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# Graph-enhanced Optimizers for Structure-aware Recommendation Embedding Evolution

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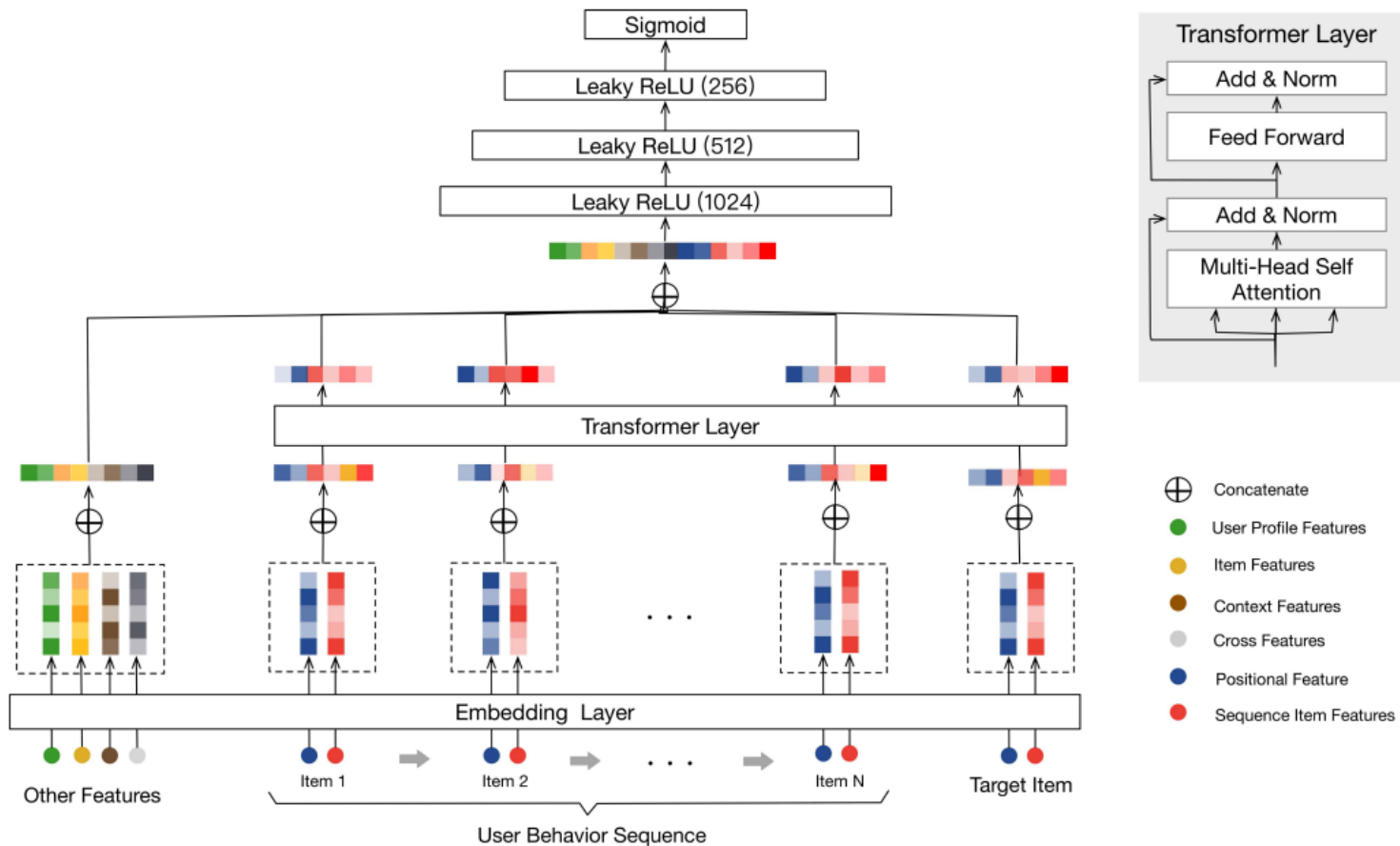
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# Recommender System

- **Embedding** is the **foundation** of recommender systems!



# Similarity

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- Weighted adjacency matrix

$$\mathcal{G} = (\mathcal{V}, \mathbf{A} = [w_{ij}]), \quad w_{ij} \uparrow.$$

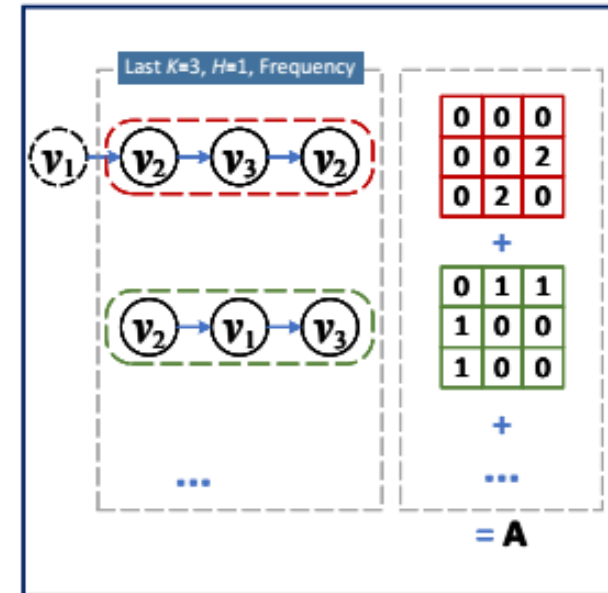
# Similarity

- Weighted adjacency matrix

$$\mathcal{G} = (\mathcal{V}, \mathbf{A} = [w_{ij}]), \quad w_{ij} \uparrow.$$

✓ Interaction data:

- items selected consecutively to be closer



# Similarity

- Weighted adjacency matrix

$$\mathcal{G} = (\mathcal{V}, \mathbf{A} = [w_{ij}]), \quad w_{ij} \uparrow.$$

- ✓ Interaction data:
  - items selected consecutively to be closer
- ✓ Intra-class proximity:
  - items of the same category to be closer

Horror/Mystery/Film-Noir

War/Drama/Romance

Comedy/Musical/Children's/Animation

Fantasy/Sci-Fi

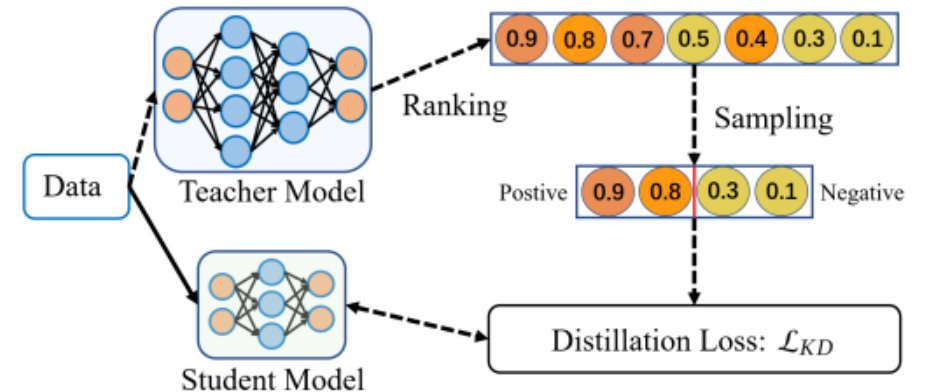
Western/Documentary

# Similarity

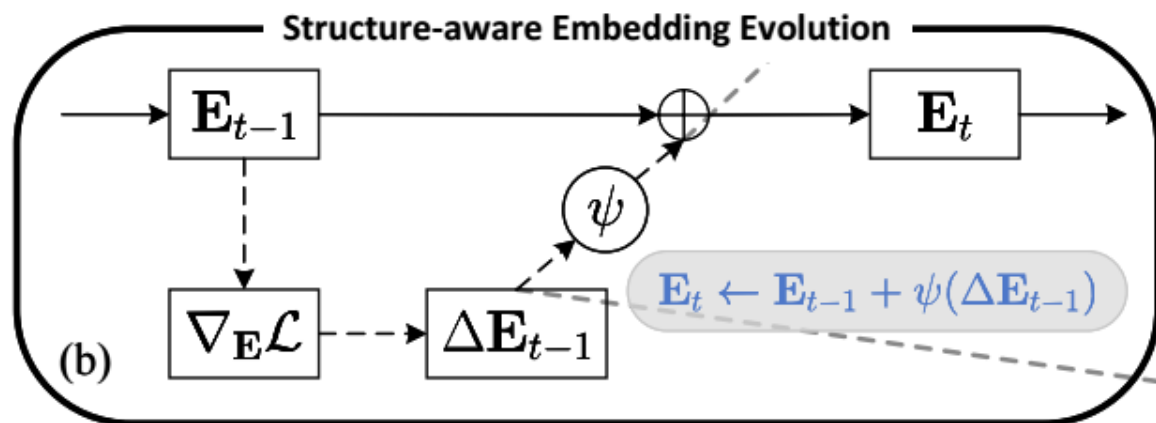
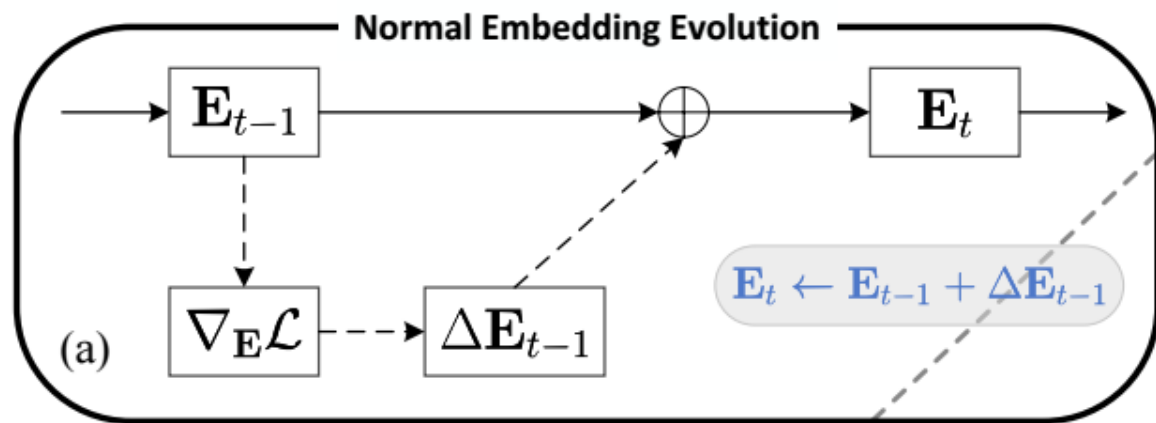
- Weighted adjacency matrix

$$\mathcal{G} = (\mathcal{V}, \mathbf{A} = [w_{ij}]), \quad w_{ij} \uparrow.$$

- ✓ Interaction data:
  - items selected consecutively to be closer
- ✓ Intra-class proximity:
  - items of the same category to be closer
- ✓ Knowledge distillation:
  - item similarity from a teacher model (larger)



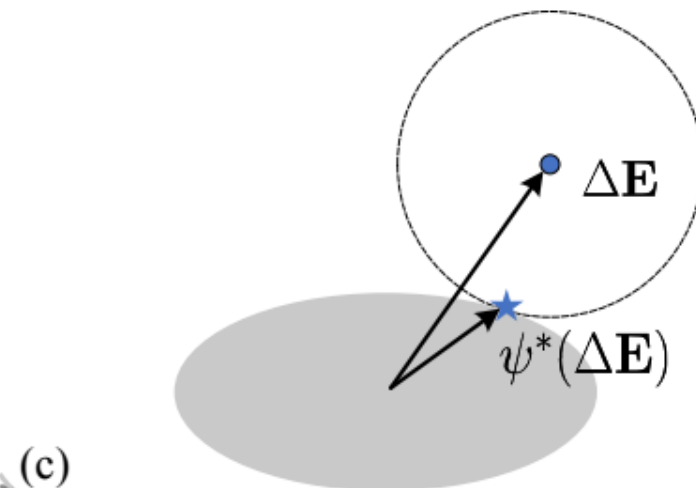
# SEvo Summary



(d) 
$$\hat{\psi}(\Delta \mathbf{E}) = \frac{1 - \beta}{1 - \beta^{L+1}} \sum_{l=0}^L \beta^l \tilde{\mathbf{A}}^l \Delta \mathbf{E}$$

$\gg$

$$\psi^*(\Delta \mathbf{E}) = \underset{\Delta}{\operatorname{argmin}} (1 - \beta) \|\Delta - \Delta \mathbf{E}\|_F^2 + \beta \operatorname{Tr}(\Delta^T \tilde{\mathbf{L}} \Delta)$$



# Interaction data

		GNN-based				MF or RNN/Transformer-based										▲%	p-value
		LightGCN	SR-GNN	LESSR	MAERec	MF-BPR +SEvo		GRU4Rec +SEvo		SASRec +SEvo		BERT4Rec +SEvo		STOSA +SEvo			
Beauty	HR@1	0.0074	0.0059	0.0088	0.0113	0.0071	0.0076	0.0061	0.0094	0.0120	0.0154	0.0157	0.0172	0.0166	<b>0.0216</b>	30.2%	6.90E-05
	HR@5	0.0289	0.0247	0.0322	0.0424	0.0272	0.0293	0.0233	0.0326	0.0404	0.0499	0.0479	0.0522	0.0479	<b>0.0544</b>	13.5%	7.69E-04
	HR@10	0.0472	0.0406	0.0506	0.0662	0.0454	0.0480	0.0395	0.0524	0.0634	0.0759	0.0716	0.0772	0.0680	<b>0.0774</b>	8.2%	2.66E-03
	NDCG@5	0.0181	0.0152	0.0205	0.0269	0.0170	0.0184	0.0146	0.0209	0.0262	0.0328	0.0319	0.0350	0.0327	<b>0.0383</b>	17.2%	9.70E-05
	NDCG@10	0.0240	0.0203	0.0264	0.0346	0.0228	0.0244	0.0198	0.0273	0.0336	0.0411	0.0395	0.0430	0.0391	<b>0.0457</b>	15.5%	8.02E-05
Toys	HR@1	0.0087	0.0100	0.0126	0.0171	0.0079	0.0099	0.0059	0.0080	0.0172	0.0192	0.0160	0.0175	0.0232	<b>0.0267</b>	15.3%	1.46E-03
	HR@5	0.0279	0.0294	0.0352	0.0532	0.0267	0.0306	0.0209	0.0276	0.0506	0.0584	0.0430	0.0492	0.0571	<b>0.0625</b>	9.6%	5.70E-03
	HR@10	0.0456	0.0439	0.0513	0.0796	0.0427	0.0477	0.0345	0.0446	0.0727	0.0844	0.0645	0.0723	0.0776	<b>0.0872</b>	9.5%	3.07E-04
	NDCG@5	0.0183	0.0198	0.0240	0.0355	0.0174	0.0203	0.0134	0.0179	0.0342	0.0392	0.0297	0.0336	0.0406	<b>0.0453</b>	11.6%	2.48E-03
	NDCG@10	0.0240	0.0245	0.0292	0.0440	0.0225	0.0258	0.0177	0.0234	0.0413	0.0475	0.0366	0.0410	0.0472	<b>0.0532</b>	12.7%	3.12E-05
Tools	HR@1	0.0067	0.0046	0.0045	0.0083	0.0058	0.0071	0.0053	0.0058	0.0099	0.0108	0.0074	0.0087	0.0095	<b>0.0133</b>	33.8%	1.23E-02
	HR@5	0.0212	0.0162	0.0157	0.0271	0.0187	0.0225	0.0174	0.0208	0.0317	0.0337	0.0244	0.0279	0.0276	<b>0.0350</b>	10.5%	8.94E-03
	HR@10	0.0326	0.0260	0.0263	0.0423	0.0293	0.0348	0.0272	0.0336	0.0466	0.0497	0.0405	0.0441	0.0417	<b>0.0502</b>	7.7%	8.25E-03
	NDCG@5	0.0140	0.0103	0.0101	0.0177	0.0123	0.0147	0.0114	0.0133	0.0210	0.0223	0.0159	0.0183	0.0186	<b>0.0244</b>	15.9%	5.57E-03
	NDCG@10	0.0176	0.0135	0.0135	0.0226	0.0157	0.0187	0.0145	0.0174	0.0258	0.0274	0.0211	0.0235	0.0231	<b>0.0293</b>	13.4%	3.79E-03
MovieLens	HR@1	0.0124	0.0383	0.0513	0.0439	0.0117	0.0133	0.0487	0.0487	0.0490	0.0517	0.0681	<b>0.0733</b>	0.0457	0.0510	7.6%	3.81E-02
	HR@5	0.0495	0.1297	0.1665	0.1563	0.0470	0.0509	0.1625	0.1663	0.1599	0.1670	0.2069	<b>0.2127</b>	0.1409	0.1569	2.8%	4.17E-03
	HR@10	0.0866	0.2009	0.2539	0.2462	0.0836	0.0876	0.2522	0.2568	0.2492	0.2567	0.3018	<b>0.3075</b>	0.2185	0.2356	1.9%	9.32E-02
	NDCG@5	0.0307	0.0842	0.1092	0.1003	0.0291	0.0319	0.1061	0.1075	0.1046	0.1096	0.1387	<b>0.1437</b>	0.0932	0.1041	3.6%	4.19E-04
	NDCG@10	0.0427	0.1071	0.1373	0.1292	0.0408	0.0436	0.1350	0.1366	0.1333	0.1385	0.1693	<b>0.1743</b>	0.1181	0.1295	2.9%	1.30E-02
<b>Avg. Improv.</b>							<b>+13.1%</b>		<b>+23.4%</b>		<b>+12.3%</b>		<b>+9.6%</b>		<b>+17.5%</b>		
<b>Avg. Train. Time</b>		2,820s	43,783s	62,457s	31,674	2,863s	<b>+173s</b>	3,582s	<b>+124s</b>	532s	<b>+37s</b>	1,256s	<b>+288s</b>	2,087s	<b>+127s</b>		
<b>Avg. Inf. Time</b>		1.19s	11.18s	9.34s	2.73s	1.13s	<b>+0s</b>	1.80s	<b>+0s</b>	1.88s	<b>+0s</b>	1.61s	<b>+0s</b>	6.72	<b>+0s</b>		



# Intra-class Representation Proximity

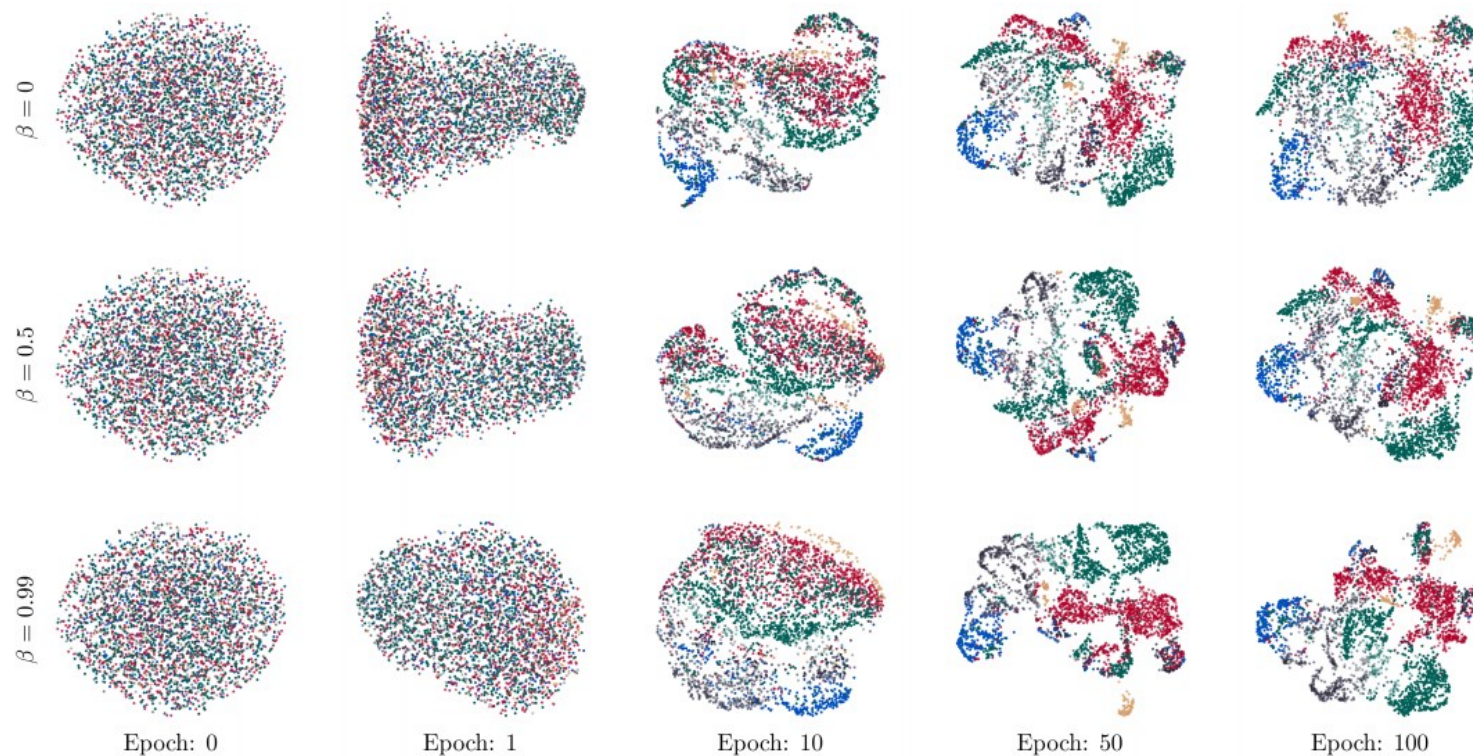


Figure 6: UMAP [29] visualization of movies based on their embeddings. For ease of differentiation, we group the 18 genres into 6 categories and colored them individually: Thriller/Crime/Action/Adventure; Horror/Mystery/Film-Noir; War/Drama/Romance; Comedy/Musical/Children's/Animation; Fantasy/Sci-Fi; Western/Documentary.

# Knowledge Distillation

- Weight estimation (kNN graph):

$$w_{ij} = \hat{w}_{ij} + \hat{w}_{ji}, \quad \hat{w}_{ij} := \exp(-d_{ij}/\tau), \quad d_{ij} = \frac{\mathbf{e}_i^T \mathbf{e}_j}{\|\mathbf{e}_i\|_2 \|\mathbf{e}_j\|_2}.$$

	HR@1	HR@5	HR@10	NDCG@5	NDCG@10
Teacher	0.0198	0.0544	0.0786	0.0374	0.0452
Student	0.0094	0.0327	0.0526	0.0210	0.0275
+KD [17]	0.0105	0.0352	0.0552	0.0229	0.0294
+RKD [33]	0.0082	0.0311	0.0515	0.0196	0.0262
+HTD [20]	0.0085	0.0344	0.0549	0.0215	0.0281
+DKD [54]	0.0138	0.0389	<b>0.0577</b>	0.0265	0.0325
Student	0.0094	0.0327	0.0526	0.0210	0.0275
+SEvo	0.0107	0.0364	0.0576	0.0236	0.0304
+DKD	<b>0.0166</b>	<b>0.0407</b>	0.0568	<b>0.0289</b>	<b>0.0341</b>

# Future Work

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- Simple graph -> Multiplex heterogeneous graph
- Dynamic graph structures:
  - **Challenge I:** Computational overhead associated with the ongoing adjacency matrix normalization
  - **Challenge II:** How to adaptively weaken the outdated historical information

Thanks!

