



Graph Collaborative Signals Denoising and Augmentation for Recommendation

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<https://github.com/zfan20/GraphDA>

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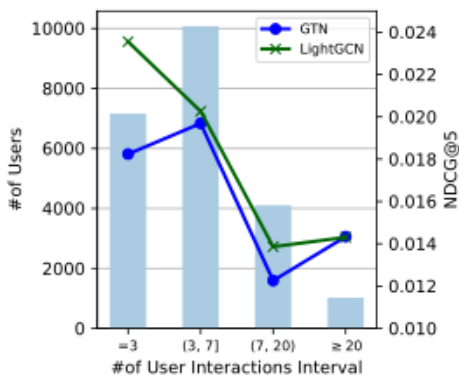
Reported by Ke Gan



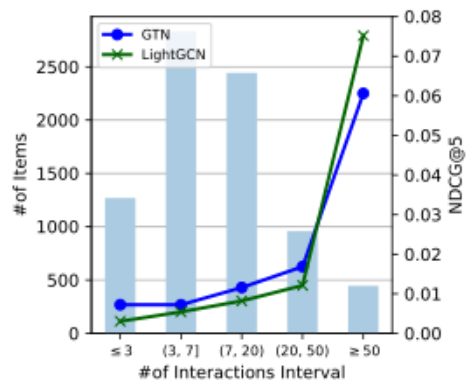
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Introduction



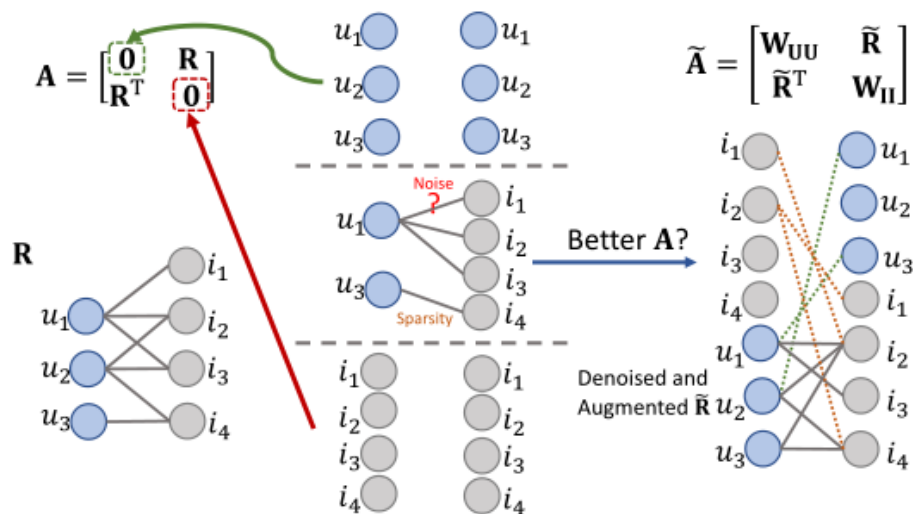
(a) Users



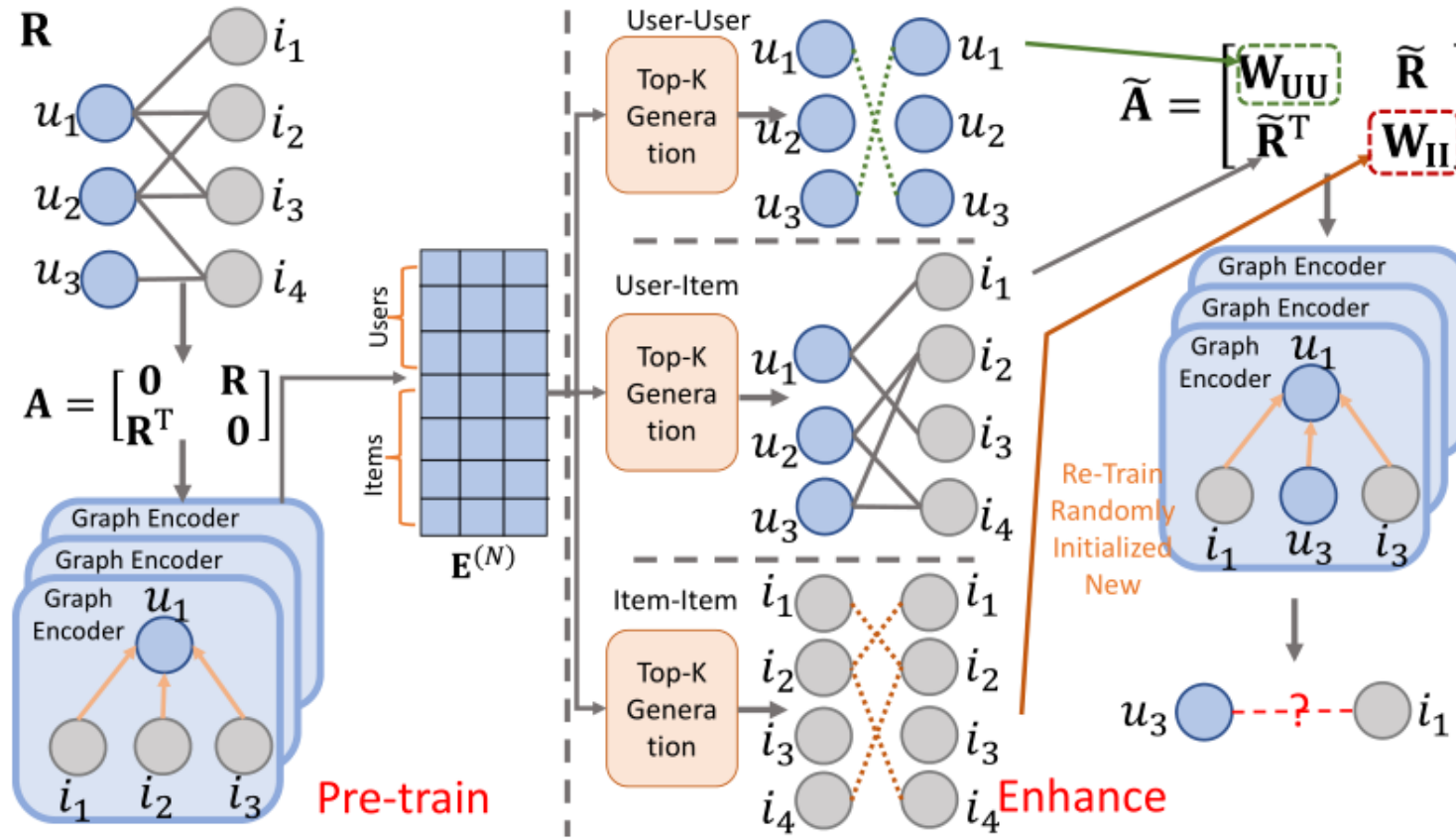
(b) Items

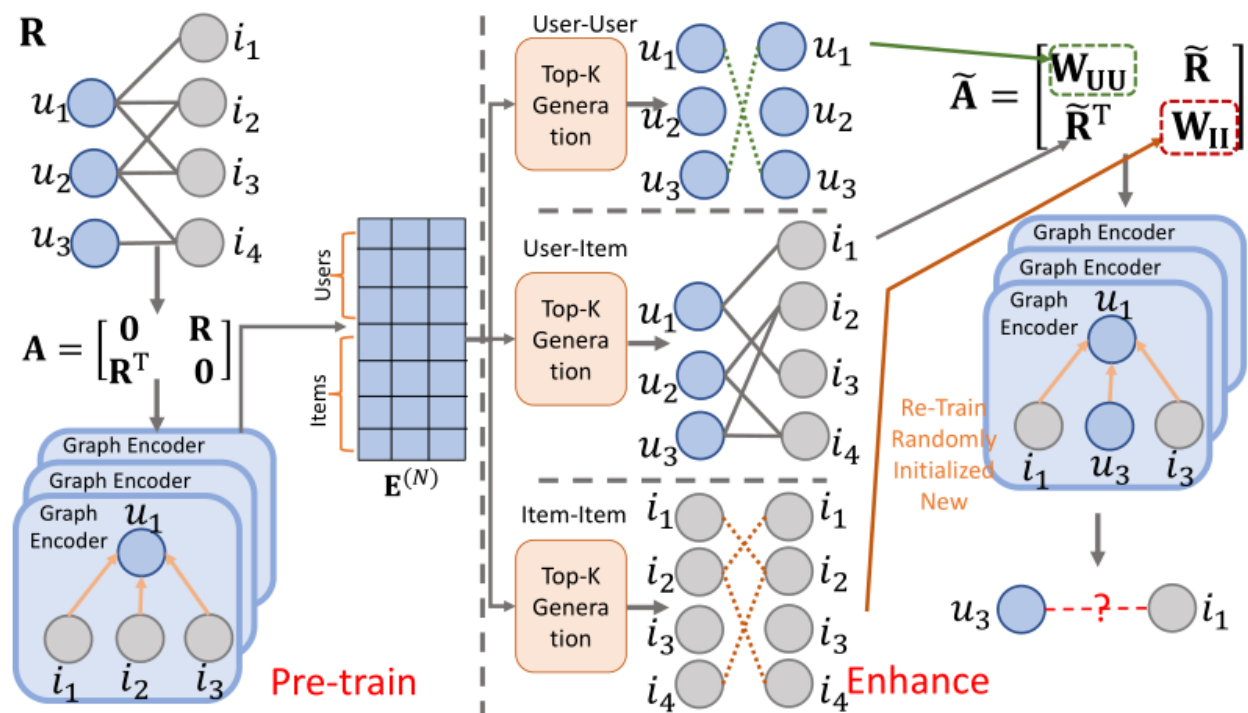
adjacency matrix can be noisy for users/items with abundant interactions and insufficient for users/items with scarce interactions

adjacency matrix ignores user-user and item-item correlations



Approach





$$\mathbf{E} \in \mathbb{R}^{(|\mathcal{U}|+|\mathcal{I}|) \times d}$$

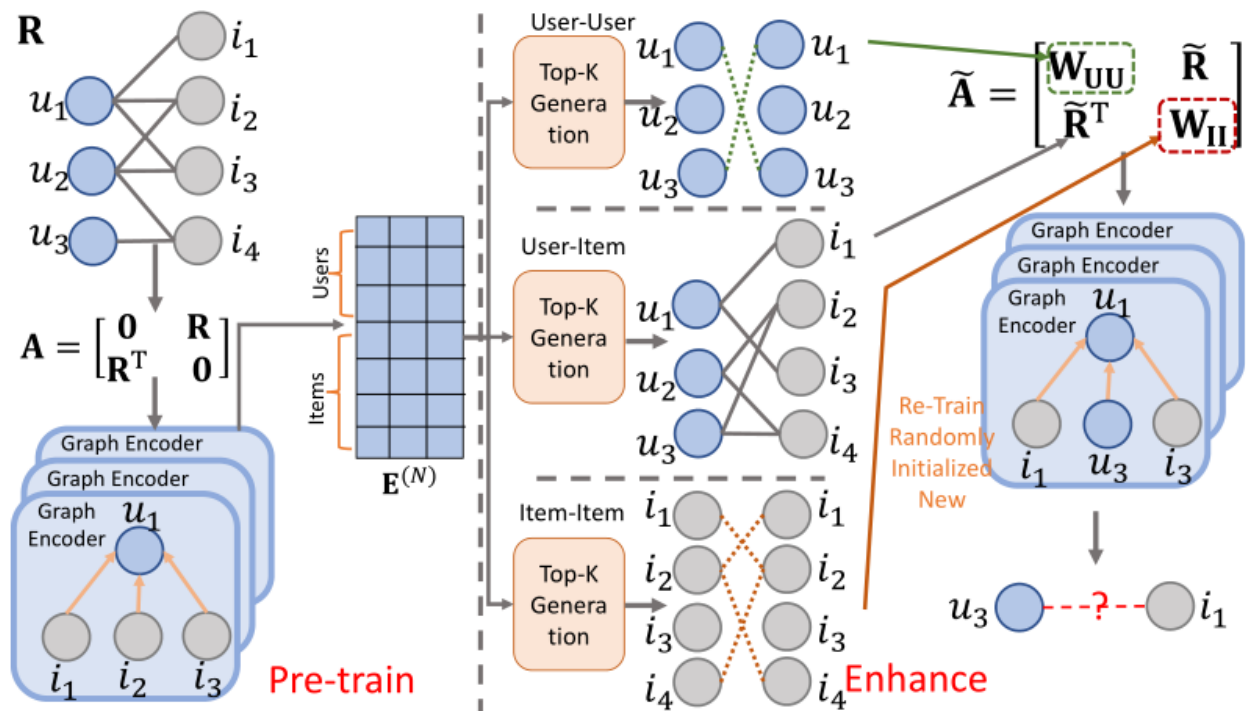
$$\mathbf{E}^{(N)} = \text{Encoder}(\mathbf{A}, \mathbf{E}) = (\mathbf{L})^{N-1} \mathbf{E}^{(0)}, \quad (1)$$

$$P(i|u, \mathbf{A}) = \sigma(\mathbf{e}_u^T \mathbf{e}_i) \quad \text{where } i \in \mathcal{I} \setminus \mathcal{I}_u^+, \quad (2)$$

$$\mathcal{L} = - \sum_{(u, i^+, i^- \in \mathcal{R})} \log \sigma(\mathbf{e}_u^T \mathbf{e}_{i^+} - \mathbf{e}_u^T \mathbf{e}_{i^-}), \quad (3)$$

matrix factorization [29].

Approach



$$\arg \max_{\{i_1, i_2, \dots, i_{U_k} \in I\}} \mathbf{e}_u^T \mathbf{E}_I^{(N)}, \quad (4)$$

We adopt the union of generated user-item interactions

$$\arg \max_{\{u_1, u_2, \dots, u_{UU_k} \in \mathcal{U}\}} \mathbf{e}_u^T \mathbf{E}_U^{(N)}, \quad (5)$$

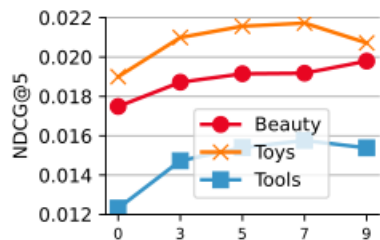
$$\tilde{\mathbf{A}} = \begin{bmatrix} \mathbf{W}_{UU} & \tilde{\mathbf{R}} \\ \tilde{\mathbf{R}}^T & \mathbf{W}_{II} \end{bmatrix}.$$



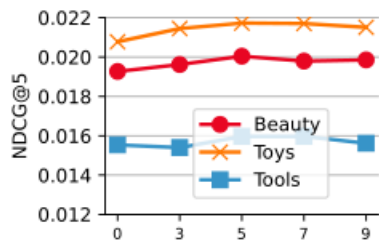
Experiment

Dataset	Beauty				Toys				Tools				Office			
Metric	H@10	N@10	H@20	N@20	H@10	N@10	H@20	N@20	H@10	N@10	H@20	N@20	H@10	N@10	H@20	N@20
NGCF	0.0447	0.0232	0.0724	0.0299	0.0461	0.0251	0.0672	0.0306	0.0329	0.0179	0.0480	0.0216	0.0261	0.0159	0.0453	0.0208
UltraGCN	0.0451	0.0234	0.0728	0.0304	0.0464	0.0250	0.0675	0.0308	0.0331	0.0179	0.0481	0.0217	0.0302	0.0171	0.0471	0.0210
GTN	0.0446	0.0230	0.0680	0.0289	0.0453	0.0248	0.0661	0.0301	<u>0.0337</u>	<u>0.0184</u>	<u>0.0484</u>	<u>0.0221</u>	0.0283	0.0161	0.0453	0.0204
LightGCN	<u>0.0471</u>	<u>0.0244</u>	<u>0.0730</u>	<u>0.0309</u>	<u>0.0512</u>	<u>0.0273</u>	<u>0.0716</u>	<u>0.0325</u>	0.0334	0.0182	0.0482	0.0219	<u>0.0355</u>	<u>0.0197</u>	<u>0.0522</u>	<u>0.0238</u>
Enhanced-UI	0.0486	0.0252	0.0755	0.0317	0.0530	0.0276	0.0765	0.0335	0.0364	0.0195	0.0527	0.0236	0.0363	0.0208	0.0565	0.0259
Improv.	+3.2%	+3.3%	+3.1%	+2.9%	+3.5%	+1.1%	+6.8%	+3.3%	+8.0%	+6.0%	+4.3%	+6.6%	+2.3%	+5.6%	+8.2%	+8.8%
GraphDA	0.0514	0.0264	0.0804	0.0336	0.0549	0.0289	0.0795	0.0347	0.0373	0.0205	0.0532	0.0245	0.0383	0.0225	0.0561	0.0270
Improv.	+9.1%	+8.2%	+8.7%	+7.9%	+7.2%	+5.9%	+11.1%	+6.9%	+10.7%	+11.4%	+5.4%	+10.8%	+7.9%	+14.2%	+7.5%	+13.4%

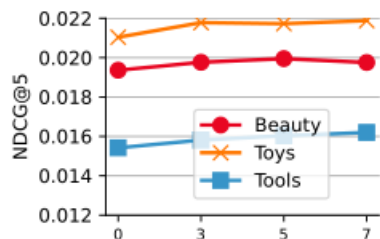
Experiment



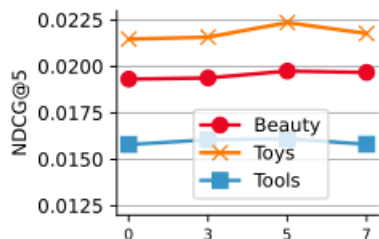
(a) Different values of U_k with best $I_k > 0$.



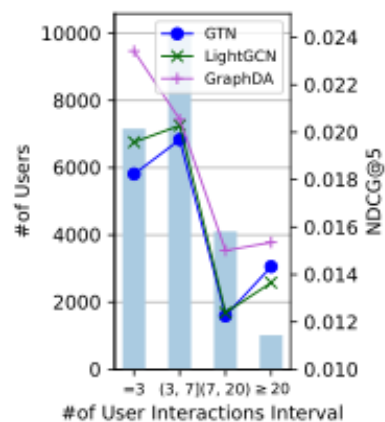
(b) Different values of I_k with best $U_k > 0$.



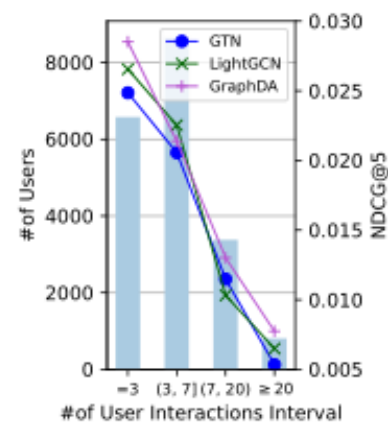
(c) Different values of UU_k



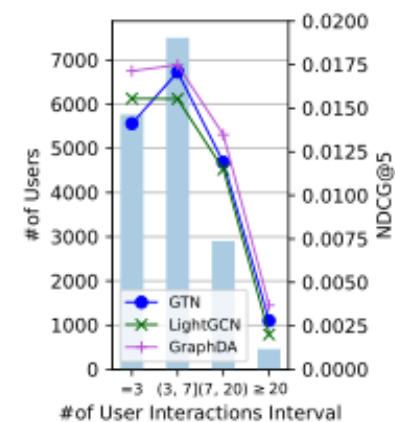
(d) Different values of II_k



(a) Beauty



(b) Toys



(c) Tools



Thank you!