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Layer-Wise Contrastive Learning for Graph Collaborative Filtering

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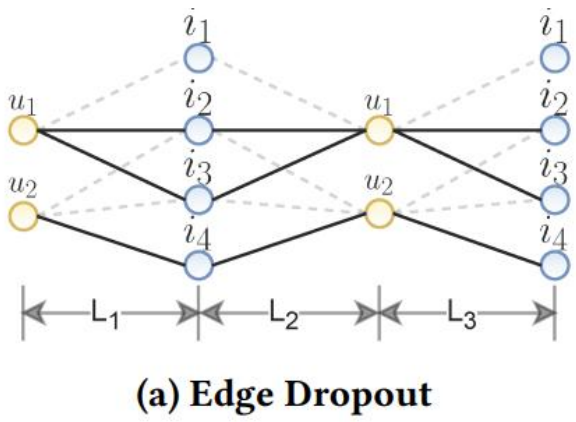
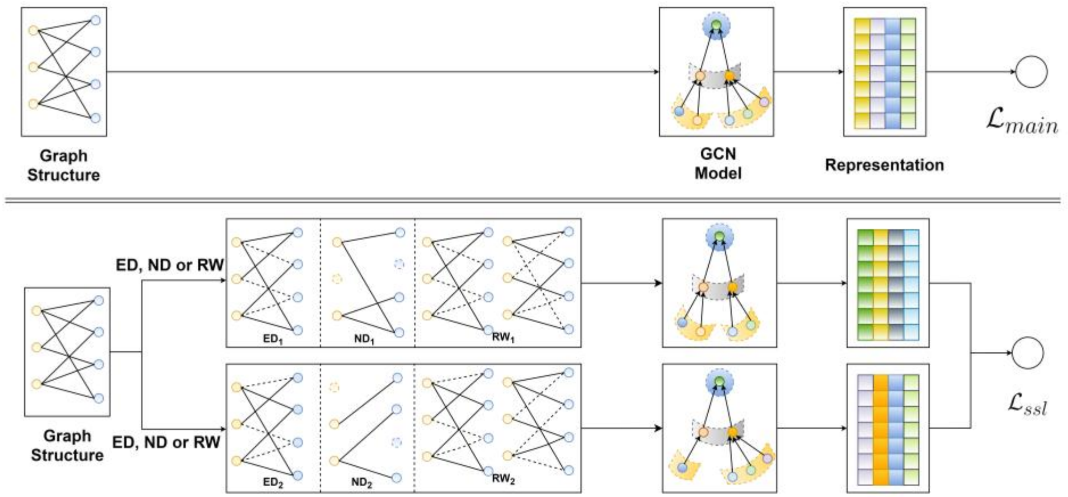
***As this is a working paper, some details have been omitted**

Backgrounds

- Collaborative Filtering(CF): The most foundational recommendation paradigm
- However, it suffers from data sparsity and popularity bias
- A promising solution: Graph Contrastive Learning



Traditional Data Augmentation

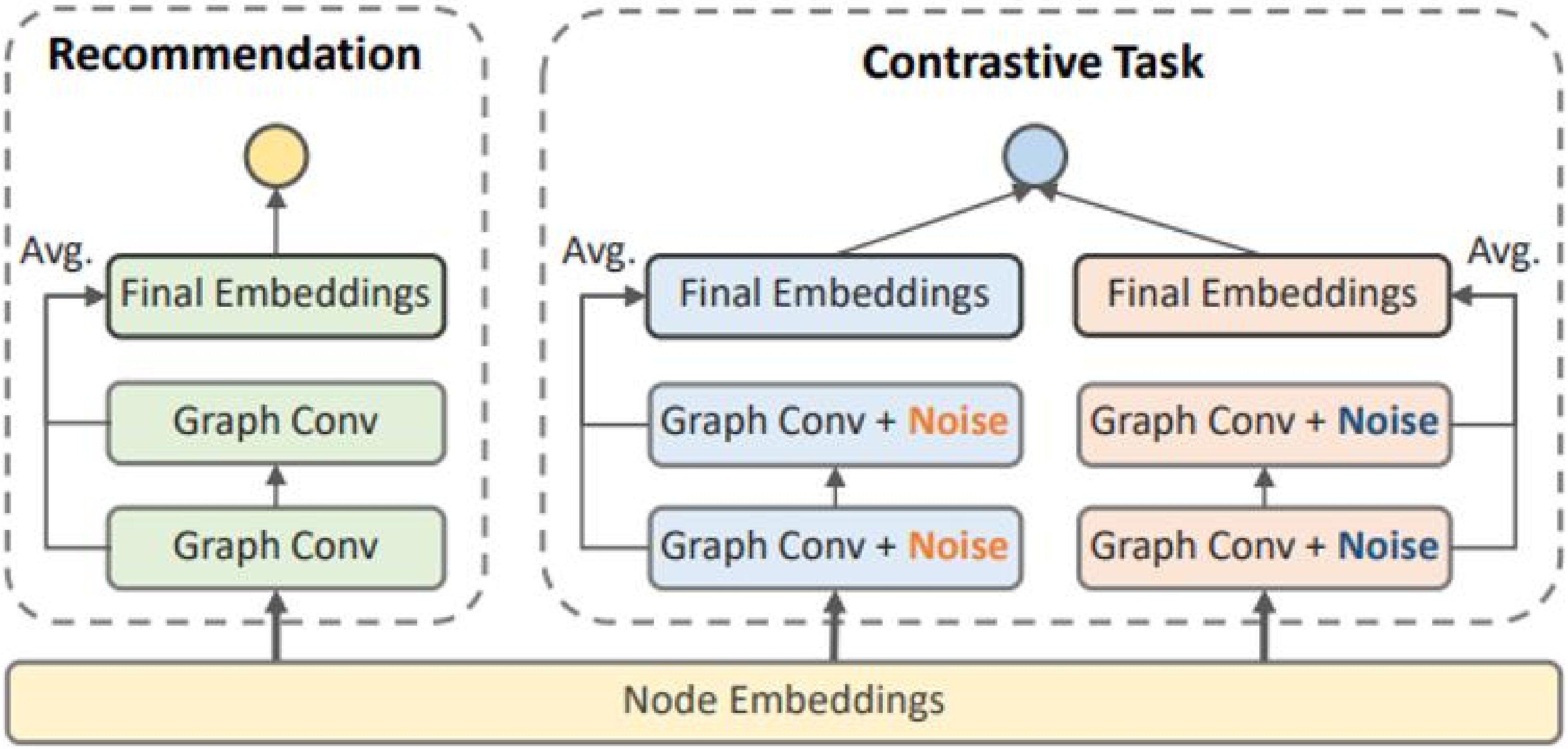


Traditional Self-Supervised Framework for CF

Contrastive learning works a lot! Why?

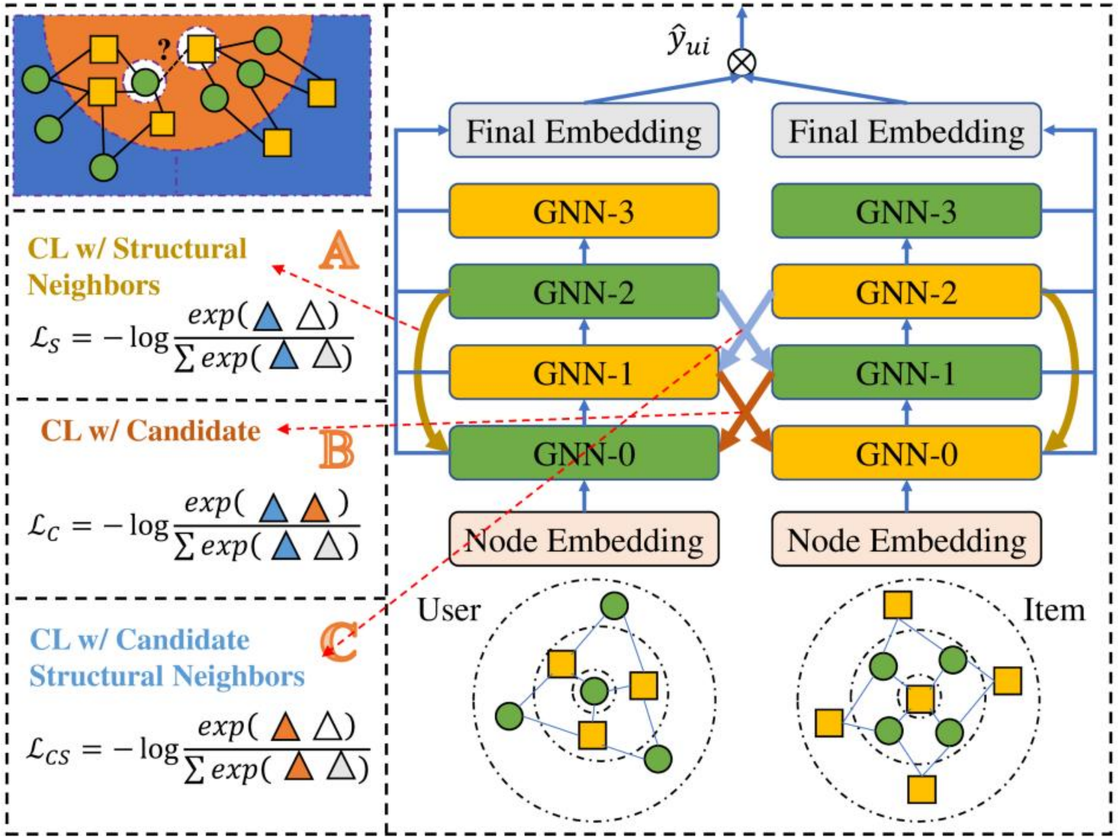
Backgrounds

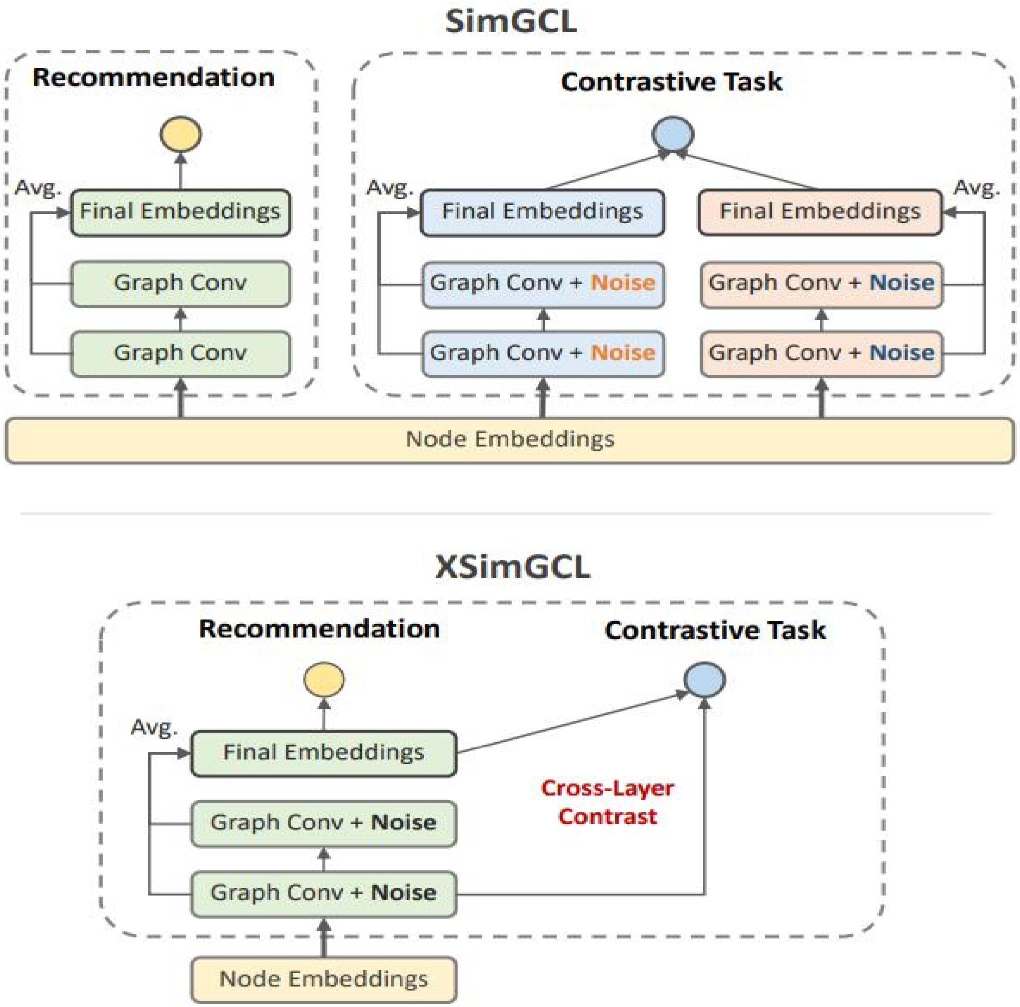
- **InfoNCE-based** contrastive learning operates by learning more evenly distributed user/item representations, which performs well.
- They argue that traditional data augmentation has very limited effectiveness, so they developed a augmentation strategy by simply adding random noise in each layer(i.e. feature-level augmentation) to achieve this target.



Motivation

- Diverse cross-layer contrastive learning

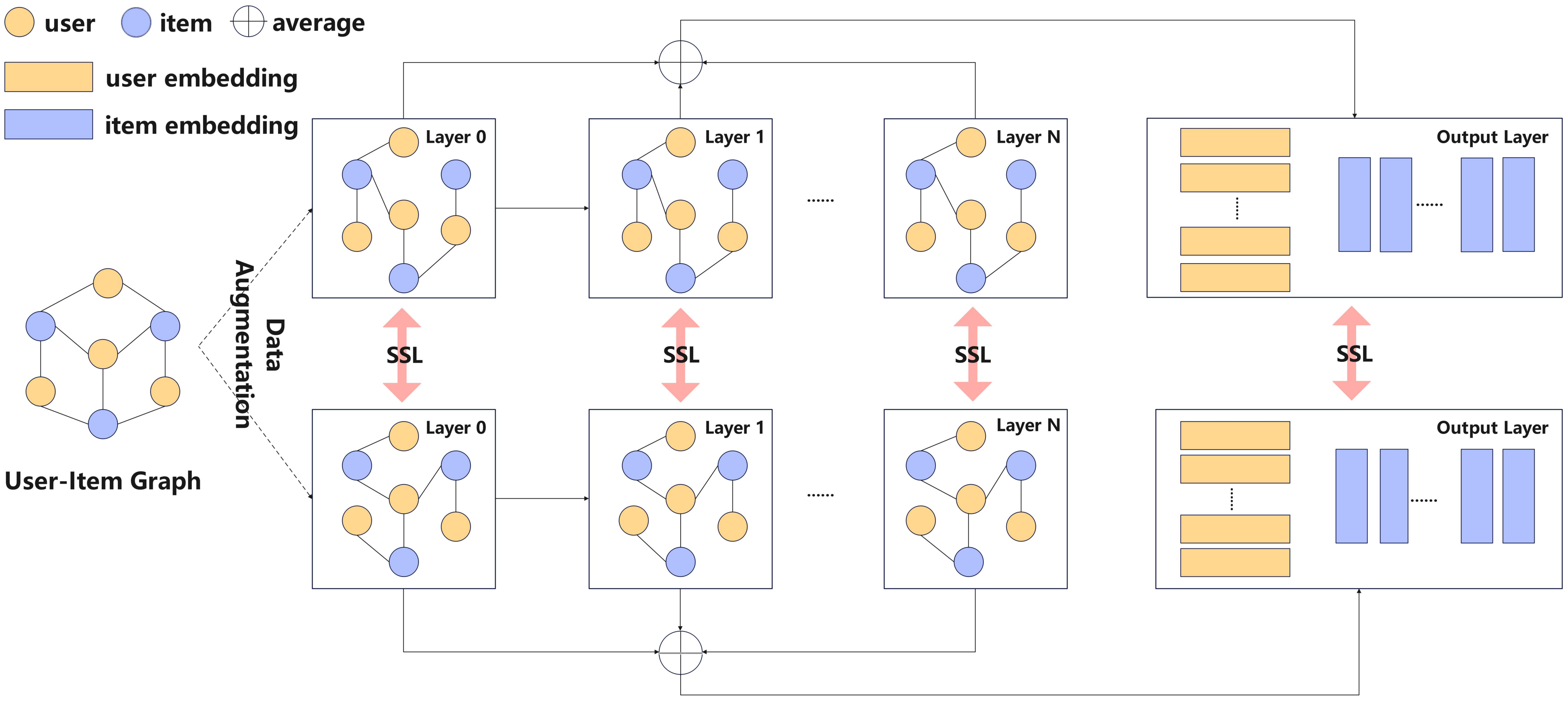




- Motivation: can we design a novel contrastive way to learn more even distribution?

Methdology

- Layer-wise contrastive learning for collaborative filtering



Experiments

Main Experiments

Dataset	Metric	BPRMF	LightGCN	BUIR	DirectAU	NCL	SGL	SimGCL	**Ours**
Yelp2018	Recall@10	0.0283	0.0350	0.0291	0.0408	0.0394	0.0396	**0.0425**	<u>0.0419</u>
	Recall@20	0.0498	0.0639	0.0497	0.0692	0.0673	0.0677	**0.0719**	<u>0.0712</u>
	Recall@50	0.0988	0.1158	0.0976	0.1326	0.1293	0.1302	**0.1358**	<u>0.1331</u>
	NDCG@10	0.0321	0.0399	0.0330	0.0472	0.0450	0.0451	**0.0485**	<u>0.0480</u>
	NDCG@20	0.0401	0.0525	0.0404	0.0573	0.0553	0.0555	**0.0593**	<u>0.0583</u>
	NDCG@50	0.0581	0.0697	0.0582	0.0808	0.0782	0.0785	**0.0827**	<u>0.0821</u>
Amazon-Book	Recall@10	0.0172	0.0225	0.0157	0.0250	0.0259	0.0275	**0.0306**	<u>0.0301</u>
	Recall@20	0.0303	0.0411	0.0271	0.0426	0.0442	0.0448	**0.0510**	<u>0.0504</u>
	Recall@50	0.0605	0.0746	0.0536	0.0829	0.0845	0.0881	**0.0915**	<u>0.0909</u>
	NDCG@10	0.0183	0.0239	0.0175	0.0279	0.0271	0.0293	**0.0324**	<u>0.0313</u>
	NDCG@20	0.0235	0.0315	0.0217	0.0344	0.0343	0.0379	<u>0.0406</u>	**0.0408**
	NDCG@50	0.0348	0.0436	0.0314	0.0491	0.0492	0.0521	**0.0553**	<u>0.0550</u>
iFashion	Recall@10	0.0382	0.0603	0.0548	0.0728	0.0617	0.0761	<u>0.0778</u>	**0.0794**
	Recall@20	0.0583	0.0906	0.0842	0.1086	0.0914	0.1109	<u>0.1138</u>	**0.1159**
	Recall@50	0.0978	0.1470	0.1411	0.1769	0.1476	0.1743	<u>0.1781</u>	**0.1804**
	NDCG@10	0.0214	0.0342	0.0305	0.0412	0.0350	0.0437	<u>0.0447</u>	**0.0456**
	NDCG@20	0.0267	0.0422	0.0383	0.0506	0.0420	0.0532	<u>0.0543</u>	**0.0551**
	NDCG@50	0.0348	0.0539	0.0501	0.0648	0.0543	0.0659	<u>0.0679</u>	**0.0692**

Experiments

Ablation Study

Method	Yelp2018		Amazon-Book	
	Recall@20	NDCG@20	Recall@20	NDCG@20
SGL	0.0677	0.0555	0.0478	0.0379
SimGCL	**0.0719**	**0.0593**	**0.0510**	0.0406
Ours-WithoutInput	0.0705	<u>0.0590</u>	0.0501	**0.0410**
Ours-WithoutFirst	0.0695	0.0577	0.0489	0.0392
Ours-WithoutSecond	0.0692	0.0573	0.0489	0.0400
Ours-WithoutOutput	0.0689	0.0567	0.0485	0.0390
Ours	<u>0.0712</u>	0.0583	<u>0.0504</u>	<u>0.0408</u>

Conclusion

Results:

- We found that directly applying layer-wise contrast can achieve a similar effect to adding uniform noise, further demonstrating that the effectiveness of contrastive learning lies in making embeddings smoother.

Future Work: