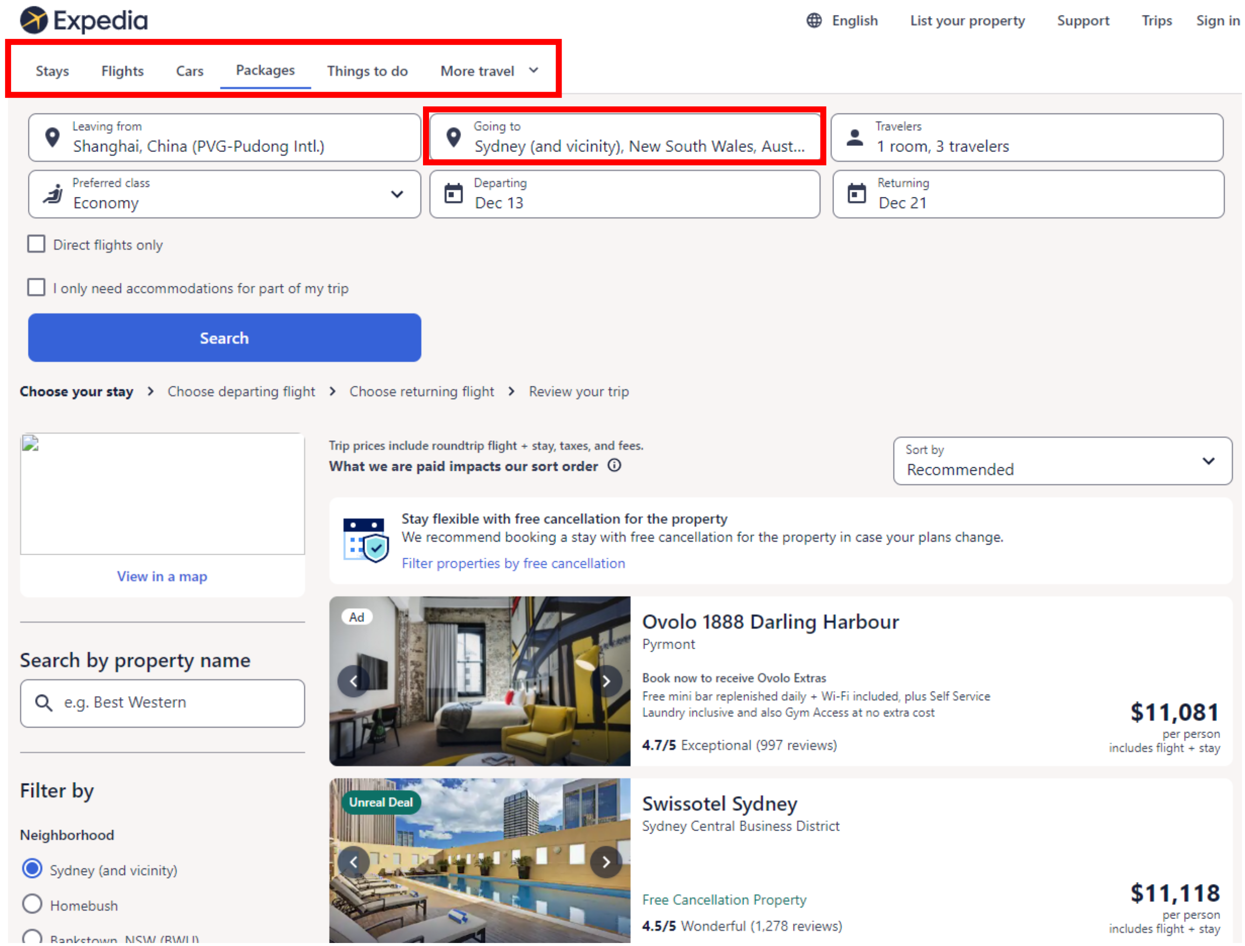
- Overview of multidomain recommender systems (Liang Hu, 25 mins)
- **Multi-item domain recommender systems (Z. Y. Lai, 20 mins)**
- Multi-user domain recommender systems (Qi Zhang, 20 mins)
- Multi-data domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-spatial domain recommender systems (Qi Zhang 20 mins)
- Multi-temporal domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-goal domain recommender systems (Liang Hu, 20 mins)
- Summary (Liang Hu, 5 mins)

Multi-item domain recommendation

- Item types
  - E.g., flights, stays, cars
- Item relations:
  - E.g., destination (flight), location (hotel)

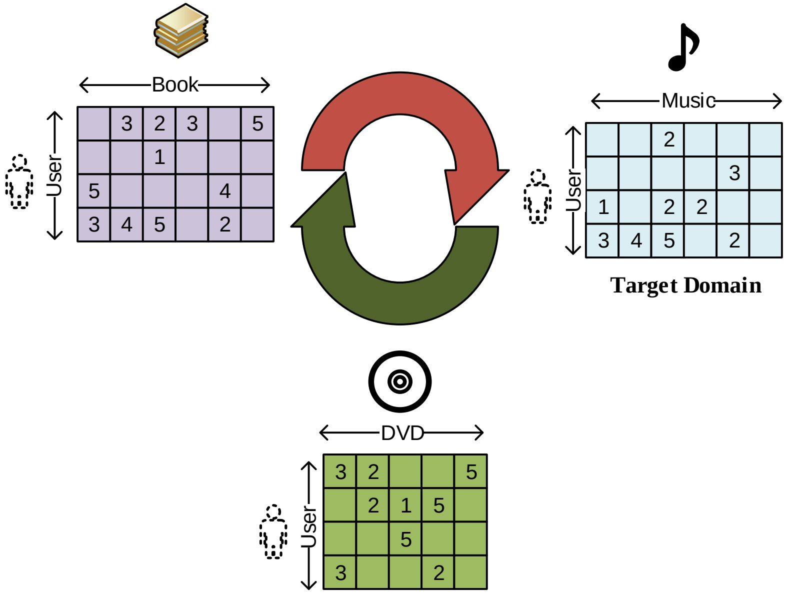


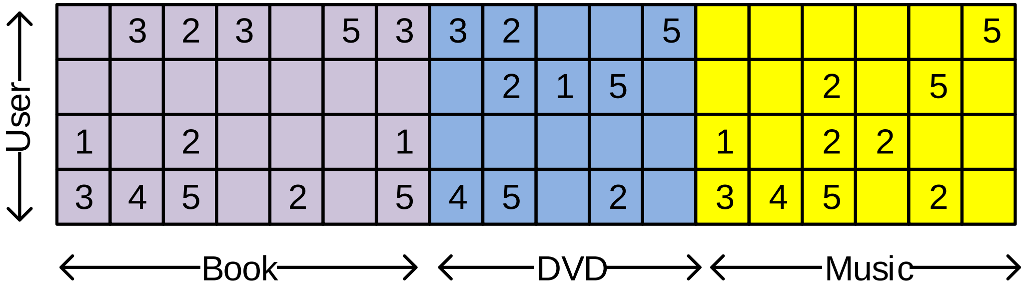
Multi-item domain recommender systems

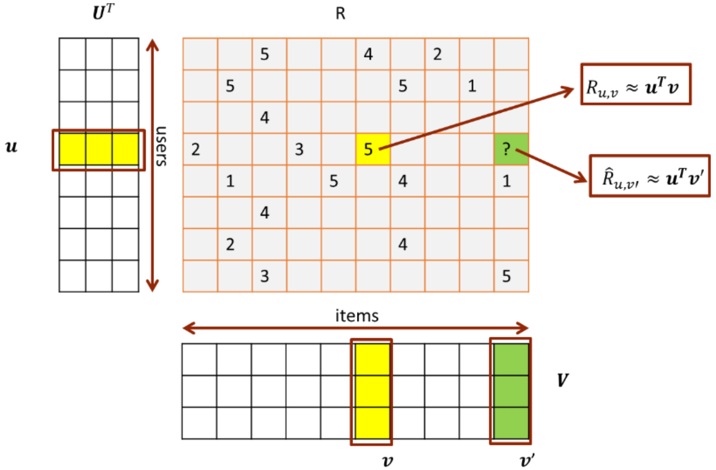
- Multi-item type modeling for multidomain recommendation
- Multi-item relationship modeling for multidomain recommendation

Cross-Domain Collaborative Filtering

- The assumption of leveraging cross-domain information in RS
  - The existence of multiple *related* domains
  - The user preference from each domain is not independent
- User-item interaction in each domain quantified by the *ratings matrix;* contains information about different domains.
- Idea: concatenate rating matrices across domains and perform naïve MF; use obtained latent to predict new review







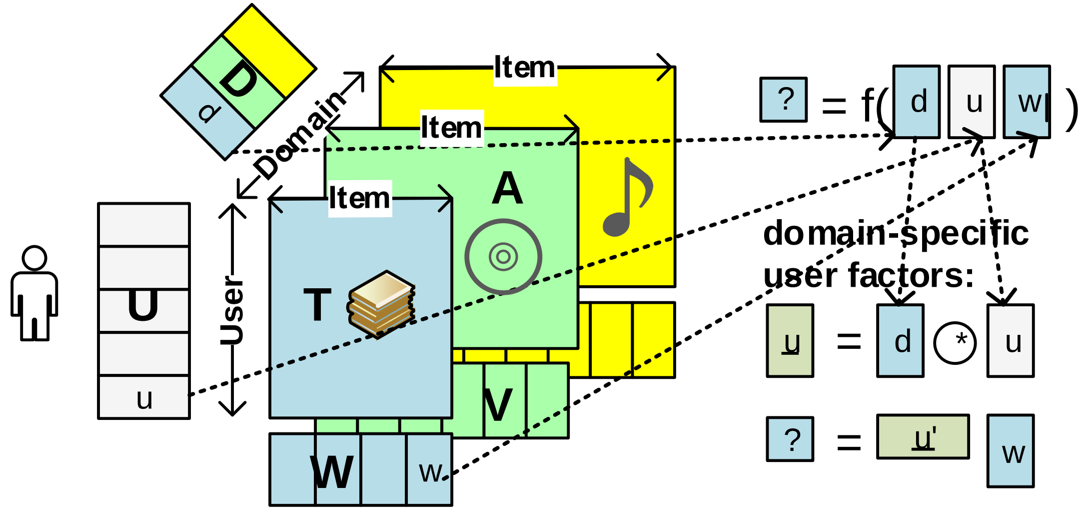
Deficiency

- Each domain has different characteristics
  - The factor of *color* has huge impact on the user preference in *clothes* domain
  - But factor of *color* has little impact on the user preference in *book* domain

- Above method using the single domain model implicitly assume the *homogeneity* of items.
  - Obviously, such assumption may decrease the prediction accuracy due to the ***heterogeneities*** of different domains.

Modeling Domain Heterogeneity

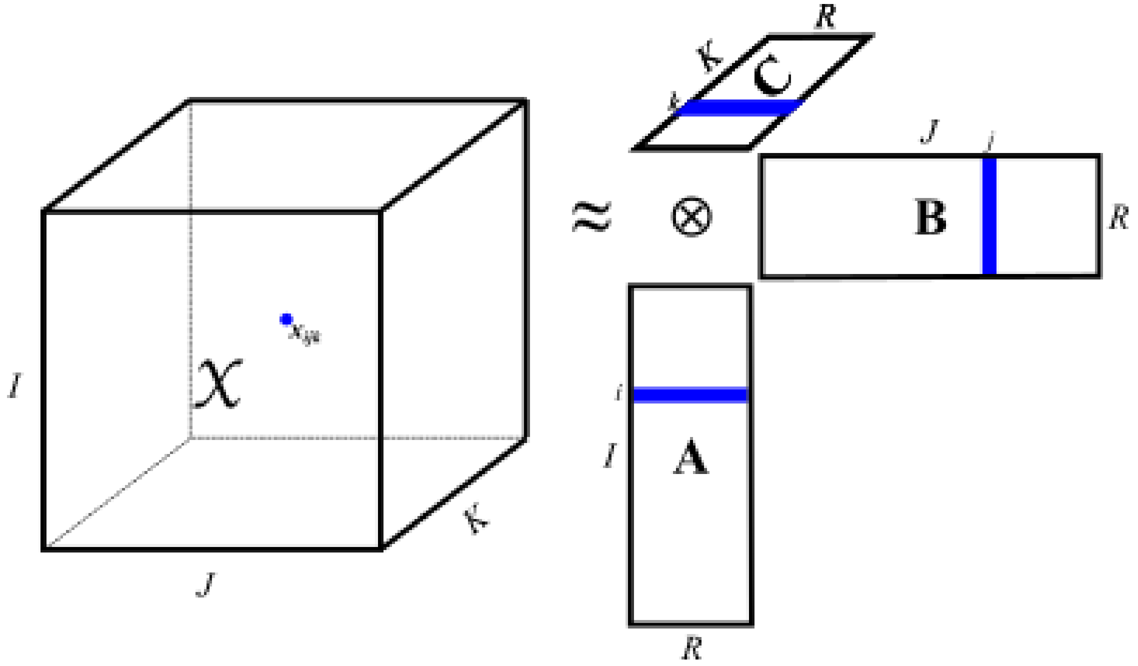
- **Domain factors** is an essential element in cross "domain" problem to model domain heterogeneity
- Triadic relation ***user-item-domain*** to reveal the domain-specific user preference

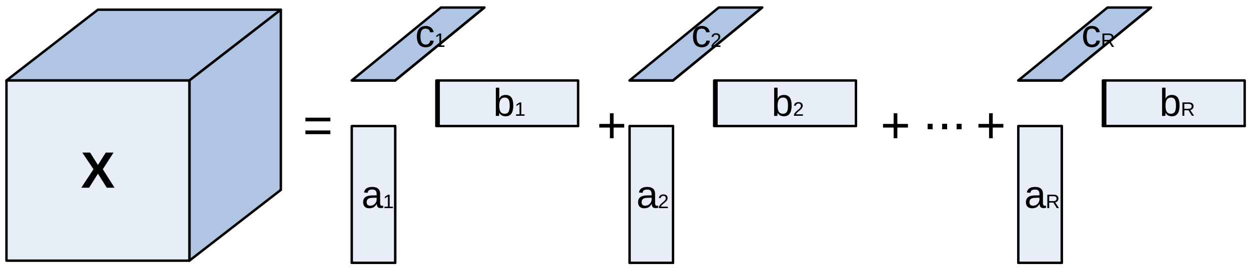


Hu, L., Cao, L., Cao, J., Gu, Z., Xu, G., & Yang, D. (2016). Learning Informative Priors from Heterogeneous Domains to Improve Recommendation in Cold-Start User Domains. *ACM Transactions on Information Systems (TOIS)*, *35*(2), 13.

Tensor Factorization over Triadic Relation

- Decompose a tensor into a sum of rank-one components
  - $\mathcal{X} = [\![\mathbf{A}, \mathbf{B}, \mathbf{C}]\!] = \sum_{r=1}^{R} \mathbf{A}_{\cdot,r} \circ \mathbf{B}_{\cdot,r} \circ \mathbf{C}_{\cdot,r}$





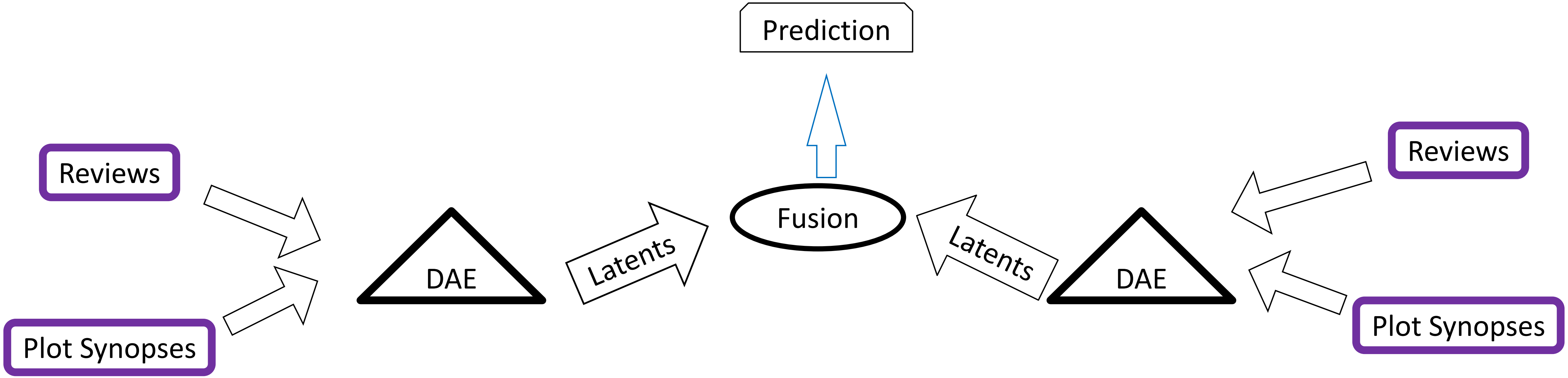
The Mean AP@5,10 and nDCG@5,10

Target Domain / Method	D1							
	TR-80%				TR-50%			
	AP@5	AP@20	nDCG@5	nDCG@20	AP@5	AP@20	nDCG@5	nDCG@20
Most-Pop	0.0161^	0.0175^	0.0269^	0.0382^	0.0322^	0.0223^	0.0567^	0.0577^
N-CDCF	0.0252*	0.0240*	0.0441*	0.0465*	0.0352*	0.0210	0.0604*	0.0534
MF-IF	0.0263*	0.0293*	0.0432*	0.0631*	0.0455*	0.0324	0.0813*	0.0854*
MF-IF-CDCF	0.0242*	0.0258*	0.0399*	0.0552*	0.0431*	0.0296	0.0763*	0.0775*
PARAFAC2	0.0213*	0.0226*	0.0350*	0.0476*	0.0395*	0.0267	0.0691*	0.0687*
CDTF-IF	0.0258*	0.0276*	0.0425*	0.0587*	0.0423*	0.0294	0.0758*	0.0767*
WITF	**0.0267***	**0.0285***	**0.0451***	**0.0623***	**0.0484***	**0.0340**	**0.0849***	**0.0872***
WITF+WRMF	**0.0271****	**0.0290****	**0.0462****	**0.0643****	**0.0486****	**0.0343****	**0.0851****	**0.0879****

Target Domain / Method	D2							
	TR-80%				TR-50%			
	AP@5	AP@20	nDCG@5	nDCG@20	AP@5	AP@20	nDCG@5	nDCG@20
Most-Pop	0.0175^	0.0194^	0.0288^	0.0424^	0.0297^	0.0231^	0.0530^	0.0591^
N-CDCF	0.0281*	0.0261*	0.0435*	0.0520*	0.0228	0.0243*	0.0380	0.0357
MF-IF	0.0320*	0.0354*	0.0528*	0.0747*	0.0501*	0.0370*	0.0872**	0.0924**
MF-IF-CDCF	0.0240*	0.0262*	0.0397*	0.0563*	0.0380*	0.0285*	0.0675	0.0724*
PARAFAC2	0.0215*	0.0234*	0.0356*	0.0506*	0.0327*	0.0251*	0.0589*	0.0638*
CDTF-IF	0.0326*	0.0337*	0.0526*	0.0662*	0.0454*	0.0316*	0.0761*	0.0750*
WITF	**0.0338***	**0.0363***	**0.0552***	**0.0753***	**0.0538***	**0.0383***	**0.0905***	**0.0909***
WITF+WRMF	**0.0343****	**0.0369****	**0.0556****	**0.0758****	**0.0542****	**0.0386****	**0.0907****	**0.0915***

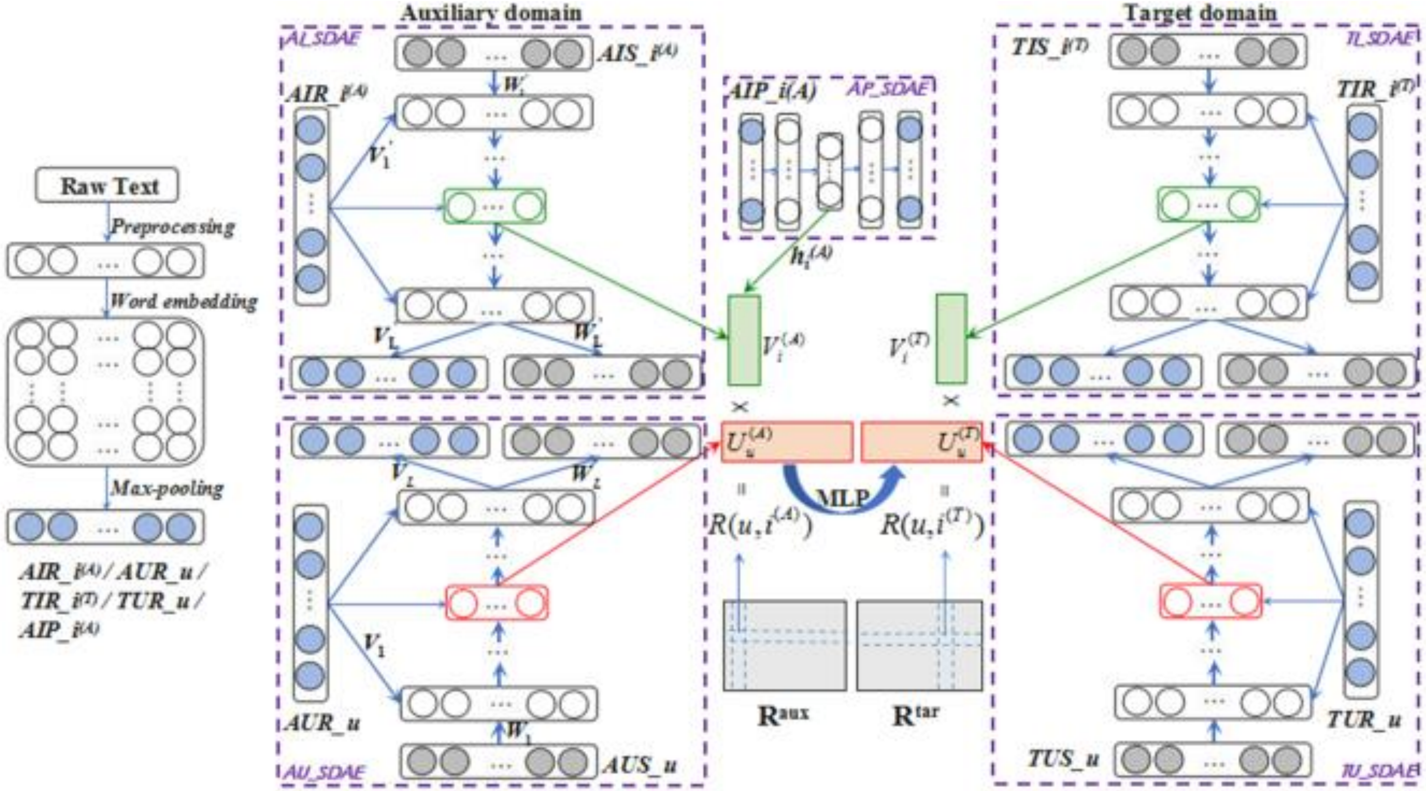
Deep Fusion of Reviews and Item Contents

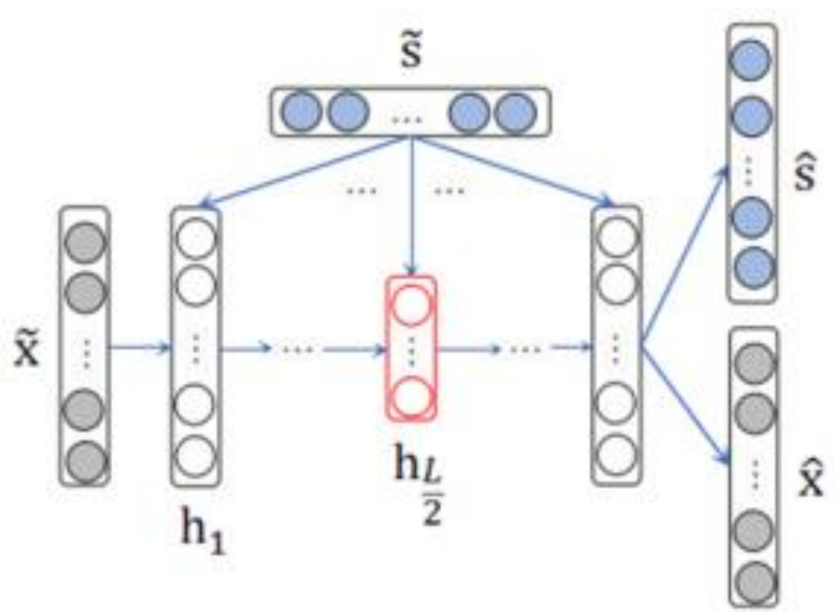
- **Problem to be solved**: How to optimize integration of multiple item data from different domains?
  - Solution could lead to better performance of CDR;
- **In this paper**: Deep fusion of latent information of item information from auxiliary and target domains.
  - Deep fusion smooths out heterogeneities in embeddings from different domains to improve prediction.
- Main components of architecture: stacked denoising autoencoders (sDAEs)
-



Fu, W., Peng, Z., Wang, S., Xu, Y., & Li, J. (2019). Deeply Fusing Reviews and Contents for Cold Start Users in Cross-Domain Recommendation Systems. *Proceedings of the AAAI Conference on Artificial Intelligence*, *33*(01), 94-101.

Deep Fusion of Reviews and Item Contents





- deep fusion of user reviews and item contents via DAEs. Sparsity is solved via deep embedding of features;
  - text from user reviews and content information (plot description) undergo word embedding and max pooling;
  - rating scores from users and items injected with review and content embedding vectors;
  - sDAE attempts to reconstruct input vector in last layer; output of middle layer is latent factor;
  - build map between *AI—SDAE / TI_SDAE with AP_SDAE;*
  - use MLPs to build nonlinear mapping between auxiliary and target domain latent factors.

Fu, W., Peng, Z., Wang, S., Xu, Y., & Li, J. (2019). Deeply Fusing Reviews and Contents for Cold Start Users in Cross-Domain Recommendation Systems. *Proceedings of the AAAI Conference on Artificial Intelligence*, *33*(01), 94-101.

Deep Fusion of Reviews and Item Contents

Vectorization of Reviews and Contents

- Using word embedding function to map words to distributed vector
  - Merge all reviews into single document
  - Pre-trained word embeddings used to obtain 300-D word vector for each word
  - Concatenate into matrix and take max value of each column as feature
  - This is 300-D vector for all reviews for user *u* in auxiliary domain; corresponding vectors for item in both domains similar

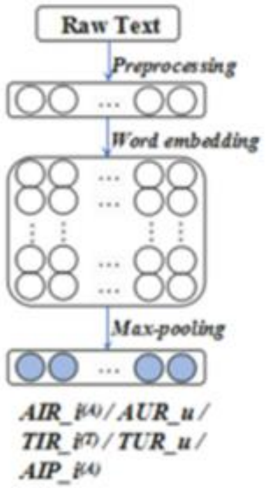
Generation of Latent Factors

- SDAEs reconstructs input from corrupted version to learn more robust mapping function;
- SDAE tries to make output of middle layer close to actual latent factor as possible;
- Take each column of rating matrix as rating vector of each item, each row as rating vector of each user
- Rating vectors + feature matrix from previous box constitute input to SDAE

Nonliner Mapping based on MLP

- Use MLP to perform nonlinear mapping of latents from auxiliary to target domain (latent space matching);

Cross-Domain Recommendation



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Datasets

- Amazon Dataset
  - http://jmcauley.ucsd.edu/data/amazon/
  - Ratings and metadata (including titles of movies) from Amazon website;
  - 142.8 million reviews in total from May 1996 to July 2014;
  - 21 categories of items;

Table 1: The Statistics of the datasets

	dataset 1		dataset 2	
Domain	Movies	Books	Movies	Music CDs
Users	792		1,464	
Items	3,550	2,271	3,605	4,611
Ratings	51,422	20,365	78,431	59,299
Density	1.83%	1.13%	1.49%	0.88%

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Deep Fusion of Reviews and Item Contents

Table 2: Recommendation performance on "Movies & Books"

		RMSE						MAE					
K	ϕ	PMF	CMF	EMCDR	DFM	R-DFM	RC-DFM	PMF	CMF	EMCDR	DFM	R-DFM	RC-DFM
10	80%	4.0892	1.5381	1.5276	0.9987	0.9893	**0.9770**	3.8438	1.2809	1.2246	0.7997	0.7958	**0.7902**
	50%	1.6204	1.5005	1.1174	0.9820	0.9719	**0.9648**	1.2326	1.2282	0.8538	0.7939	0.7865	**0.7808**
	20%	1.3839	1.4653	1.0482	0.9594	0.9583	**0.9535**	1.0611	1.1914	0.8246	0.7756	0.7719	**0.7694**
20	80%	4.1113	1.2624	1.5500	0.9990	0.9790	**0.9744**	3.8986	0.9884	1.2777	0.7996	0.7898	**0.7886**
	50%	1.7428	1.2470	1.1648	0.9721	0.9700	**0.9632**	1.3770	0.9625	0.8984	0.7859	0.7844	**0.7774**
	20%	1.4198	1.2146	1.0305	0.9609	0.9565	**0.9514**	1.1098	0.9432	0.7824	0.7758	0.7704	**0.7667**
30	80%	4.1103	1.5437	1.6676	0.9838	0.9807	**0.9721**	3.9034	1.2050	1.3633	0.7938	0.7904	**0.7858**
	50%	1.7933	1.3455	1.1823	0.9682	0.9646	**0.9591**	1.4537	1.0441	0.9413	0.7816	0.7752	**0.7671**
	20%	1.4835	1.2760	1.0548	0.9581	0.9532	**0.9468**	1.1892	0.9917	0.8176	0.7706	0.7645	**0.7590**

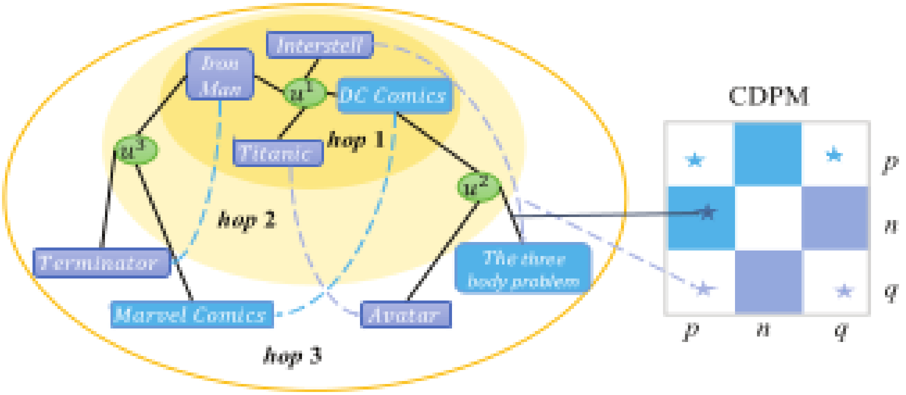
Table 3: Recommendation performance on "Movies & Music CDs"

		RMSE						MAE					
K	ϕ	PMF	CMF	EMCDR	DFM	R-DFM	RC-DFM	PMF	CMF	EMCDR	DFM	R-DFM	RC-DFM
10	80%	4.1154	1.6483	1.6757	1.0976	1.0726	**1.0706**	3.8374	1.3804	1.3660	0.8824	0.8611	**0.8589**
	50%	1.6585	1.6456	1.1887	1.0741	1.0637	**1.0578**	1.2419	1.3658	0.9289	0.8666	0.8564	**0.8461**
	20%	1.4015	1.6318	1.0857	1.0657	1.0513	**1.0490**	1.0466	1.3512	0.8464	0.8483	0.8360	**0.8005**
20	80%	4.1353	1.3287	1.7407	1.0917	1.0724	**1.0698**	3.8760	1.0275	1.4479	0.8773	0.8603	**0.8573**
	50%	1.6942	1.3269	1.2273	1.0719	1.0553	**1.0507**	1.3122	1.0081	0.9593	0.8653	0.8431	**0.8410**
	20%	1.4624	1.3039	1.0802	1.0546	1.0516	**1.0477**	1.1460	0.9898	0.8308	0.8267	0.8218	**0.7782**
30	80%	4.1894	1.5249	1.6540	1.0880	1.0720	**1.0661**	3.9655	1.1787	1.3451	0.8739	0.8591	**0.8522**
	50%	1.7951	1.3944	1.2093	1.0713	1.0637	**1.0586**	1.4315	1.0749	0.9456	0.8669	0.8532	**0.8483**
	20%	1.5190	1.3505	1.0852	1.0594	1.0580	**1.0557**	1.2106	1.0323	0.8190	0.8328	0.7836	**0.7778**

- 'Movies' is the auxiliary and 'Books'+ 'Music' the target domains;
- choice of baselines: reflect lack of cross modal information (PMF is single domain), or lack of robustness (choice of K for CMF)
- Closest performance from EMCDR: semi-deep framework where matrix factorized latents are learned and mapped from target to domain via MLPs (no deep fusion)
- Deep fusion of latents improves performance considerably.

Fu, W., Peng, Z., Wang, S., Xu, Y., & Li, J. (2019). Deeply Fusing Reviews and Contents for Cold Start Users in Cross-Domain Recommendation Systems. *Proceedings of the AAAI Conference on Artificial Intelligence*, *33*(01), 94-101.

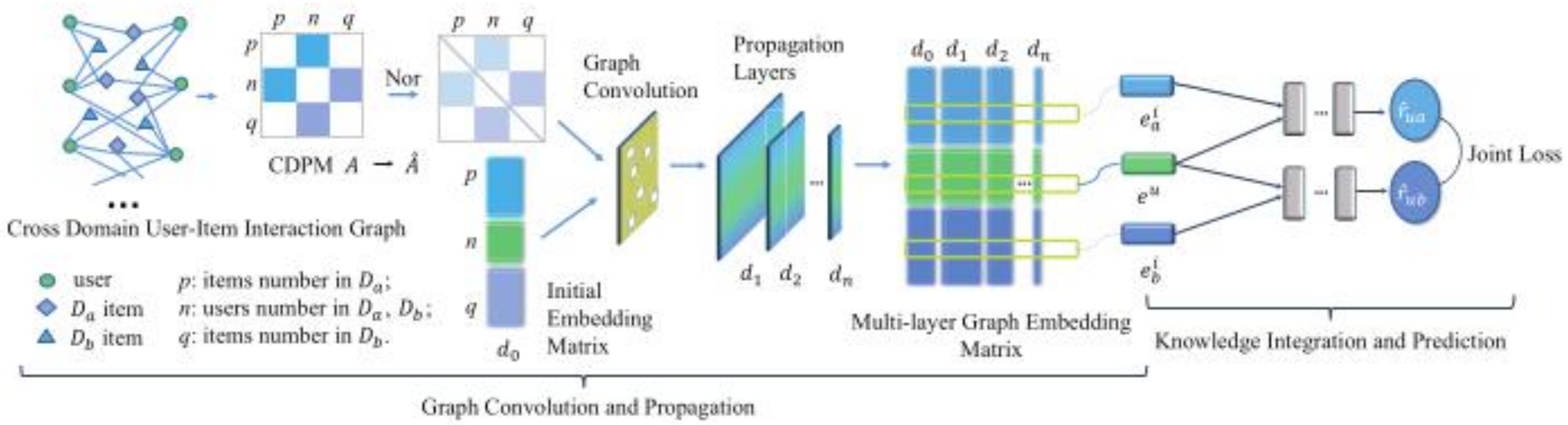
CDR via Preference Propagation GraphNet



- **Problem to be solved:** latent transfer models unable to account for structural information.
  - E.g., users interested in *Ironman* could conceivably be interested in DC or Marvel *comic books* as well, but this cannot be modeled via transfer.
  - Example of higher-order hops in a graph model, relating multiple items (slight overlap with item relations section).
- **In this paper:** user preference graph model, uses graphs to link different items depending on preference.
  - captures cross-domain data via longer-range hopping between nodes

Cheng Zhao, Chenliang Li, and Cong Fu. 2019. Cross-Domain Recommendation via Preference Propagation GraphNet. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management (CIKM '19). Association for Computing Machinery, New York, NY, USA, 2165–2168.

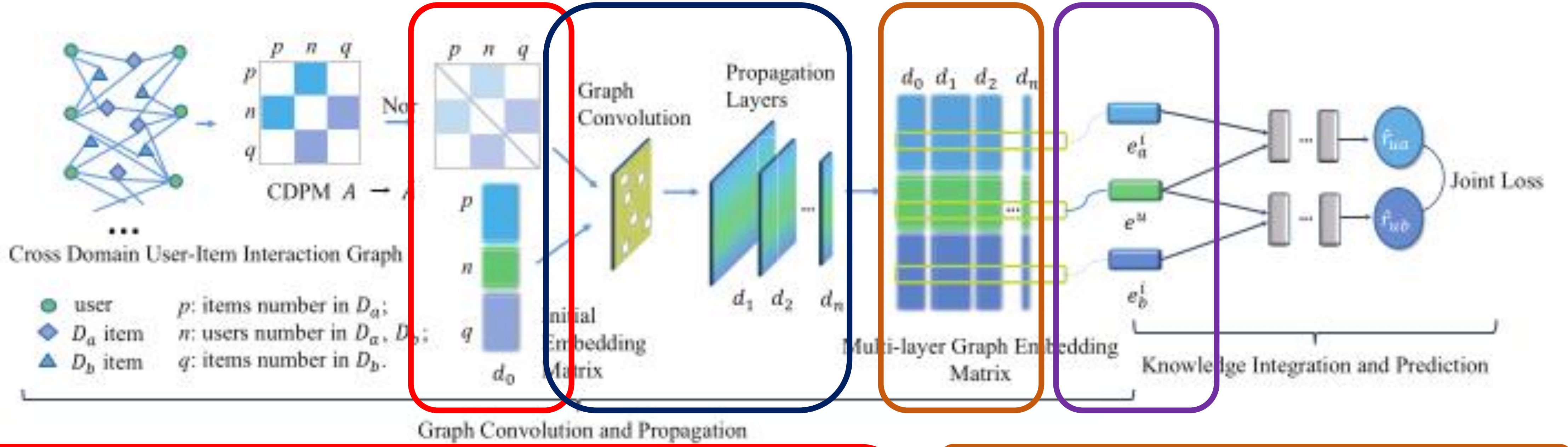
CDR via Preference Propagation GraphNet



- includes structural information bridging domains neglected in most embedding methods; also items in different domains might share similar properties.
- user preferences modeled via multihop model, which define CDPM to model cross-domain item interactions;
- CDPM and original embeddings fed to GC and propagation layers; different filter size ensure full spectrum of preference captured;
- Knowledge integration via MLP to fuse user and item embeddings (items from both domains);

Cheng Zhao, Chenliang Li, and Cong Fu. 2019. Cross-Domain Recommendation via Preference Propagation GraphNet. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management (CIKM '19). Association for Computing Machinery, New York, NY, USA, 2165–2168.

CDR via Preference Propagation GraphNet



- A is CDPM; 1 if interactions, 0 if no interactions
- Define $\hat{A} = D^{-1}(A + I)$
- Map IDs of $u, i_a, i_b \rightarrow$ embeddings e^u, e^{i_a}, e^{i_b}
- Form embedding matrix $E_0 = \left[e_1^{i_a}, \dots, e_p^{i_a}, e_1^u, \dots, e_n^u, e_1^{i_b}, \dots, e_p^{i_b}\right]$
- Feed E_0 and $\hat{A}$ to graph propagation and convolution layers

- $E = \left[E_0, E_1, \dots, E_{l_n}\right] = [E_a^i, E^u, E_b^i]^{\mathrm{T}}$

- Propagation process: $E_l = \sigma(\hat{A}\mathrm{E}_{l-1}W_l + b_l)$

Cheng Zhao, Chenliang Li, and Cong Fu. 2019. Cross-Domain Recommendation via Preference Propagation GraphNet. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management (CIKM '19). Association for Computing Machinery, New York, NY, USA, 2165–2168.

CDR via Preference Propagation GraphNet

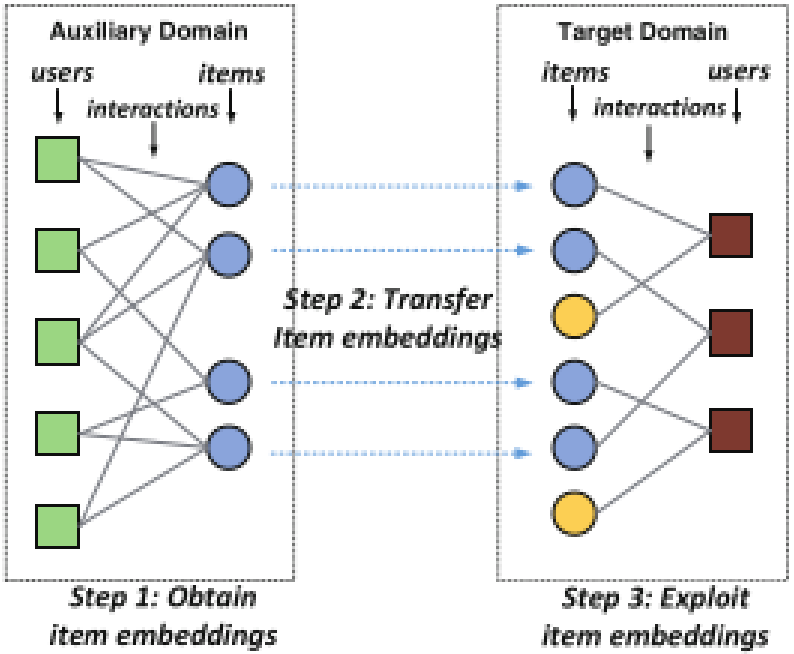
Datasets	# users	# items	# ratings	density
Books	37, 388	269, 301	1, 254, 288	0.012%
Movies and TV	37, 388	49, 273	792, 319	0.043%
CDs and Vinyl	5, 331	55, 848	376, 347	0.126%
Digital Music	5, 331	3, 563	63, 303	0.333%

Metrics	Dataset	BPRMF	NeuMF	NeuMF+	CoNet	SCoNet	PPGN-IP	PPGN
HR@10	Books	.3654	.4300	.4291	.5223	.5141	.4594	**.5770**
	Movies and TV	.4538	.5665	.5605	.6460	.6465	.5689	**.6909**
	CDs and Vinyl	.5532	.6421	.6655	.7539	.7547	<u>.7668</u>	**.7839**
	Digital Music	.4742	.5322	.5991	.7179	.7205	<u>.7492</u>	**.7874**
MRR@10	Books	.1543	.2241	.2249	.3273	.3261	.1835	**.3280**
	Movies and TV	.2034	.2775	.2742	.3651	.3829	.2498	**.3869**
	CDs and Vinyl	.2742	.3092	.3593	.4735	.4875	.4192	**.5012**
	Digital Music	.1431	.1549	.2472	.3855	.3878	<u>.4112</u>	**.4388**
NDCG@10	Books	.2365	.2725	.2724	.3396	.3370	.2470	**.3574**
	Movies and TV	.2654	.3445	.3416	.4060	.4210	.3164	**.4249**
	CDs and Vinyl	.3532	.3933	.4303	.5227	.5291	.5020	**.5697**
	Digital Music	.2045	.2432	.3297	.4436	.4603	<u>.4911</u>	**.5147**

- Dataset: Amazon-5cores dataset from previous slide;
- baselines have similar deficiencies: takes single domain data into account (BPRMF,NeuMF); unguided sharing of user embeddings (NeuMF+) and unguided cross-domain embedding transfer (CoNet)
- taking user preference into account and systematically aggregating embeddings lead to significant improvements.

Cheng Zhao, Chenliang Li, and Cong Fu. 2019. Cross-Domain Recommendation via Preference Propagation GraphNet. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management (CIKM '19). Association for Computing Machinery, New York, NY, USA, 2165–2168.

CDR via Item-Interactions (no user data)

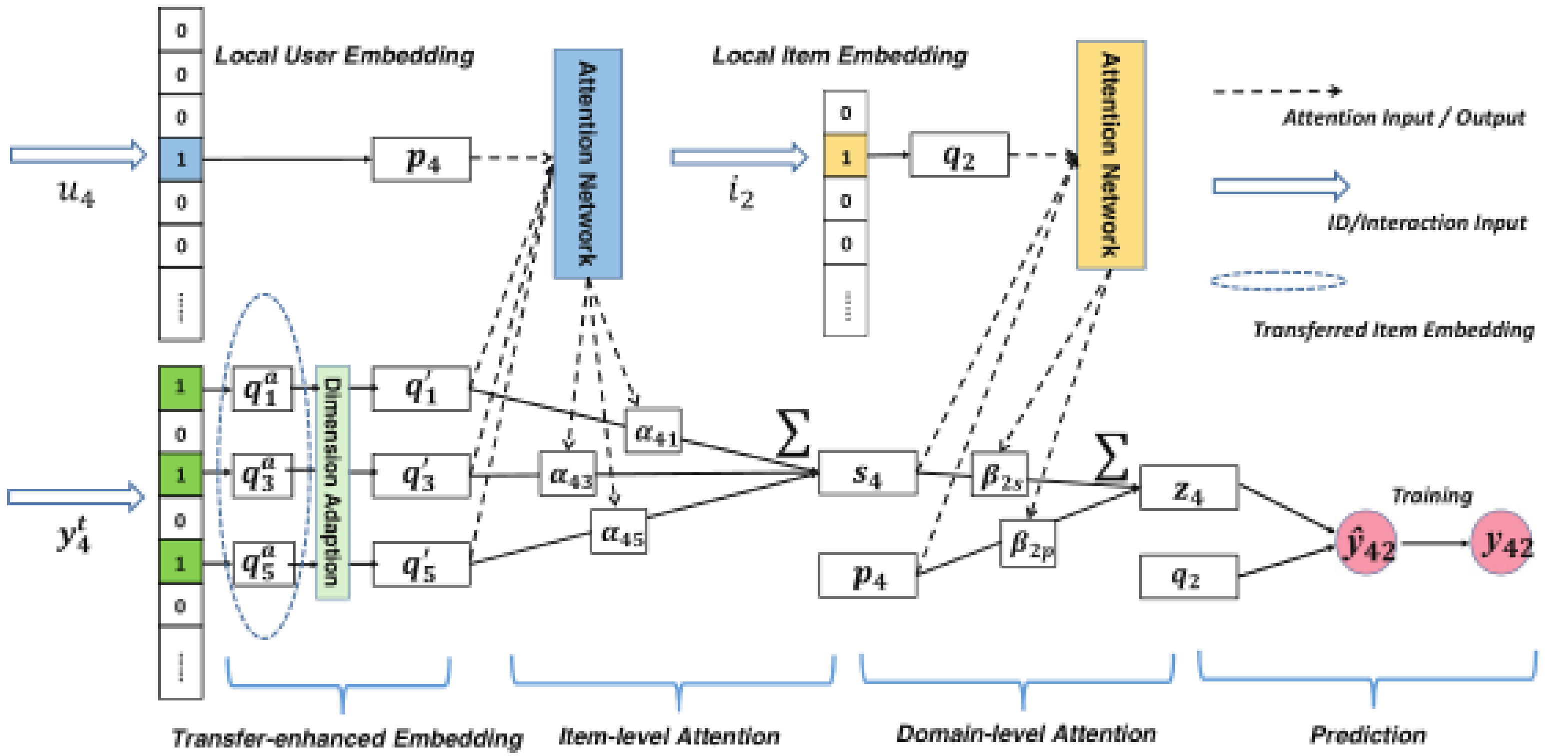


- **Problem to be solved:** privacy for users; ensuring users cannot be identified from purchase records.
  - But still ensuring high quality CDR.
  - Important for most commercial use of CDR.

- **In this paper:** Only *item* embeddings are transferred from auxiliary to target domain
  - Not all item embeddings need to be transferred; *which* is obtained via item-level attention mechanism.
  - Additional *domain* level attention to adjust importance of domains.

Chen Gao, Xiangning Chen, Fuli Feng, Kai Zhao, Xiangnan He, Yong Li, and Depeng Jin. 2019. Cross-domain Recommendation Without Sharing User-relevant Data. In The World Wide Web Conference (WWW '19). Association for Computing Machinery, New York, NY, USA, 491–502.

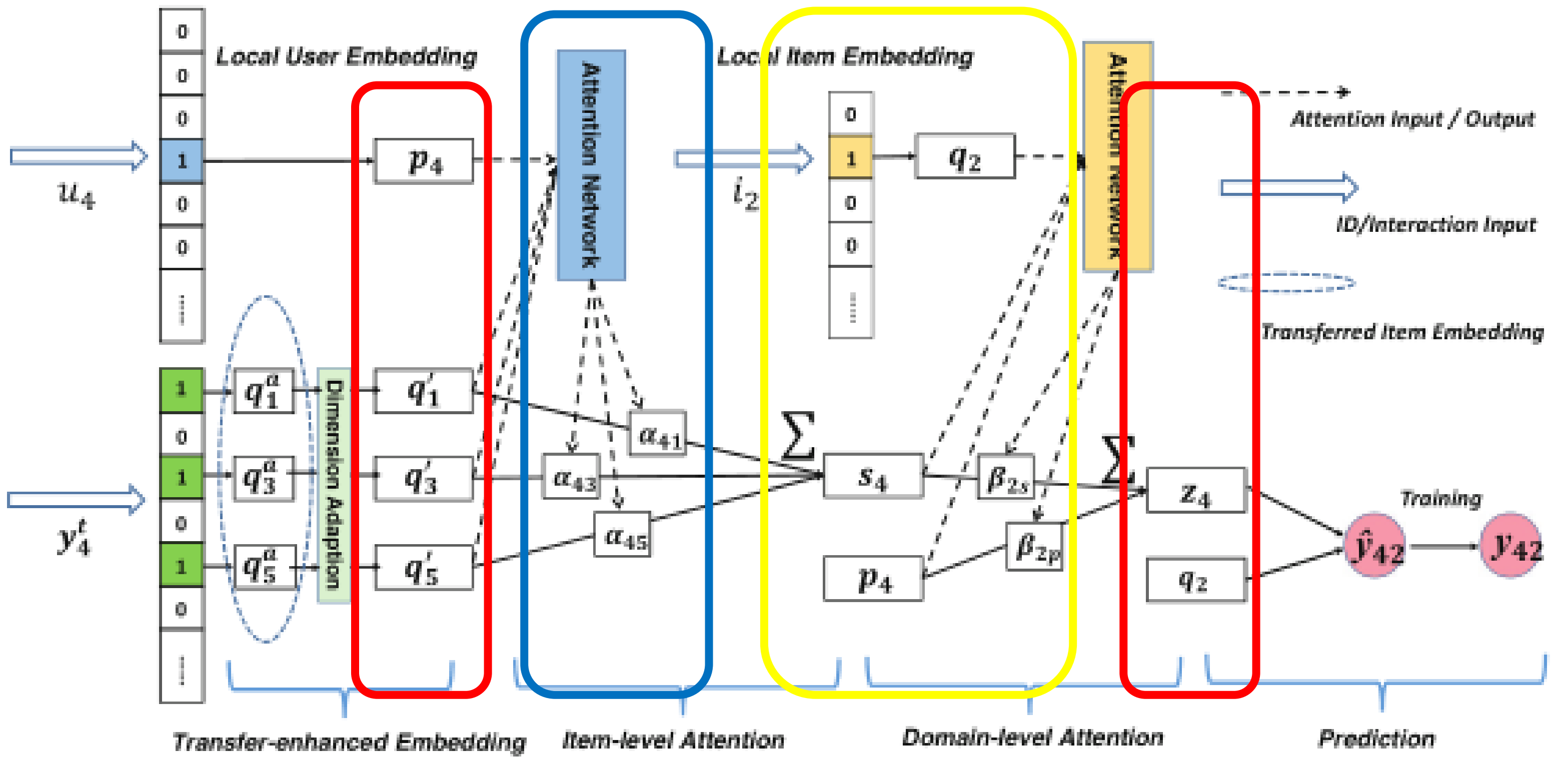
CDR via Item-Interactions (no user data)



- interesting aspect of CDR: recommendation with user privacy
- only embedding of bridge items are transferred (instead of full user-item matrix) from aux to target.

Chen Gao, Xiangning Chen, Fuli Feng, Kai Zhao, Xiangnan He, Yong Li, and Depeng Jin. 2019. Cross-domain Recommendation Without Sharing User-relevant Data. In The World Wide Web Conference (WWW '19). Association for Computing Machinery, New York, NY, USA, 491–502.

CDR via Item-Interactions (no user data)



Chen Gao, Xiangning Chen, Fuli Feng, Kai Zhao, Xiangnan He, Yong Li, and Depeng Jin. 2019. Cross-domain Recommendation Without Sharing User-relevant Data. In The World Wide Web Conference (WWW '19). Association for Computing Machinery, New York, NY, USA, 491–502.

- p_u are local user embeddings (one-hot), $q'_j = W_0^T q_j^a + b_0$

- Item-level Attention: $\frac{e^{a_{uj}}}{\sum_{\{k|y_{uk}^t=1\}} e^{a_{uk}}}, a_{uj} = w_1^T ReLU\left(\boldsymbol{p}_u \odot \boldsymbol{q'}_j\right) + b_1$

- Domain-level Attention: $\beta_{si} = \frac{e^{b_{si}}}{e^{b_{si}+e^{b_{pi}}}}, \beta_{pi} = \frac{e^{a_{pi}}}{e^{b_{si}+e^{b_{pi}}}}, b_{s(p)i} = w_2\ ReLU\left(\boldsymbol{p}_u(\boldsymbol{s}_u) \odot \boldsymbol{q}\ \ _i\right) + b_2$

CDR via Item-Interactions (no user data)

			ML-NF Dataset						
Group	**Method**	**User-relevant Data**	**HR(NDCG)@1**	**HR@2**	**NDCG@2**	**HR@5**	**NDCG@5**	**HR@10**	**NDCG@10**
Cross Domain	**NATR**	**Preserved**	**0.1315**	**0.1976**	**0.1403**	**0.3776**	**0.2110**	**0.5781**	**0.2726**
	ItemCST	Preserved	0.0795	0.1475	0.1005	0.3068	0.1670	0.4846	0.2228
	CMF	Shared	0.1023	0.1903	0.1283	0.3675	0.2025	0.5483	0.2593
Single Domain	NATR-local	Preserved	0.0947	0.1769	0.1253	0.3402	0.1894	0.5183	0.2440
	PMF	Preserved	0.0668	0.1162	0.0796	0.2721	0.1375	0.4494	0.1956
	GMF	Preserved	0.0706	0.1174	0.0816	0.2681	0.1410	0.4284	0.1918

			TC-IQI Dataset						
Group	**Method**	**User-relevant Data**	**HR(NDCG)@1**	**HR@2**	**NDCG@2**	**HR@5**	**NDCG@5**	**HR@10**	**NDCG@10**
Cross Domain	**NATR**	**Preserved**	**0.2010**	0.2660	**0.2104**	**0.4513**	**0.2881**	0.6035	**0.3365**
	ItemCST	Preserved	0.1161	0.2129	0.1445	0.4194	0.2309	0.6079	0.2904
	CMF	Shared	0.1649	**0.3101**	0.2101	0.4499	0.2668	**0.6595**	0.3326
Single Domain	NATR-local	Preserved	0.1677	0.2552	0.1776	0.4214	0.2412	0.5864	0.2948
	PMF	Preserved	0.0848	0.1238	0.0945	0.2291	0.1326	0.3309	0.1694
	GMF	Preserved	0.1584	0.2445	0.1729	0.4101	0.2425	0.6021	0.3029

- baseline models: are of single domain (PMF, GMF, NATR) and hence unable to take multi-domain data into account; are unable to perform well under assumption that only bridge user embeddings are transferred to the target domain (ItemCST, CMF);
- Improved performance attributed to:
  - Cross-domain learning (PMF, GMF, NATR-local);
  - Taking historical interactions into account (PMF, GMF);
  - Taking explicit preference of users into account (GMF).

Chen Gao, Xiangning Chen, Fuli Feng, Kai Zhao, Xiangnan He, Yong Li, and Depeng Jin. 2019.
Cross-domain Recommendation Without Sharing User-relevant Data. In The World Wide Web Conference (WWW '19). Association for Computing Machinery, New York, NY, USA, 491–502.

Multi-item domain recommender systems

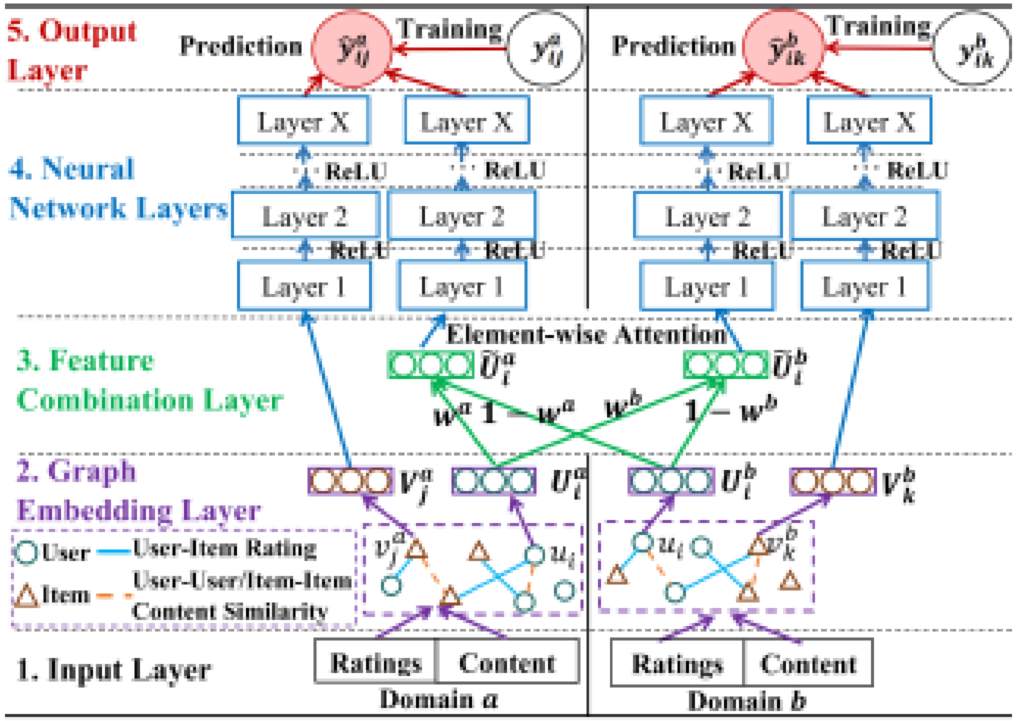
- Multi-item type modeling for multidomain recommendation
- Multi-item relationship modeling for multidomain recommendation

Hybrid Graph and Attentional Framework for CDR

- **Problem to be solved:**
  - Leverage data richness and diversity to generate representative item relationships and embeddings.
  - Optimize item embeddings to improve recommendation.
- **In this paper:** hybrid architecture with both graph and attention for dual-target CDR;
  - heterogeneous graph to deal with rich and diverse data forms
  - attention mechanism to combine embedding learned from common users from both domains

Zhu, F., Wang, Y., Chen, C., Liu, G., & Zheng, X. (2020). A Graphical and Attentional Framework for Dual-Target Cross-Domain Recommendation. *IJCAI*.

Hybrid Graph and Attentional Framework for CDR



- Architecture:
  - **Input**: explicit feedback (ratings, comments) + side information (user profiles, item details);
  - **Graph embedding**: user-item, user-user and item-item relationships obtained via ratings and content information;
  - **Feature combination**: use element-wise attention to combine common users' embeddings from different domains
  - **MLP layer**: to model nonlinear relationships between users and items on each domain
  - **Output**: predictions on probability of user-item interaction.

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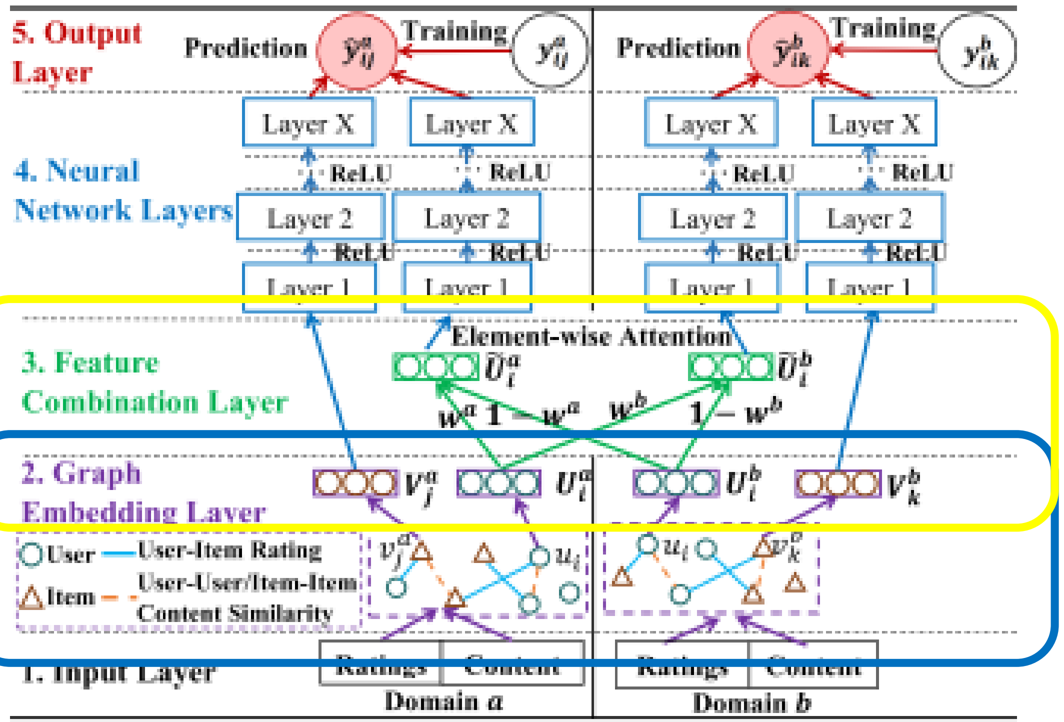
Hybrid Graph and Attentional Framework for CDR



- Document embedding: Doc2vec
- Graph construction: weights of edges are $\frac{R}{\max(R)}$, normalized ratings, while edges are generated between users u_i and u_l with probability $P(i,l) = \alpha \cdot sim(UC_i, UC_l)$;
- Graph embedding: Node2vec

- Feature combination for domain a:
$$\widetilde{U}_i^a = W^a \odot U_i^a + (1 - W^a) \odot U_i^b$$

Zhu, F., Wang, Y., Chen, C., Liu, G., & Zheng, X. (2020). A Graphical and Attentional Framework for Dual-Target Cross-Domain Recommendation. *IJCAI*.

Hybrid Graph and Attentional Framework for CDR

Model			Training Data	Encoding	Embedding	Transfer Strategy
Baselines	Single-Domain Recommendation (SDR)	**NeuMF** [He *et al.*, 2017]	Rating	One-hot	Non-linear MLP	-
		DMF [Xue *et al.*, 2017]	Rating	Rating Vector	Non-linear MLP	-
	Single-Target Cross-Domain Recommendation (CDR)	**CTR-RBF** [Xin *et al.*, 2015]	Rating & Content	Topic Modeling	Linear MF	Mapping & Transfer Learning
		BPR_DCDCSR [Zhu *et al.*, 2018]	Rating	Random Initialization	Linear MF	Combination & MLP
		TMH [Hu *et al.*, 2019]	Rating & Content	One-hot	Non-linear MLP	Mapping & Transfer Learning & Attention
	Dual-Target CDR	**DMF_DTCDR_Concat** [Zhu *et al.*, 2019]	Rating & Content	Rating Vector	Non-linear MLP	Multi-task Learning & Concatenation
		DDTCDR [Li and Tuzhilin, 2019]	Rating	One-hot & Multi-hot	Non-linear MLP	Dual Transfer Learning
Our Methods	Dual-Target CDR	**GA-DTCDR_Average** (a variant of GA-DTCDR for ablation study)	Rating & Content	Heterogeneous Graph	Graph Embedding	Combination (**Average-Pooling**)
		GA-DTCDR	Rating & Content	Heterogeneous Graph	Graph Embedding	Combination (**Element-wise Attention**)

Task	Domain	SDR Baselines				Single-Target CDR Baselines					
		NeuMF		DMF		CTR-RBF		BPR_DCDCSR		TMH	
		HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG
Task1	DoubanBook (Sparser)	.3810	.2151	.3841	.2265	.3830	.2217	.3954	.2419	.4199	**.2583***
($k=8$)	DoubanMovie (Richer)	.5266	.2911	.5498	.3114	-	-	-	-	-	-
Task 1	DoubanBook (Sparser)	.3833	.2181	.3854	.2356	.3870	.2256	.4014	.2413	.4331	**.2522***
($k=16$)	DoubanMovie (Richer)	.5282	.2939	.5573	.3141	-	-	-	-	-	-
Task 1	DoubanBook (Sparser)	.3899	.2182	.3871	.2340	.3956	.2264	.4079	.2436	**.4468***	**.2647***
($k=32$)	DoubanMovie (Richer)	.5411	.2991	.5612	.3254	-	-	-	-	-	-
Task 1	DoubanBook (Sparser)	.3908	.2226	.3917	.2362	.4017	.2314	.4107	.2454	**.4504***	**.2768***
($k=64$)	DoubanMovie (Richer)	.5449	.3152	.5632	.3387	-	-	-	-	-	-
Task 1	DoubanBook (Sparser)	.4012	.2310	.4046	.2451	.4171	.2532	.4111	.2431	**.4523***	**.2814***
($k=128$)	DoubanMovie (Richer)	.5512	.3301	.5776	.3505	-	-	-	-	-	-

Task	Domain	Dual-Target CDR Baselines				Dual-Target CDR (our)				Improvement (GA-DTCDR vs. best baselines)	
		DMF_DTCDR_Concat		DDTCDR		GA-DTCDR_Average		**GA-DTCDR**			
		HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG
Task1	DoubanBook (Sparser)	**.4412***	.2571	.4033	.2257	.4057	.2513	**.4479**	**.2759**	1.52%	6.81%
($k=8$)	DoubanMovie (Richer)	**.6032***	**.3732***	.5612	.3185	.5968	.3546	**.6518**	**.4025**	8.06%	7.85%
Task 1	DoubanBook (Sparser)	**.4408***	.2513	.4054	.2292	.4190	.2577	**.4706**	**.2900**	6.76%	14.99%
($k=16$)	DoubanMovie (Richer)	**.6080***	**.3721***	.5750	.3595	.6013	.3596	**.6566**	**.4014**	10.80%	7.87%
Task 1	DoubanBook (Sparser)	.4318	.2461	.4180	.2344	.4346	.2610	**.4758**	**.2896**	6.50%	9.41%
($k=32$)	DoubanMovie (Richer)	**.6011***	**.3718***	.5739	.3386	.6374	.3896	**.6747**	**.4187**	12.24%	12.61%
Task 1	DoubanBook (Sparser)	.4265	.2452	.4258	.2430	.4423	.2671	**.4882**	**.3026**	8.40%	9.32%
($k=64$)	DoubanMovie (Richer)	**.5998***	**.3649***	.5825	.3553	.6416	.3941	**.6817**	**.4205**	13.65%	15.23%
Task 1	DoubanBook (Sparser)	.4317	.2510	.4225	.2439	.4490	.2691	**.4995**	**.3098**	10.44%	10.09%
($k=128$)	DoubanMovie (Richer)	**.5991***	**.3680***	.5863	.3589	.6449	.3981	**.6957**	**.4406**	16.12%	19.73%

Task	Domain	SDR Baselines				Single-Target CDR Baselines					
		NeuMF		DMF		CTR-RBF		BPR_DCDCSR		TMH	
		HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG
Task 2	DoubanMusic (Sparser)	.3135	.1703	.3127	.1812	.3227	.1895	.3259	.1894	.3579	.2034
($k=8$)	DoubanMovie (Richer)	.5266	.2911	.5498	.3114	-	-	-	-	-	-
Task 2	DoubanMusic (Sparser)	.3190	.1731	.3170	.1891	.3121	.1761	.3261	.1901	.3612	.2137
($k=16$)	DoubanMovie (Richer)	.5282	.2939	.5573	.3141	-	-	-	-	-	-
Task 2	DoubanMusic (Sparser)	.3198	.1771	.3218	.1912	.3141	.1844	.3271	.1931	**.3701***	**.2202***
($k=32$)	DoubanMovie (Richer)	.5411	.2991	.5612	.3254	-	-	-	-	-	-
Task 2	DoubanMusic (Sparser)	.3242	.1791	.3267	.1926	.3324	.1916	.3304	.2001	**.3882***	**.2323***
($k=64$)	DoubanMovie (Richer)	.5449	.3152	.5632	.3387	-	-	-	-	-	-
Task 2	DoubanMusic (Sparser)	.3314	.1810	.3301	.1971	.3412	.1954	.3452	.2074	**.3946***	**.2430***
($k=128$)	DoubanMovie (Richer)	.5512	.3301	.5776	.3505	-	-	-	-	-	-

Task	Domain	Dual-Target CDR Baselines				Dual-Target CDR (our)				Improvement (GA-DTCDR vs. best baselines)	
		DMF_DTCDR_Concat		DDTCDR		GA-DTCDR_Average		**GA-DTCDR**			
		HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG
Task 2	DoubanMusic (Sparser)	**.3614***	**.2117***	.3302	.1930	.3690	.2109	**.3852**	**.2166**	6.59%	2.31%
($k=8$)	DoubanMovie (Richer)	**.5873***	**.3867***	.5655	.3629	.5987	.3731	**.6470**	**.3983**	10.17%	3.00%
Task 2	DoubanMusic (Sparser)	**.3663***	**.2213***	.3451	.2092	.3706	.2037	**.3947**	**.2256**	7.75%	1.94%
($k=16$)	DoubanMovie (Richer)	**.5887***	**.3863***	.5704	.3676	.6058	.3716	**.6426**	**.3950**	9.16%	2.25%
Task 2	DoubanMusic (Sparser)	.3607	.2201	.3463	.2050	.3789	.2056	**.4133**	**.2318**	14.58%	5.32%
($k=32$)	DoubanMovie (Richer)	**.5770***	**.3758***	.5739	.3726	.6145	.3754	**.6677**	**.4141**	15.72%	10.19%
Task 2	DoubanMusic (Sparser)	.3571	.2109	.3466	.2045	.3812	.2144	**.4384**	**.2489**	12.93%	7.15%
($k=64$)	DoubanMovie (Richer)	**.5787***	**.3705***	.5719	.3621	.6120	.3681	**.6817**	**.4284**	17.80%	15.63%
Task 2	DoubanMusic (Sparser)	.3580	.2132	.3520	.2117	.3996	.2207	**.4491**	**.2604**	13.81%	7.16%
($k=128$)	DoubanMovie (Richer)	**.5792***	.3742	.5748	**.3762***	.6311	.3859	**.7068**	**.4526**	22.03%	20.31%

Task	Domain	SDR Baselines				Single-Target CDR Baselines					
		NeuMF		DMF		CTR-RBF		BPR_DCDCSR		TMH	
		HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG
Task 3	DoubanMovie (Sparser)	.5266	.2911	.5498	.3114	.5514	.3156	.5762	.3347	.5987	.3487
($k=8$)	MovieLens (Richer)	.7818	.5024	.8115	.5219	-	-	-	-	-	-
Task 3	DoubanMovie (Sparser)	.5282	.2939	.5573	.3141	.5631	.3213	.5816	.3438	.6031	.3580
($k=16$)	MovieLens (Richer)	.7901	.5084	.8143	.5212	-	-	-	-	-	-
Task 3	DoubanMovie (Sparser)	.5411	.2991	.5612	.3254	.5721	.3347	.5821	.3447	.6108	**.3733***
($k=32$)	MovieLens (Richer)	.7978	.5124	.8180	**.5231***	-	-	-	-	-	-
Task 3	DoubanMovie (Sparser)	.5449	.3152	.5632	.3387	.5704	.3327	.5926	.3559	.6186	**.3754***
($k=64$)	MovieLens (Richer)	.7935	.5149	**.8231***	.5277	-	-	-	-	-	-
Task 3	DoubanMovie (Sparser)	.5512	.3301	.5776	.3505	.5912	.3741	.6142	.3904	.6314	**.3927***
($k=128$)	MovieLens (Richer)	.8042	.5205	**.8319***	.5344	-	-	-	-	-	-

Task	Domain	Dual-Target CDR Baselines				Dual-Target CDR (our)				Improvement (GA-DTCDR vs. best baselines)	
		DMF_DTCDR_Concat		DDTCDR		GA-DTCDR_Average		**GA-DTCDR**			
		HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG	HR	NDCG
Task 3	DoubanMovie (Sparser)	**.6387***	**.3628***	.6070	.3522	.6140	.3572	**.6486**	**.4005**	6.85%	10.39%
($k=8$)	MovieLens (Richer)	**.8328***	**.5293***	.8211	.5283	.8225	.5241	**.8541**	**.5372**	2.56%	1.49%
Task 3	DoubanMovie (Sparser)	**.6391***	**.3606***	.6100	.3518	.6266	.3710	**.6514**	**.4018**	1.92%	11.43%
($k=16$)	MovieLens (Richer)	**.8312***	**.5260***	.8263	.5170	.8280	.5277	**.8547**	**.5381**	2.83%	1.02%
Task 3	DoubanMovie (Sparser)	**.6530***	.3631	.6137	.3460	.6310	.3776	**.6598**	**.4087**	1.04%	9.48%
($k=32$)	MovieLens (Richer)	**.8243***	.5213	.8111	.5167	.8301	.5280	**.8612**	**.5478**	4.48%	4.72%
Task 3	DoubanMovie (Sparser)	**.6477***	.3605	.6200	.3544	.6423	.3841	**.6654**	**.4101**	2.73%	9.24%
($k=64$)	MovieLens (Richer)	.8200	**.5382***	.8130	.5198	.8324	.5320	**.8668**	**.5516**	5.31%	2.50%
Task 3	DoubanMovie (Sparser)	**.6521***	.3642	.6222	.3714	.6489	.3792	**.6812**	**.4198**	4.46%	6.90%
($k=128$)	MovieLens (Richer)	.8267	**.5401***	.8210	.5311	.8349	.5381	**.8642**	**.5512**	3.88%	2.06%

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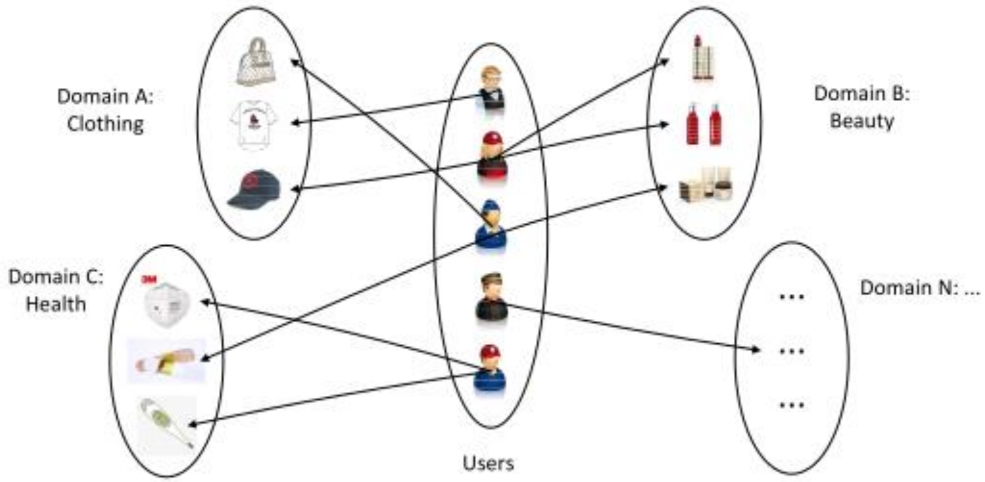
Heterogeneous Graph Framework for Multi-Target Cross-Domain Recommendation



- **Problem to be solved:** how to optimally combine item information from different domains for CDR?
- **In this paper:** graphs at multiple levels
  - Inter-domain shared graph
  - Intra domain graph

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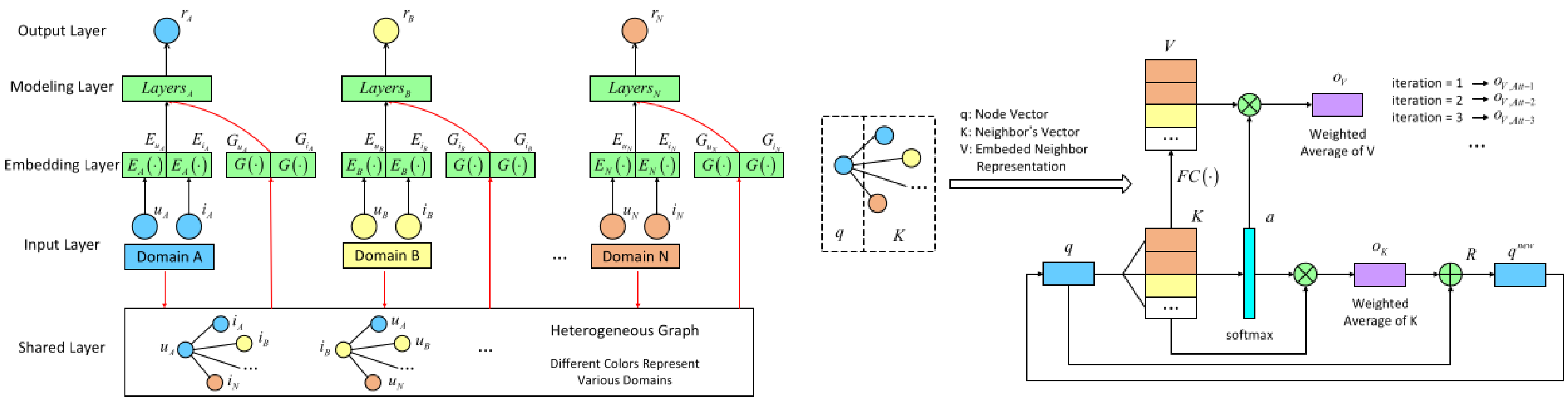
Heterogeneous Graph Framework for Multi-Target Cross-Domain Recommendation



- novel multitarget architecture; build heterogenous graphs for each domain and combine embedding of intra- with inter-domain embeddings;
  - intra-domain embedding simple to obtain and results in E_{u_A} and E_{i_A} for domain A;
  - cross-domain embedding obtained via *heterogenous graphs* for u_A and i_A (G_{u_A} and G_{i_A});
- recurrent attention iteratively aggregates neighbor information wrt specific node in graph;

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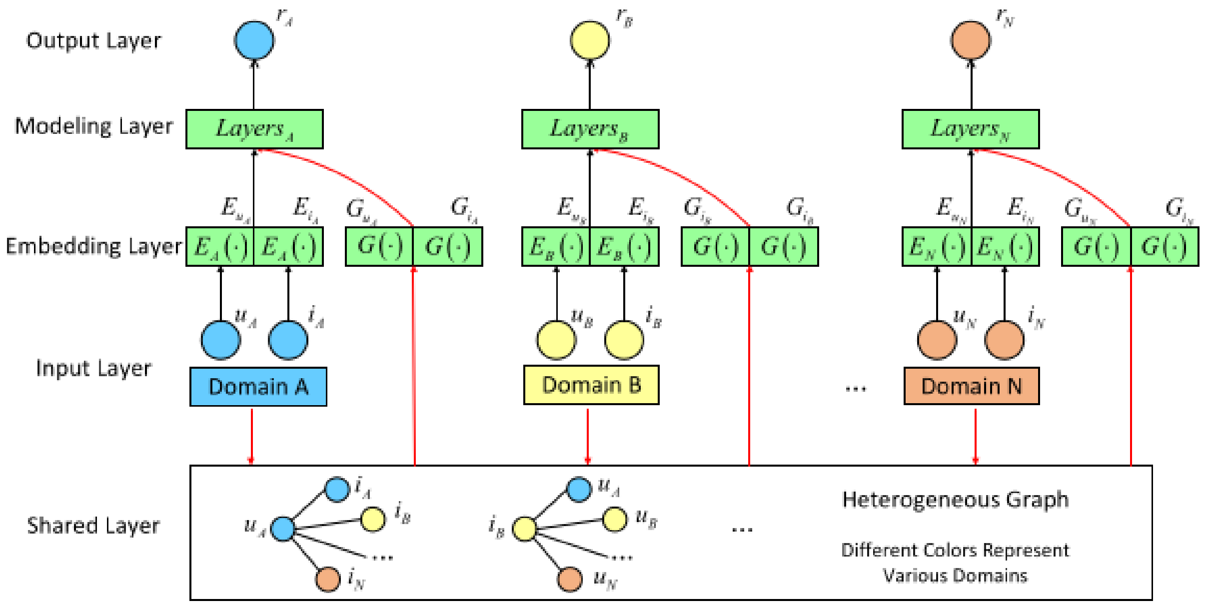
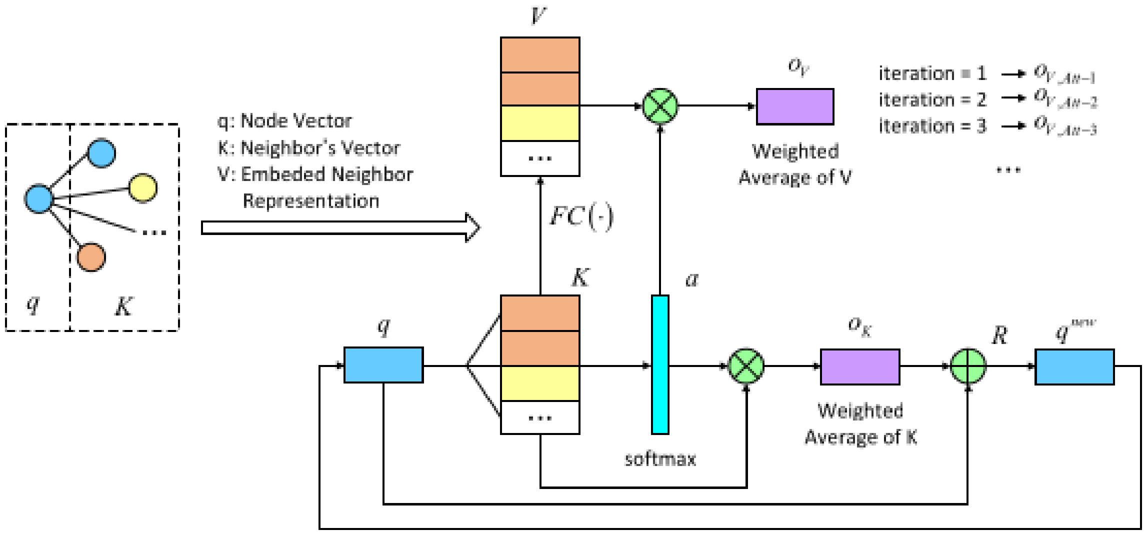
Heterogeneous Graph Framework for Multi-Target Cross-Domain Recommendation





- Intermediate graph embeddings:
  - $q = h_{u_A}$ (user vector)
  - $K = \{h_j | j \in N(u_A)\} = \{h_{i_A}, h_{i_B}, \ldots, h_{i_N}\}$ (neighbors' vector)
  - $V = \{Ph_j + p | h_j \in K\}$ (embedded neighbor)
- Cross domain embedding is then:
  - $o_V = \max(V)$ (aggregated neighbor representation)
  - $G_{u_A} = \mathrm{ReLU}(W \cdot CONCAT(q, o_V) + w)$
- Utilize attention mechanism to calculate weights a;
  - $o_V = V \cdot a$
- Iteratively refine process of obtaining a and q
  - $o_K = K \cdot a$
  - $q^{new} = R \cdot (q + o_K)$

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Heterogeneous Graph Framework for Multi-Target Cross-Domain Recommendation

Table 2: Performance comparison of baselines and our models.

Task		Task 1			Task 2		
Domain Evaluation on test set		Music	Instrument AUC (%)	Video	Clothing	Beauty AUC (%)	Health
Baselines	BPR [11]	65.36	51.15	67.20	53.84	**59.13**	59.68
	DDTCDR [7]	65.21	53.46	67.40	52.50	57.97	60.23
	GraphSAGE-pool [3]	65.50	59.10	71.30	53.17	58.59	60.04
Our HeroGRAPH	HeroGRAPH-Att-1	66.52	60.14	71.20	52.84	58.40	**60.26**
	HeroGRAPH-Att-2	**67.98**	**62.56**	**73.80**	**54.73**	58.18	60.21
	HeroGRAPH-Att-3	66.38	**62.56**	68.80	51.95	57.23	58.63

Table 3: Performance comparison on sparse set. Items in sparse set appear no more than 5 times in test set.

Task - sparse		Task 1 - sparse			Task 2 - sparse		
Domain		Music	Instrument	Video	Clothing	Beauty	Health
Number of feedbacks in test set	whole set	687	868	4,988	36,002	23,389	41,622
	sparse set	634	647	1,685	23,266	11,363	18,324
	proportion	92.28%	74.53%	33.78%	64.62%	48.58%	44.02%
Evaluation on sparse set			AUC (%)			AUC (%)	
Baselines	BPR [11]	64.51	51.62	**63.32**	52.64	55.25	52.85
	DDTCDR [7]	67.04	51.93	60.50	52.03	54.69	**53.78**
	GraphSAGE-pool [3]	66.26	54.56	61.40	52.74	**55.51**	53.49
Our HeroGRAPH	HeroGRAPH-Att-1	66.25	56.72	63.20	52.11	54.79	53.57
	HeroGRAPH-Att-2	**68.30**	57.34	60.90	**53.26**	53.88	53.75
	HeroGRAPH-Att-2	67.67	**58.73**	59.30	51.84	53.17	52.18

- Dataset: Amazon 5-core dataset. Chose six domains and divided into two tasks
- baselines are single-domain (BPR-MF) and a DTCDR method extended to handle three domains (DDTCDR);
- Recurrent attention also show good performance compared to non-attention baseline (GraphSAGE);
- graph based methods, especially with attention, is able to model user-item relations for CDR with good results.

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Next chapter

- Overview of multidomain recommender systems (Liang Hu, 25 mins)
- Multi-item domain recommender systems (Z. Y. Lai, 20 mins)
- **Multi-user domain recommender systems (Qi Zhang, 20 mins)**
- Multi-data domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-spatial domain recommender systems (Qi Zhang 20 mins)
- Multi-temporal domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-goal domain recommender systems (Liang Hu, 20 mins)
- Summary (Liang Hu, 5 mins)