



TPR: Text-aware Preference Ranking for Recommender Systems

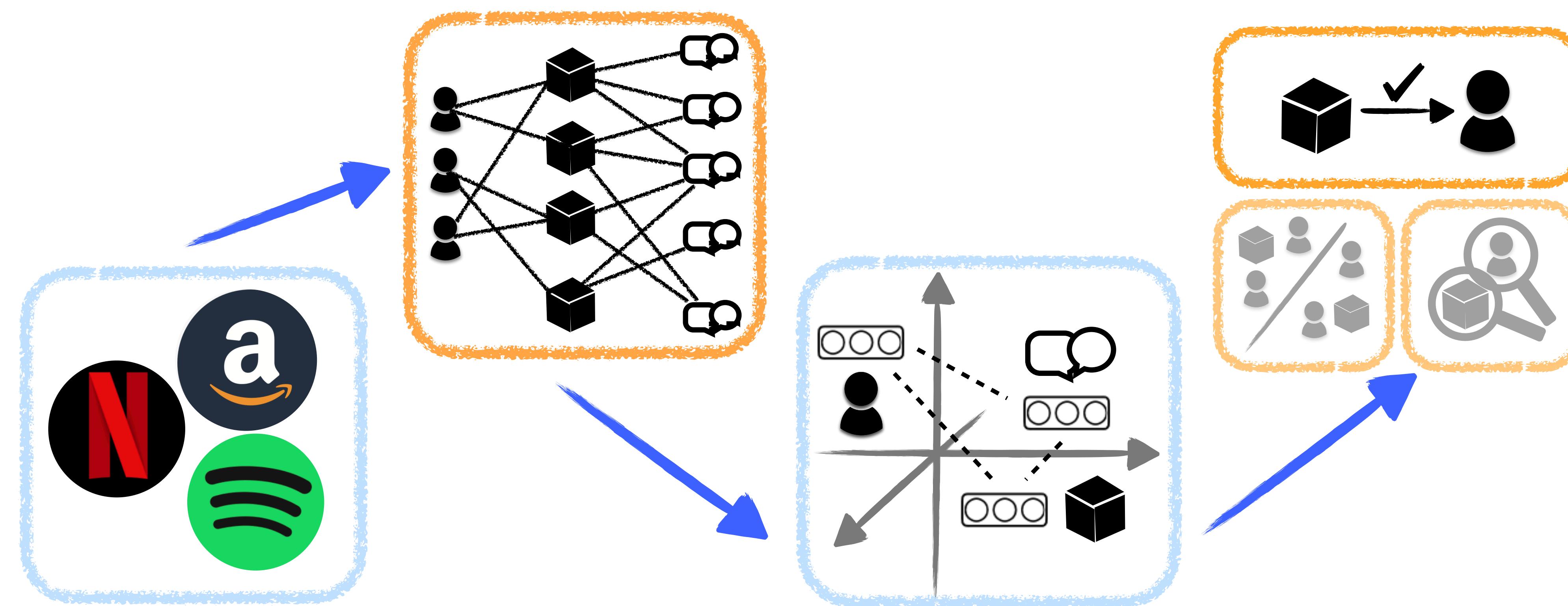
Yu-Neng Chuang, Chih-Ming Chen,
Prof. Chuan-Ju, Wang, Prof. Ming-Feng Tsai,
Prof. Yuan Fang, and Prof. Ee-Peng Lim



Introduction

- What is graph embedding?

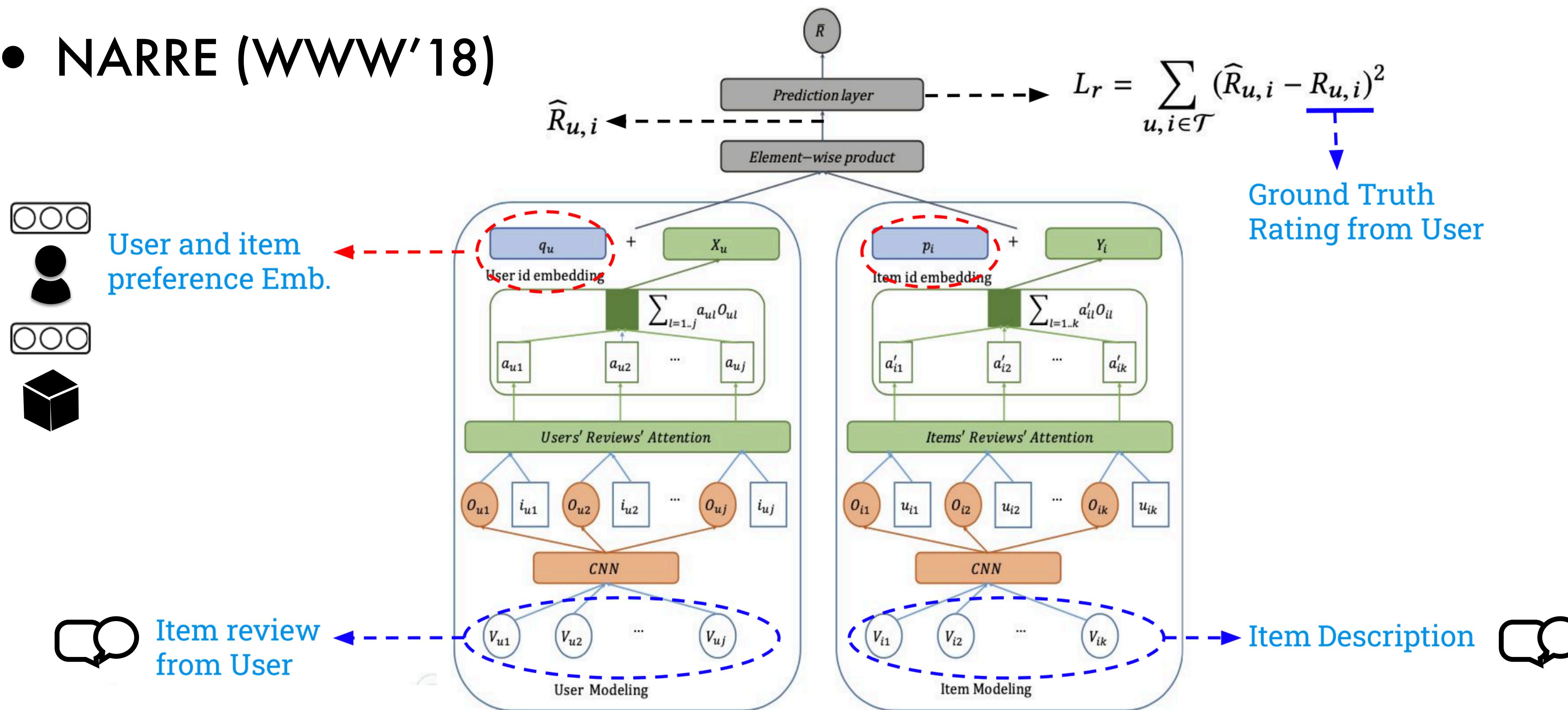
Allen Chung



Related work - Textual-based Recommendation

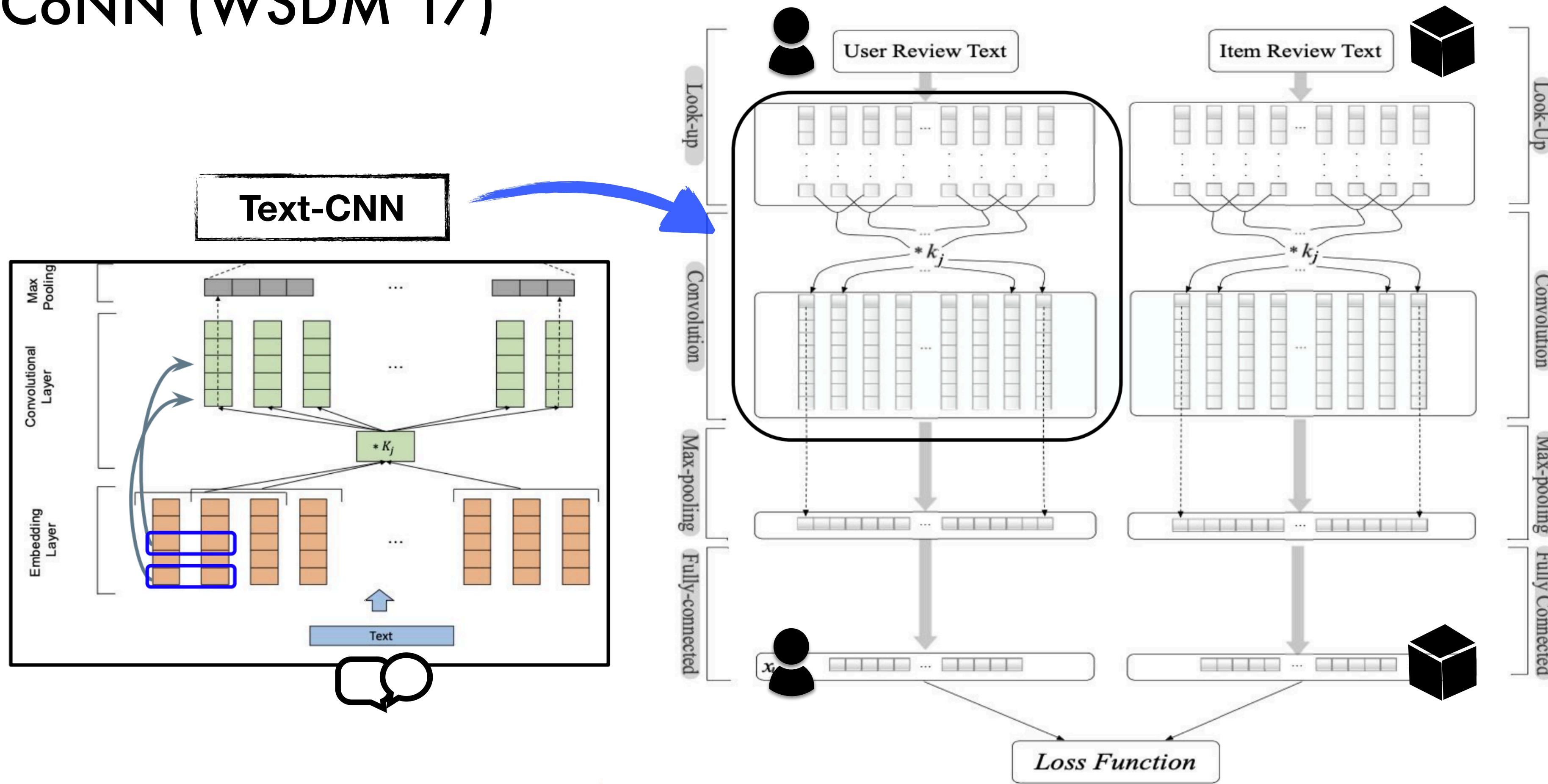
- NARRE (WWW'18)

Allen Chung



Related work - Textual-based Recommendation

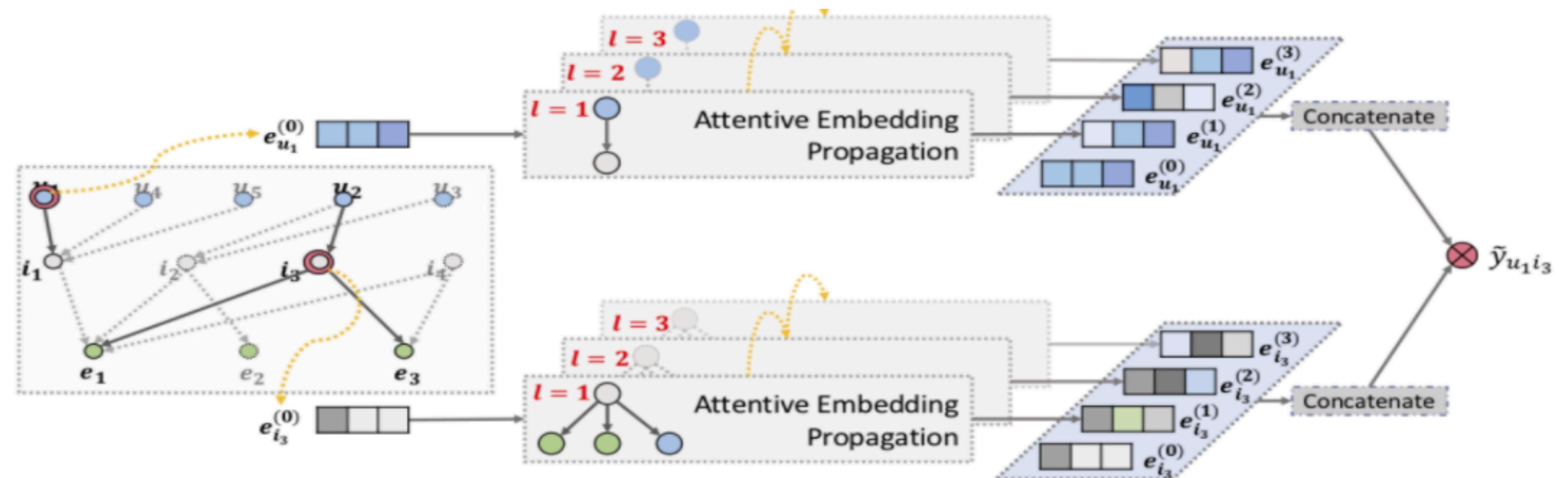
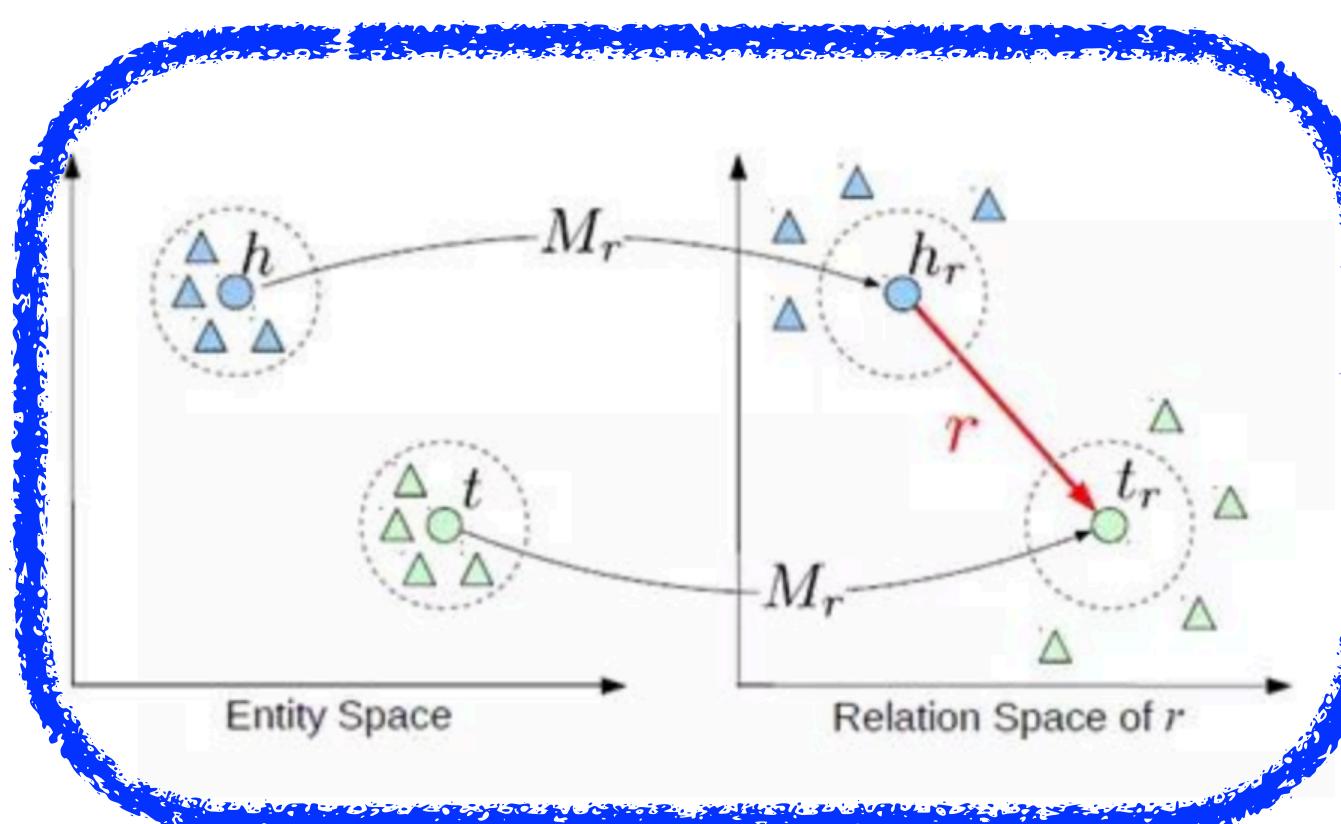
- DeepCoNN (WSDM'17)



Related work - Textual-based Recommendation

- KGAT: Knowledge Graph Attention Network for REC. (KDD'19)

Allen Chung



Learning TranR

$$g(h, r, t) = \|\mathbf{W}_r \mathbf{e}_h + \mathbf{e}_r - \mathbf{W}_r \mathbf{e}_t\|_2^2$$

$$\mathcal{L}_{KG} = \sum_{(h, r, t, t') \in \mathcal{T}} -\ln \sigma(g(h, r, t') - g(h, r, t))$$

GCN aggregation

$$\mathbf{e}_h^{(1)} = f(\mathbf{e}_h, \mathbf{e}_{N_h})$$

$$\mathbf{e}_{N_h}^{(l-1)} = \sum_{(h, r, t) \in N_h} \pi(h, r, t) \mathbf{e}_t^{(l-1)},$$

Concat all layers

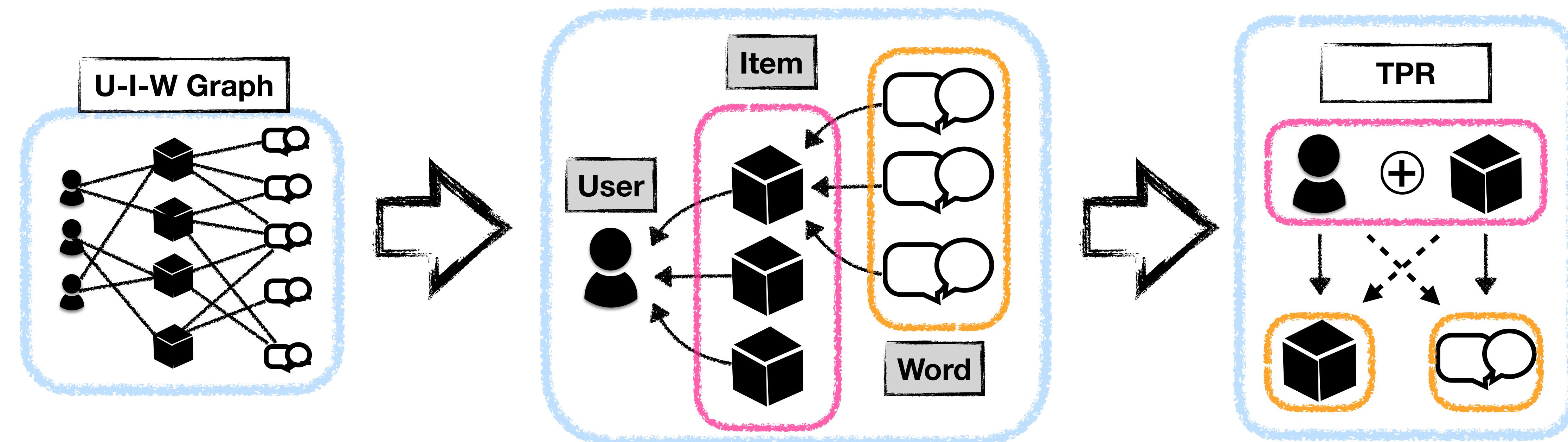
$$\mathbf{e}_u^* = \mathbf{e}_u^{(0)} \parallel \dots \parallel \mathbf{e}_u^{(L)}, \quad \mathbf{e}_i^* = \mathbf{e}_i^{(0)} \parallel \dots \parallel \mathbf{e}_i^{(L)}$$

$$\mathcal{L}_{CF} = \sum_{(u, i, j) \in O} -\ln \sigma(\hat{y}(u, i) - \hat{y}(u, j))$$

Text-aware Preference Ranking

- Motivation: Seeking a method to jointly learn the feature from user log and text

Allen Chung



Text-aware Preference Ranking

- Two ranking structures, IPR and WRR, model the relation of U-I and I-W pairs

Item Preference Ranking (IPR)

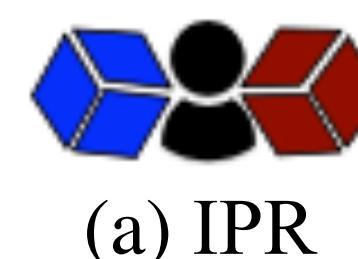
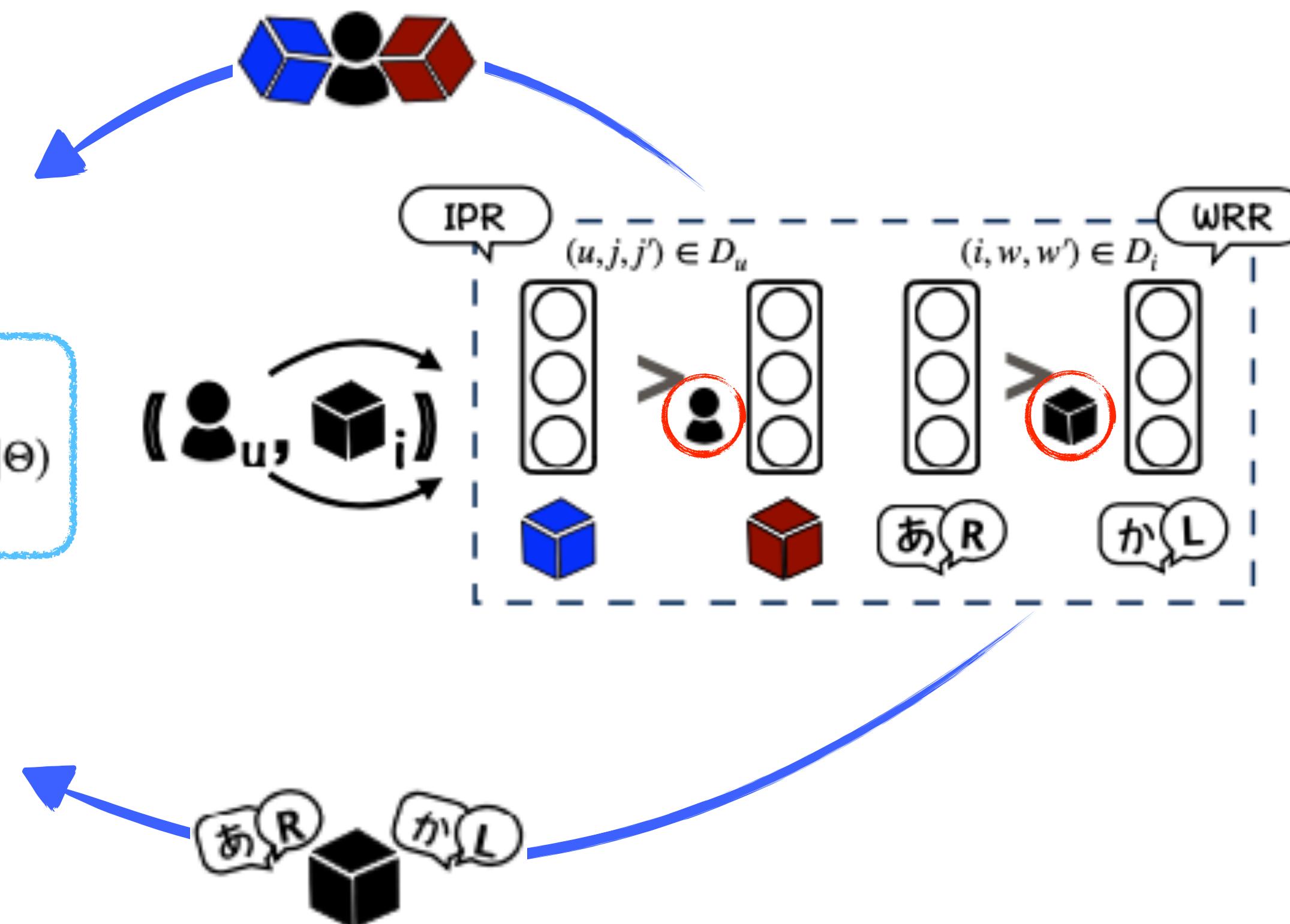
$$p(j >_u j' | \Theta) = \sigma(\langle \Theta_u, \Theta_j - \Theta_{j'} \rangle)$$

Allen Chung

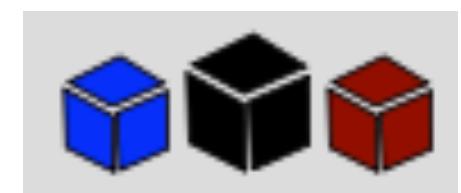
$$O_{\text{TPR}} \equiv \max \prod_{(u,i) \in E_{u,i}} p(\overbrace{>_u}^{\text{IPR}}, \overbrace{>_i}^{\text{WRR}} | \Theta)$$

$$p(w >_i w' | i) = \sigma(\langle \Theta_i, \Theta_w - \Theta_{w'} \rangle)$$

Word Relatedness Ranking (WRR)



(a) IPR



(b) Item-to-item

$$\begin{aligned} p(j >_u j', w >_i w' | \Theta) \\ = \sigma(\langle \Theta_u + \Theta_i, (\Theta_j - \Theta_{j'}) + (\Theta_w - \Theta_{w'}) \rangle) \\ = \sigma(\langle \Theta_u, (\Theta_j - \Theta_{j'}) \rangle + \langle \Theta_u, (\Theta_w - \Theta_{w'}) \rangle + \\ \langle \Theta_i, (\Theta_j - \Theta_{j'}) \rangle + \langle \Theta_i, (\Theta_w - \Theta_{w'}) \rangle), \end{aligned}$$

(c) User-to-word

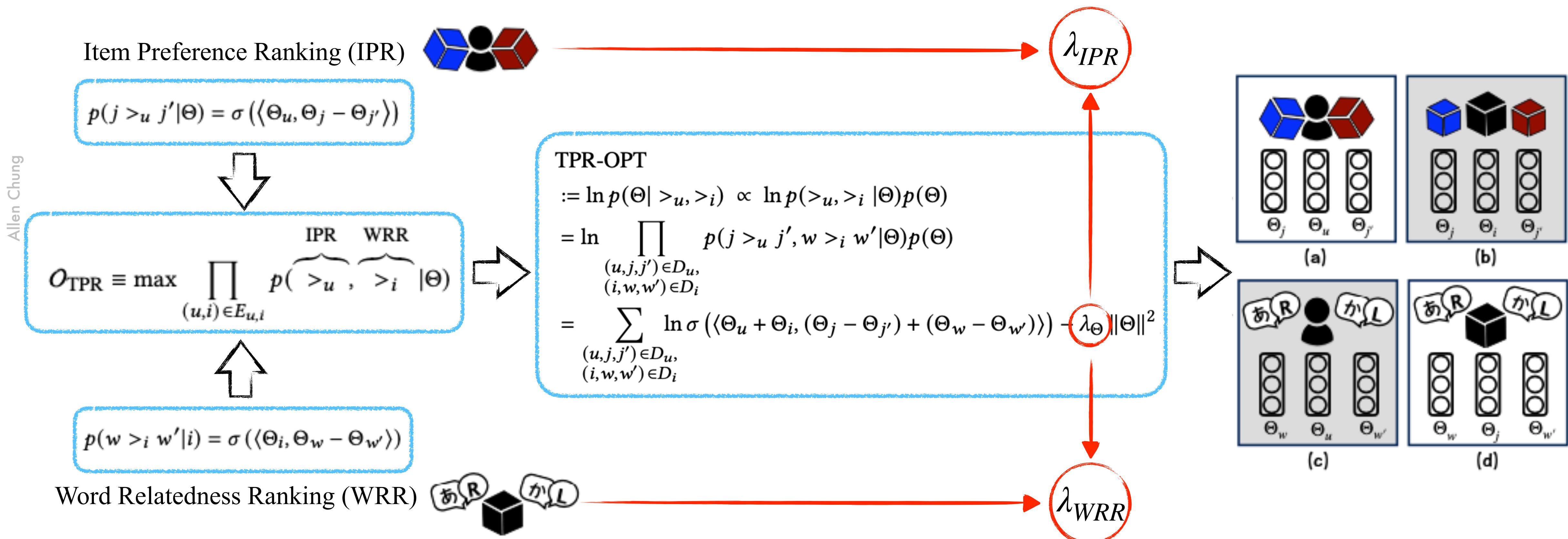


(d) WRR



Text-aware Preference Ranking

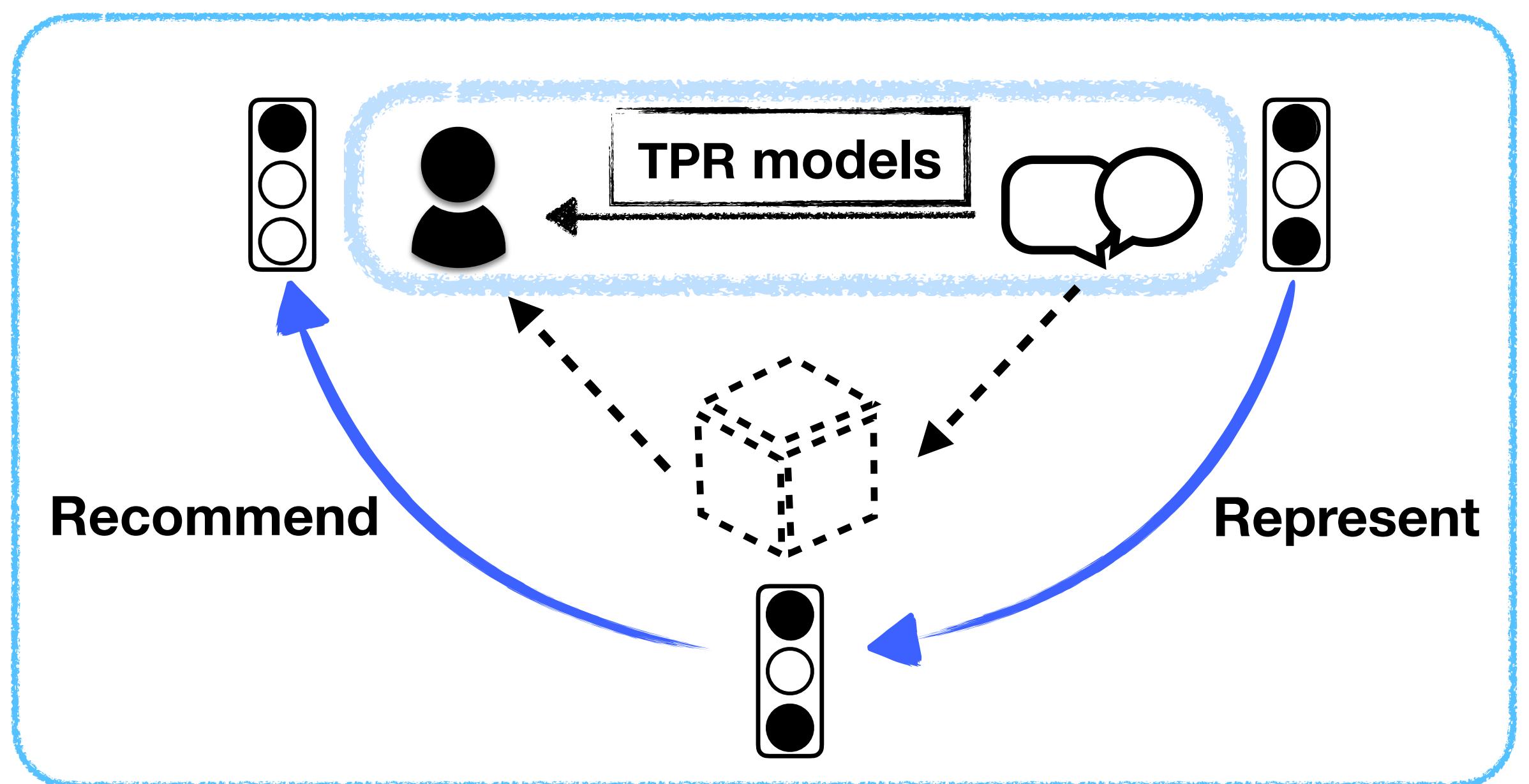
- Seeking a method to jointly learn two ranking structures : IPR and WRR



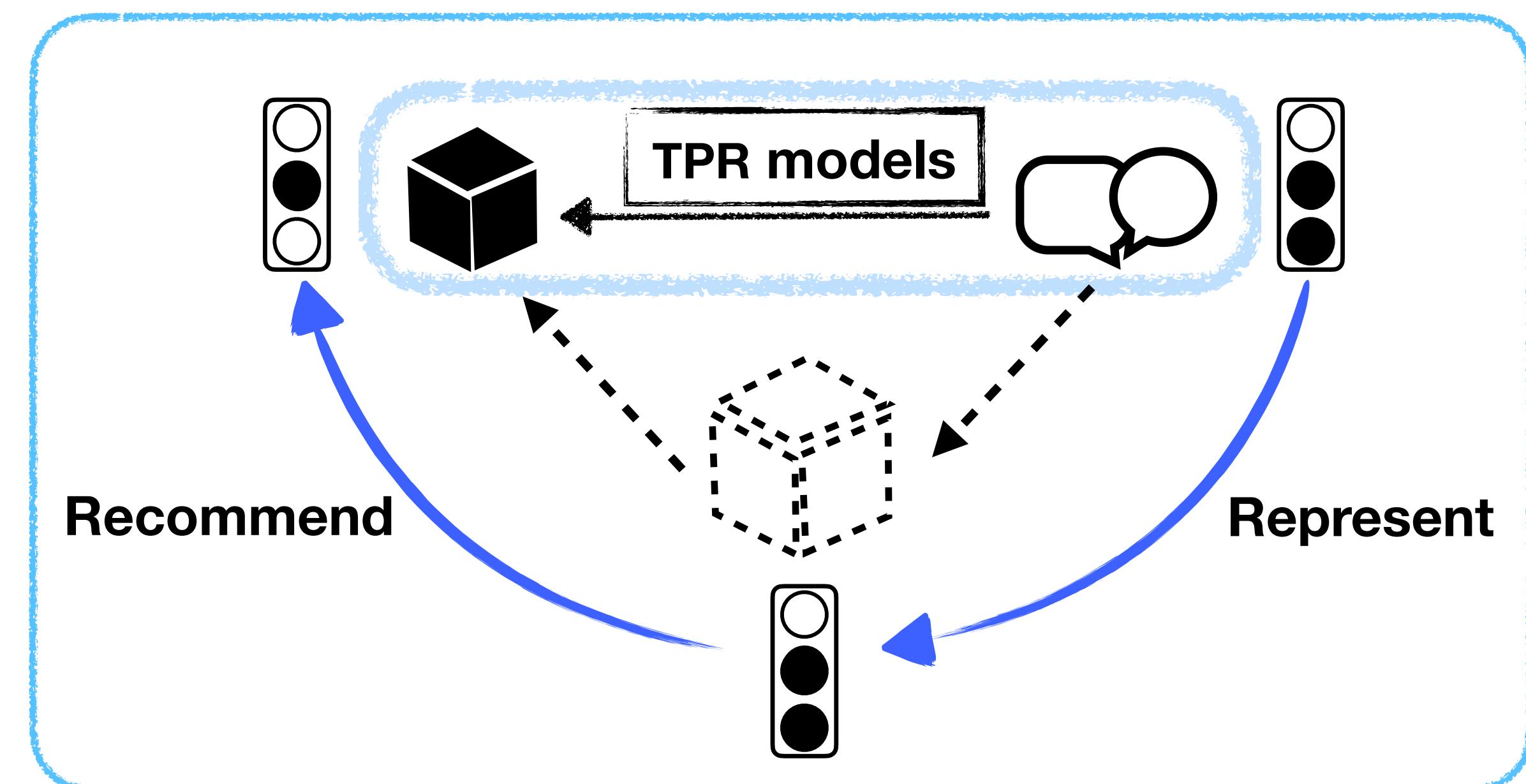
Text-aware Preference Ranking

- Solutions of TPR to solve cold-start problem

Allen Chung



(a) User-Item



(b) Item-Item

Experiment Results

- Datasets : Six different public real-world datasets.

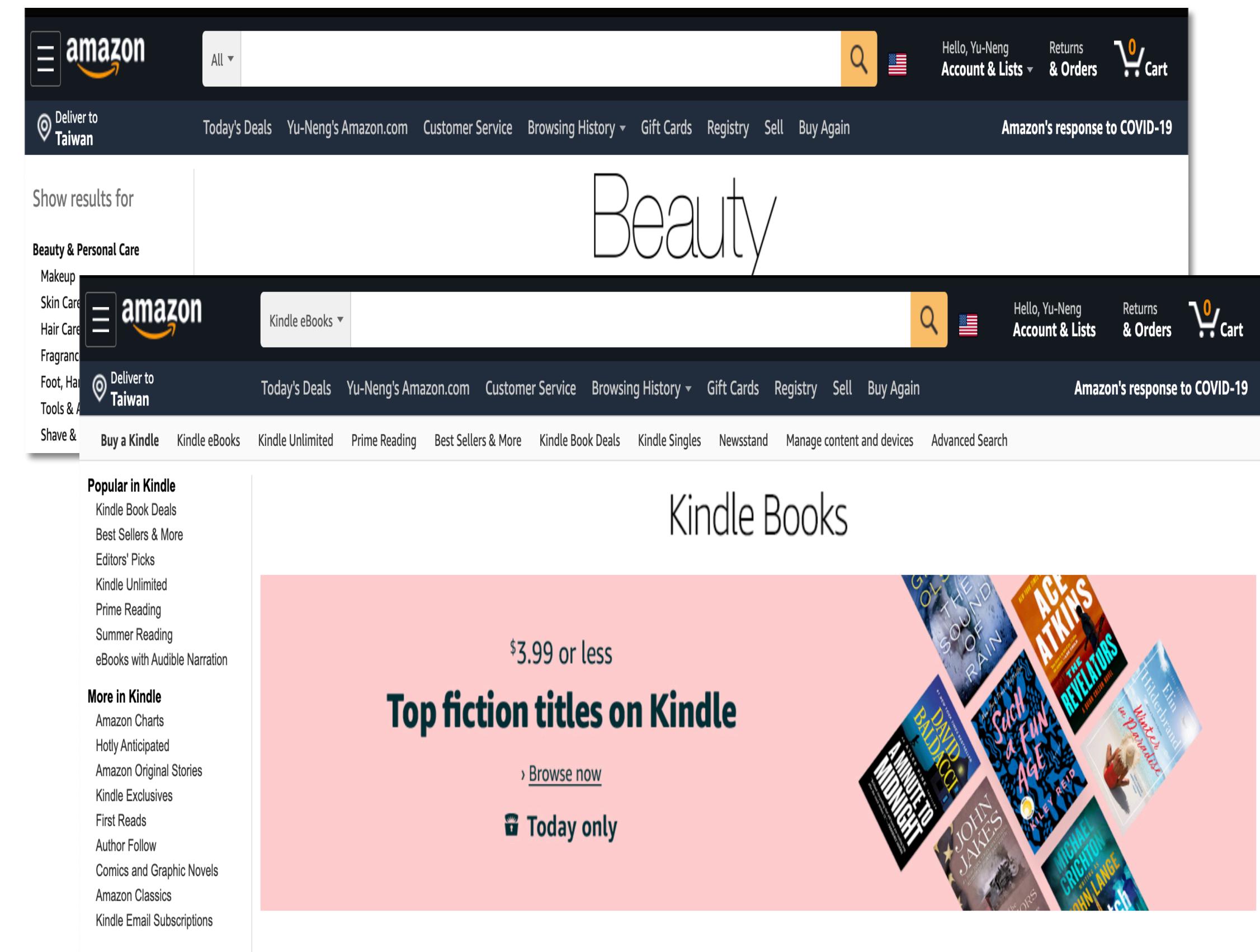
- Each of the dataset contains

A. User-item interaction log (U-I)

B. Item with its textual description (I-W)

Allen Chung

	Users	Items	Words	U-I edges	I-W edges
Amazon-Magazine	2,825	1,299	6,740	11,685	9,4381
Amazon-Beauty	4,801	4,865	4,115	11,685	159,475
Amazon-Application	11,823	5,554	9,712	42,675	410,079
Amazon-Software	13,634	9,325	11,111	57,793	766,112
Amazon-Fashion	19,875	36,080	5,076	75,596	442,136
Amazon-Kindle	363,303	356,634	36,445	3,334,521	6,794,209



Experiment Results

- Top-K recommendation performance (IPR 

	Amazon-Magazine		Amazon-Beauty		Amazon-Applications		Amazon-Fashion	
	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10
BPR [20]	0.3306	0.1734	0.4278	0.3468	0.3035	0.1590	0.1563	0.1223
WARP [23]	0.3435	0.1892	0.3468	0.3437	0.3016	0.1655	0.1815	0.1298
SINE [25]	0.0360	0.0083	0.0549	0.0157	0.1283	0.0280	0.0865	0.0181
HPE [3]	0.3419	0.1377	† 0.4773	† 0.3652	† 0.3552	0.1736	† 0.2126	† 0.1393
GATE [13]	0.2720	0.0489	0.3940	0.0812	0.1336	0.0225	0.0819	0.0186
CKE [26]	0.3838	0.2061	0.4208	0.3450	0.2933	0.1562	0.1581	0.1230
KGAT [22]	† 0.4156	† 0.2156	0.4321	0.3558	0.3213	† 0.1862	0.1862	0.1268
TPR ($\lambda_{WRR} = 0.001$)	0.3681	0.1599	* 0.4950	*0.3735	*0.3937	*0.1779	*0.2394	*0.1525
TPR ($\lambda_{WRR} = 0.005$)	0.4101	0.1880	*0.4925	*0.3783	*0.4097	*0.1951	*0.2270	*0.1462
TPR ($\lambda_{WRR} = 0.01$)	0.4182	0.1840	*0.4840	*0.3793	*0.3997	*0.1971	*0.2258	*0.1482
Improv. (%)	-0.62%	-12.80%	+3.70%	+3.86%	+15.34%	+5.85%	+6.77%	+6.38%
	Amazon-Software		Amazon-Kindle		Course		SG-OPN	
	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10
BPR [20]	† 0.3669	0.1779	0.4414	0.2097	0.5731	0.4129	0.1008	0.0339
WARP [23]	0.3423	0.1556	† 0.5461	† 0.3392	0.5340	0.3639	† 0.2623	† 0.1131
SINE [25]	0.0976	0.0257	0.2812	0.1394	0.0357	0.0168	0.0412	0.0150
HPE [3]	0.3658	0.1405	0.5228	0.2803	0.3391	0.2294	0.0047	0.0040
GATE [13]	0.1326	0.0202	-	-	0.4477	0.3170	0.0010	0.0035
CKE [26]	0.3448	0.1497	-	-	† 0.6094	† 0.4583	0.1050	0.0837
KGAT [22]	0.3907	† 0.1847	-	-	0.5902	0.4294	0.1473	0.0512
TPR ($\lambda_{WRR} = 0.001$)	*0.3898	0.1615	*0.5682	*0.3448	0.5735	0.4177	*0.3110	*0.1411
TPR ($\lambda_{WRR} = 0.005$)	*0.4252	0.1844	*0.6065	*0.3722	0.6014	0.4422	*0.3094	*0.1392
TPR ($\lambda_{WRR} = 0.01$)	*0.4319	*0.1956	*0.6164	*0.3804	*0.6155	0.4468	*0.3086	*0.1434
Improv. (%)	+17.71%	+5.90%	+12.87%	+12.14%	+1.00%	-2.50%	+18.56%	+24.75%

Experiment Results

- Item-to-word reconstruction (WRR)



	Amazon-Magazine		Amazon-Beauty		Amazon-Applications		Amazon-Fashion		Amazon-Software	
	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10
HPE [3]	† 0.7378	† 0.5910	† 0.7423	† 0.5651	† 0.7015	† 0.5383	† 0.5680	† 0.4927	† 0.5788	† 0.3682
CKE [26]	0.0441	0.0502	0.0222	0.0296	0.0435	0.0398	0.0124	0.0134	0.0635	0.0670
KGAT [22]	0.5273	0.4414	0.2884	0.2386	0.4109	0.2758	0.1869	0.1609	0.5138	0.3206
TPR ($\lambda_{WRR} = 0.001$)	*0.8371	*0.7653	*0.8244	*0.7343	*0.8530	*0.7595	*0.8645	*0.8037	*0.7159	*0.4703
TPR ($\lambda_{WRR} = 0.005$)	0.6294	0.5448	0.4738	0.3849	0.6109	0.5025	0.4930	0.4348	0.5476	0.3552
TPR ($\lambda_{WRR} = 0.01$)	0.5279	0.4411	0.4270	0.3580	0.4743	0.3722	0.3284	0.2825	0.4632	0.2949

Table 6: Performance on item-to-word reconstruction

Allen Chung

<

Experiment Results

- User-to-word recommendation()

Allen Chung

	Amazon-Magazine		Amazon-Beauty		Amazon-Applications		Amazon-Fashion		Amazon-Software	
	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10
HPE [3]	† 0.2002	† 0.1938	† 0.2206	† 0.1684	† 0.1955	† 0.1543	† 0.0829	† 0.0725	† 0.2414	† 0.1971
CKE [26]	0.0374	0.0576	0.0173	0.0263	0.0435	0.0398	0.0189	0.0213	0.0691	0.0723
KGAT [22]	0.0248	0.0375	0.0117	0.0161	0.0123	0.0201	0.0463	0.0644	0.0073	0.0153
TPR ($\lambda_{WRR} = 0.001$)	0.1996	0.1941	0.3411	*0.2943	0.1891	0.1556	*0.1053	*0.0833	*0.3018	0.2332
TPR ($\lambda_{WRR} = 0.005$)	*0.2249	*0.2190	*0.3728	*0.3147	0.1818	0.1537	*0.1134	*0.0865	*0.2872	*0.2482
TPR ($\lambda_{WRR} = 0.01$)	*0.2274	*0.2198	*0.3589	*0.2948	0.1690	0.1447	*0.1050	*0.0767	*0.2625	*0.2455

Table 7: Performance on user-to-word recommendation

Experiment Results

- Item-to-Item recommendation ()

	Amazon-Magazine		Amazon-Beauty		Amazon-Applications		Amazon-Fashion		Amazon-Software	
	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10
BPR [20]	0.3637	0.1964	0.4433	0.3689	0.3472	† 0.1871	0.1655	0.1244	0.3993	† 0.1933
WARP [23]	0.2769	0.1615	0.4248	0.3577	0.2686	0.1438	0.1435	0.1130	0.2989	0.1444
SINE [25]	0.1365	0.0877	0.2813	0.1041	0.1873	0.0857	0.1663	0.1160	0.2636	0.1065
HPE [3]	0.3584	0.1376	0.4575	0.3584	0.3380	0.1600	† 0.2091	† 0.1326	0.3552	0.1501
CKE [26]	0.3903	0.1986	0.4469	0.3570	0.3353	0.1838	0.1585	0.1245	0.3766	0.1887
KGAT [22]	† 0.3972	† 0.2049	† 0.4587	† 0.3710	† 0.3645	0.1864	0.1530	0.1155	† 0.4066	0.1699
TPR ($\lambda_{WRR} = 0.001$)	0.3911	0.1781	*0.4855	*0.3803	*0.3786	0.1890	*0.2330	*0.1541	0.3992	0.1736
TPR ($\lambda_{WRR} = 0.005$)	*0.4155	0.2038	*0.4822	*0.3797	*0.3990	*0.1960	*0.2195	*0.1487	*0.4233	0.1946
TPR ($\lambda_{WRR} = 0.01$)	*0.4201	0.2057	*0.4755	*0.3819	*0.3859	*0.2036	*0.2133	*0.1477	*0.4245	*0.1993
Improv. (%)	+5.76%	+0.39%	+5.84%	+2.93%	+9.46%	+8.81%	+11.42%	+16.21%	+4.40%	+3.10%

Table 3: Performance on item-to-item recommendation

Experiment Results

- Cold-start user-to-item recommendation

Allen Chung

	Amazon-Magazine		Amazon-Beauty		Amazon-Applications		Amazon-Fashion		Amazon-Software	
	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10
HPE [3]	† 0.2454	† 0.0609	† 0.1203	† 0.0419	† 0.0794	† 0.0101	† 0.1326	† 0.0344	† 0.1149	† 0.0114
CKE [26]	0.0636	0.0343	0.0093	0.0058	0.0072	0.0035	0.0090	0.0046	0.0104	0.0056
KGAT [22]	0.0363	0.0254	0.0152	0.0035	0.0033	0.0035	0.0152	0.0035	0.0083	0.0035
TPR ($\lambda_{WRR} = 0.001$)	*0.2636	*0.0875	*0.1654	*0.0640	*0.1569	*0.0340	*0.1698	*0.0700	*0.1511	*0.0337
TPR ($\lambda_{WRR} = 0.005$)	*0.2590	*0.0919	*0.1483	*0.0570	*0.1175	*0.0200	0.1354	*0.0527	0.1176	0.0168
TPR ($\lambda_{WRR} = 0.01$)	*0.2863	0.0609	*0.1320	*0.0501	*0.1026	*0.0167	0.1055	0.0374	0.0887	0.0106

Table 4: Performance on cold-start user-to-item recommendation

Experiment Results

- Cold-start item-to-item recommendation

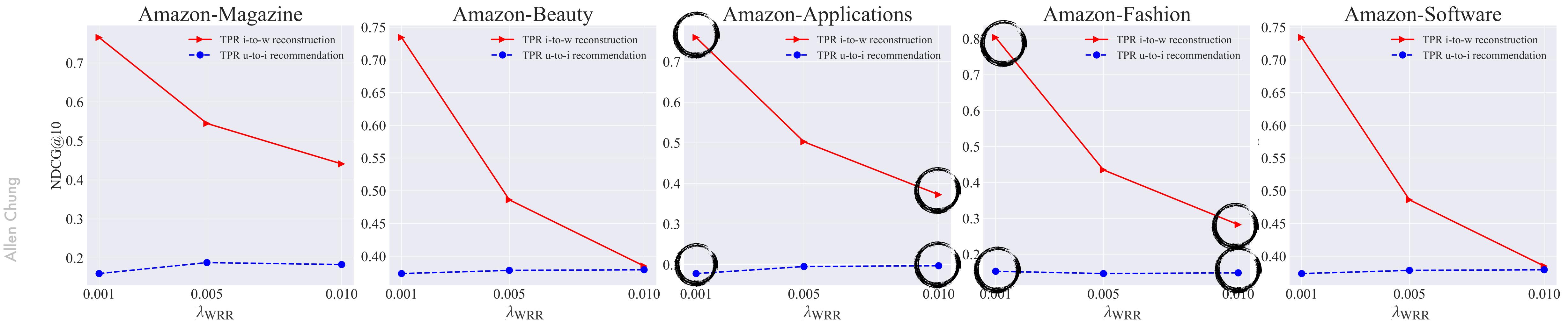
	Amazon-Magazine		Amazon-Beauty		Amazon-Applications		Amazon-Fashion		Amazon-Software	
	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10
HPE [3]	† 0.2454	† 0.0609	† 0.1203	† 0.0419	† 0.0794	† 0.0101	† 0.1326	† 0.0344	† 0.1149	† 0.0114
CKE [26]	0.0636	0.0343	0.0093	0.0058	0.0072	0.0035	0.0090	0.0046	0.0104	0.0056
KGAT [22]	0.0363	0.0254	0.0152	0.0035	0.0033	0.0035	0.0152	0.0035	0.0083	0.0035
TPR ($\lambda_{WRR} = 0.001$)	*0.2636	*0.0875	*0.1654	*0.0640	*0.1569	*0.0340	*0.1698	*0.0700	*0.1511	*0.0337
TPR ($\lambda_{WRR} = 0.005$)	*0.2590	*0.0919	*0.1483	*0.0570	*0.1175	*0.0200	0.1354	*0.0527	0.1176	0.0168
TPR ($\lambda_{WRR} = 0.01$)	*0.2863	0.0609	*0.1320	*0.0501	*0.1026	*0.0167	0.1055	0.0374	0.0887	0.0106

Table 4: Performance on cold-start user-to-item recommendation

Experiment Results

- Sensitivity check on regularization term (λ_{WRR} & λ_{IPR})

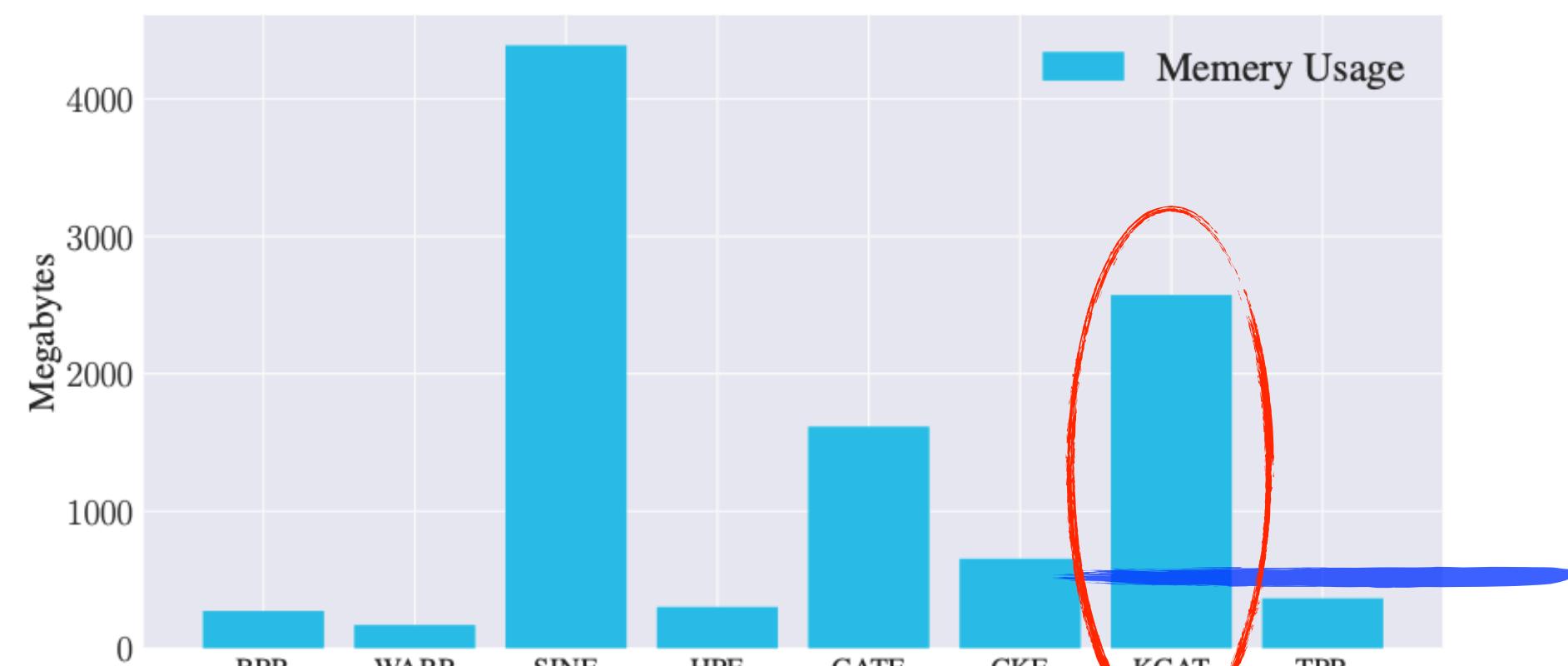
—●— Item-to-word reconstruction
—→— User-to-item recommendation



- A smaller λ_{WRR} can benefit modeling the relation between item and text
- A larger λ_{IPR} can prevent overfitting problems on modeling User-Item relation
- A trade-off parameter provides the flexibility on modeling different tasks.

Experiment Results

- Memory and Time Usage in Top-K recommendation



SOTA among all baselines

Conclusion

- Design a framework on joint association of **user-item interaction** and relations between **items and associated text**
- TPR comprehensively modeling **four types of ranking relations** on the **six different tasks** to attest the effectiveness of the learned embeddings
- TPR achieves high modeling efficiency in terms of **execution time** and **memory usage**.

TPR Implementation

- TPR is now publicly available on GitHub:
 - Repo: <https://github.com/cnclabs/codes.tpr.rec>
- TPR is implemented on the framework of SMORe:
 - Repo: <https://github.com/cnclabs/smore>



Thanks For Your Listening!

Any Question?