	LightGCN	0.2861	0.6971	0.2476	0.7770	0.1545	0.2747	0.2521	0.3408
	BoostGCN	**0.2982***	**0.7234***	**0.2641***	**0.8063***	**0.2001**	**0.3517**	**0.2965**	**0.3937**
	Improv.	**+4.23%**	**+3.77%**	**+6.66%**	**+3.77%**	**+29.51%**	**+28.03%**	**+17.61%**	**+15.52%**
3	LightGCN	0.2727	0.6719	0.2467	0.7763	0.1461	0.2598	0.2468	0.3329
	BoostGCN	**0.2894**	**0.7075**	**0.2601**	**0.7959**	**0.1991**	**0.3493**	**0.3030**	**0.4031**
	Improv.	**+6.12%**	**+5.30%**	**+5.43%**	**+2.51%**	**+36.28%**	**+34.45%**	**+22.77%**	**+21.09%**
4	LightGCN	0.2021	0.5339	**0.2405**	**0.7643**	0.1396	0.2494	0.2294	0.3138
	BoostGCN	**0.2973**	**0.7134**	0.2373	0.7556	**0.2026***	**0.3547***	**0.3165***	**0.4151***
	Improv.	**+47.11%**	**+33.62%**	-1.33%	-1.14%	**+45.13%**	**+42.22%**	**+37.97%**	**+32.28%**

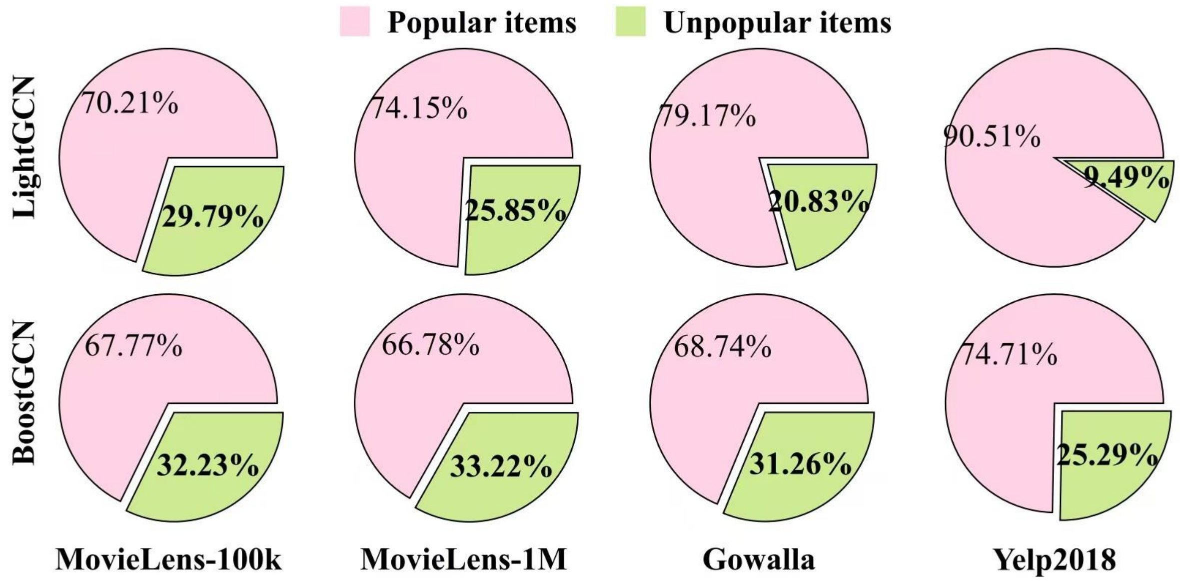
- ✓ ***We conducted experiments on four datasets***
- ✓ ***BoostGCN outperforms the latest existing baselines.***
- ✓ ***In terms of layer ablation, BoostGCN far outperforms popular framework, LightGCN, in the performance of each layer.***

Training Efficiency

Dataset	Model	Best R@5	Training Time
100k (K=2)	LightGCN	0.2861	45s
	BoostGCN	**0.2982**	**23s**
	Improv.	**+4.23%**	**+49%**
1M (K=2)	LightGCN	0.2476	1174s
	BoostGCN	**0.2641**	**440s**
	Improv.	**+6.66%**	**+63%**
Gowa. (K=4)	LightGCN	0.2294	2762s
	BoostGCN	**0.3165**	**859s**
	Improv.	**+37.97%**	**+69%**
Yelp (K=4)	LightGCN	0.1396	4525s
	BoostGCN	**0.2026**	**438s**
	Improv.	**+45.13%**	**+90%**

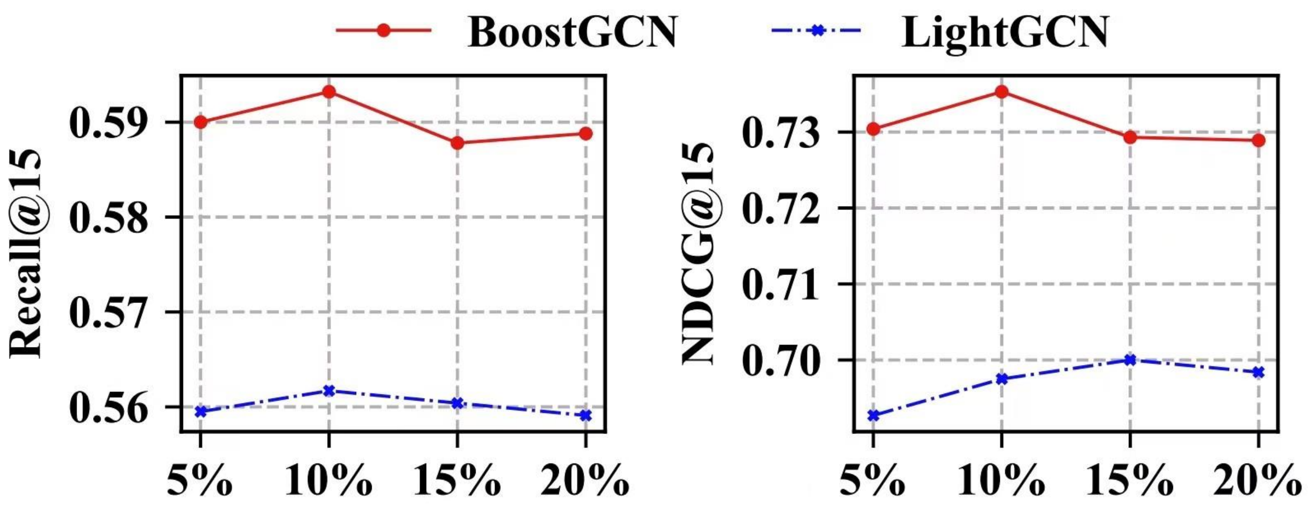
✓ ***BoostGCN not only far outperforms LightGCN in performance, but also significantly improves training efficiency.***

Popularity Debiasing



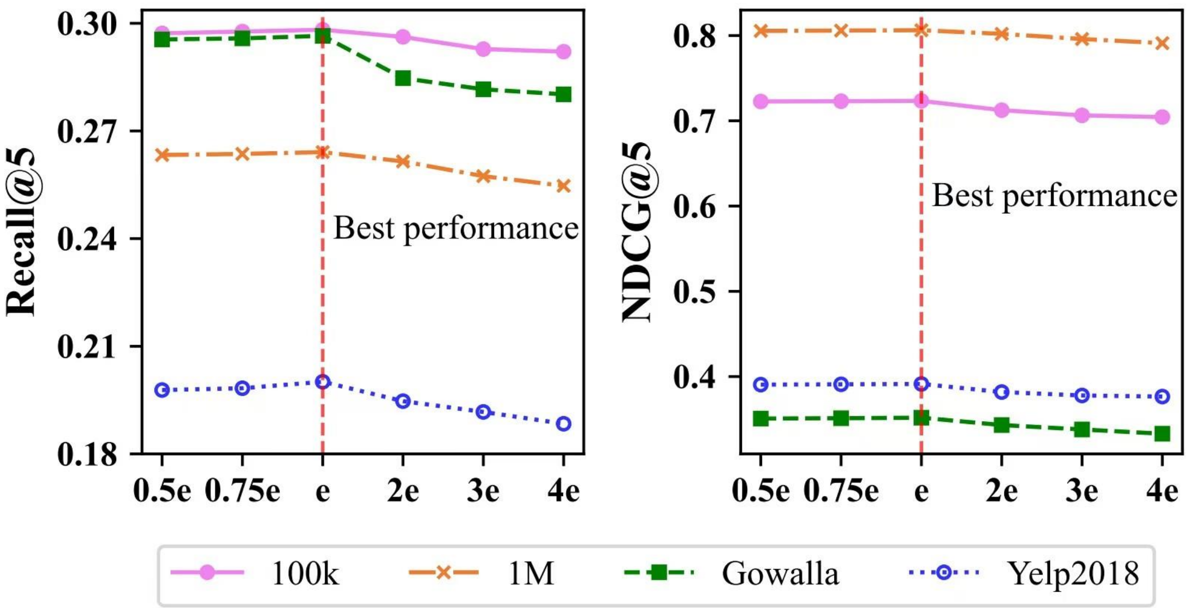
✓ ***BoostGCN is able to recommend about 2%-16% more unpopular items, achieving a better performance of popularity debiasing.***

Noise Resistance



- ✓ *We randomly added 5%-20% spurious interactions to the dataset and compared it with LightGCN.*
- ✓ *We can see that BoostGCN outperforms LightGCN at different noise levels, demonstrating its superior noise resistance.*

Parameter Friendly



- ✓ ***BoostGCN achieves optimal performance with $\beta = e$ on all datasets when the parameter β ranges from {0.5e, 0.75e, e, 2e, 3e, 4e}.***

NEURAL INFORMATION PROCESSING SYSTEMS

Thank You for Listening

You can contact us with

Jiaxin Wu[1], Chenglong Pang[2], Guangxiong Chen[1], Jie Zhao[1,*]

[1]Guangdong University of Technology [2]Donghua University

WeChat

Email

704276515@qq.com

clongdwyyx@163.com

3122003350@mail2.gdut.edu.cn

zhaojie@gdut.edu.cn