Data Science & Machine Intelligence Lab

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Hyper Meta-Path Contrastive Learning for Multi-Behavior Recommendation

Haoran Yang[1], Hongxu Chen[1], Lin Li[2], Philip S. Yu[3], Guandong Xu[1]

[1]University of Technology Sydney

[2]Wuhan University of Technology

[3]University of Illinois at Chicago

WUHAN UNIVERSITY OF TECHNOLOGY

Background

- Rapid Development of E-Commerce
  - Online shopping is rapidly increasing.
  - Plenty of logs about user behaviors are generated and stored on e-cmmerce platforms.
- Different Behaviors Are Meanningful
  - Many traditional recommendation systemns pay more attention to purchasing, ignoring other behaviors.
  - For example, the adding-to-cart behavior is obviously a stronger signal compared with the click behavior.

Figure 1: An example of multiple types of user feedback. Generally there are strong transfer relations among different behaviors.[1]

[1]C. Chen, M. Zhang, Y. Zhang, W. Ma, Y. Liu, and S. Ma, "Efficient heterogeneous collaborative filtering without negative sampling for recommendation," in The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, IAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2020, New York, NY, USA, February 7-12, 2020. AAAI Press, 2020, pp. 19–26. [Online]. Available: https://aaai.org/ojs/index.php/AAAI/article/view/5329

Challenges (1)

- Meta-path for User Behavior Modeling
  - Various meta-path schemas existing in heterogeneous graphs.
  - Researchers usually take exhaustion method to find out the best meta-path schema.
  - Lack of interpretability.

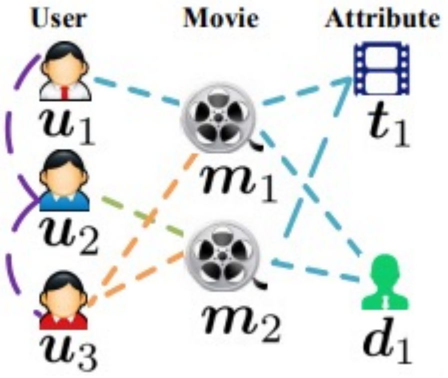


Figure 2: Heterogeneous information network for movie recommendation.[2]

So many schemas, which should we take?

$$U \rightarrow M \rightarrow T$$
$$U \rightarrow M \rightarrow D$$
$$U \rightarrow M \rightarrow U$$
$$U \rightarrow M \rightarrow T \rightarrow U$$

[2]Hu, B., Shi, C., Zhao, W.X., & Yu, P.S. (2018). Leveraging Meta-path based Context for Top- N Recommendation with A Neural Co-Attention Model. Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining.

Challenges (2)

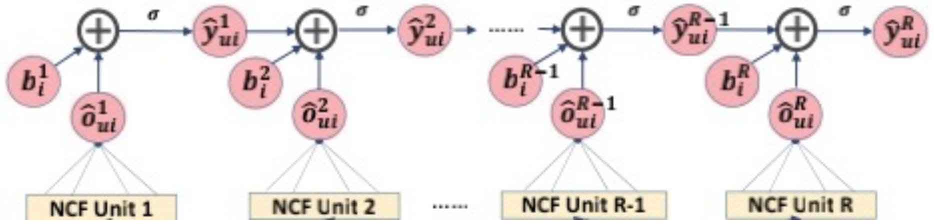


Figure 3: Relations among different behaviors in NMTR[4]

- Multi-Task Learning Based Multi-Behavior Recommendation Models
  - Introduce more supervision signals from training set to improve models.
  - But still fail to capture complex dependencies among different behaviors. For example, NMTR assumes that different behaviors are cascading and EHCF gives a simple transferring among different behaviors.

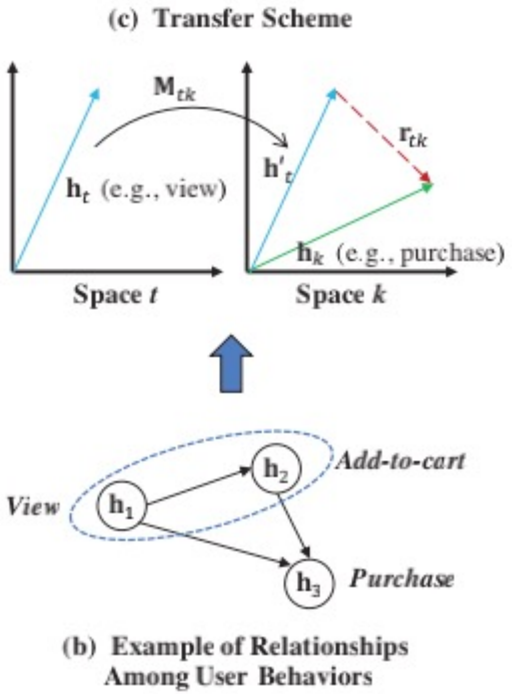


Figure 4: Behavior embeddings transformation in EHCF.[5]

[4]Gao, C., He, X., Gan, D., Chen, X., Feng, F., Li, Y., Chua, T., Yao, L., Song, Y., & Jin, D. (2021). Learning to Recommend With Multiple Cascading Behaviors. IEEE Transactions on Knowledge and Data Engineering, 33, 2588-2601.
[5]Chen, C., Zhang, M., Zhang, Y., Ma, W., Liu, Y., & Ma, S. (2020). Efficient Heterogeneous Collaborative Filtering without Negative Sampling for Recommendation. AAAI.

Motivation

- Enrich Graph Structure in Recommendation Systems
  - We propose hyper meta-path to combine the meta-paths between the same user and the same item with different behaviors according to chronological order.
  - Leveraging interaction information among different meta-paths to enrich graph structures.
- Graph Contrastive Learning for Recommendation Systems
  - As mentioned previously, existing works fail to capture the complex dependecies among different behaviors.
  - We do not take a simple and fixed schema like NMTR and EHCF. Instead, we take a contrastive manner.
  - Adaptively learning behavior pattern embedding via contrasting user behaviors regarding to different products.

Hyper Meta-Graph

- Meta-Paths
  - cannot capture the interaction information among meta-paths.
- Hyper Meta-Path
  - Utilize the advantages of meta-paths and hyperedges
  - capture the complex interaction information among meta-paths.

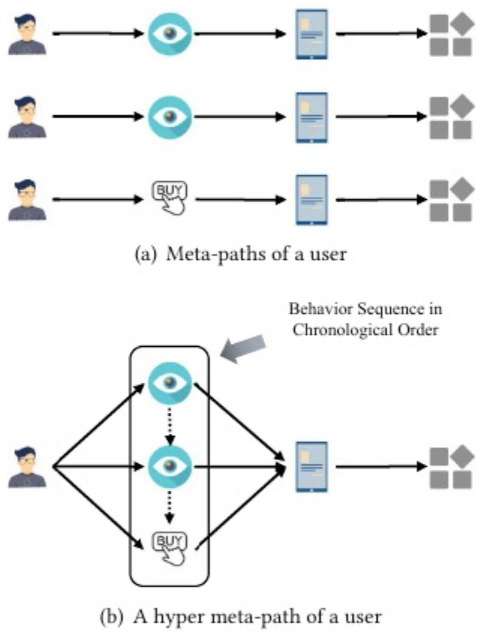
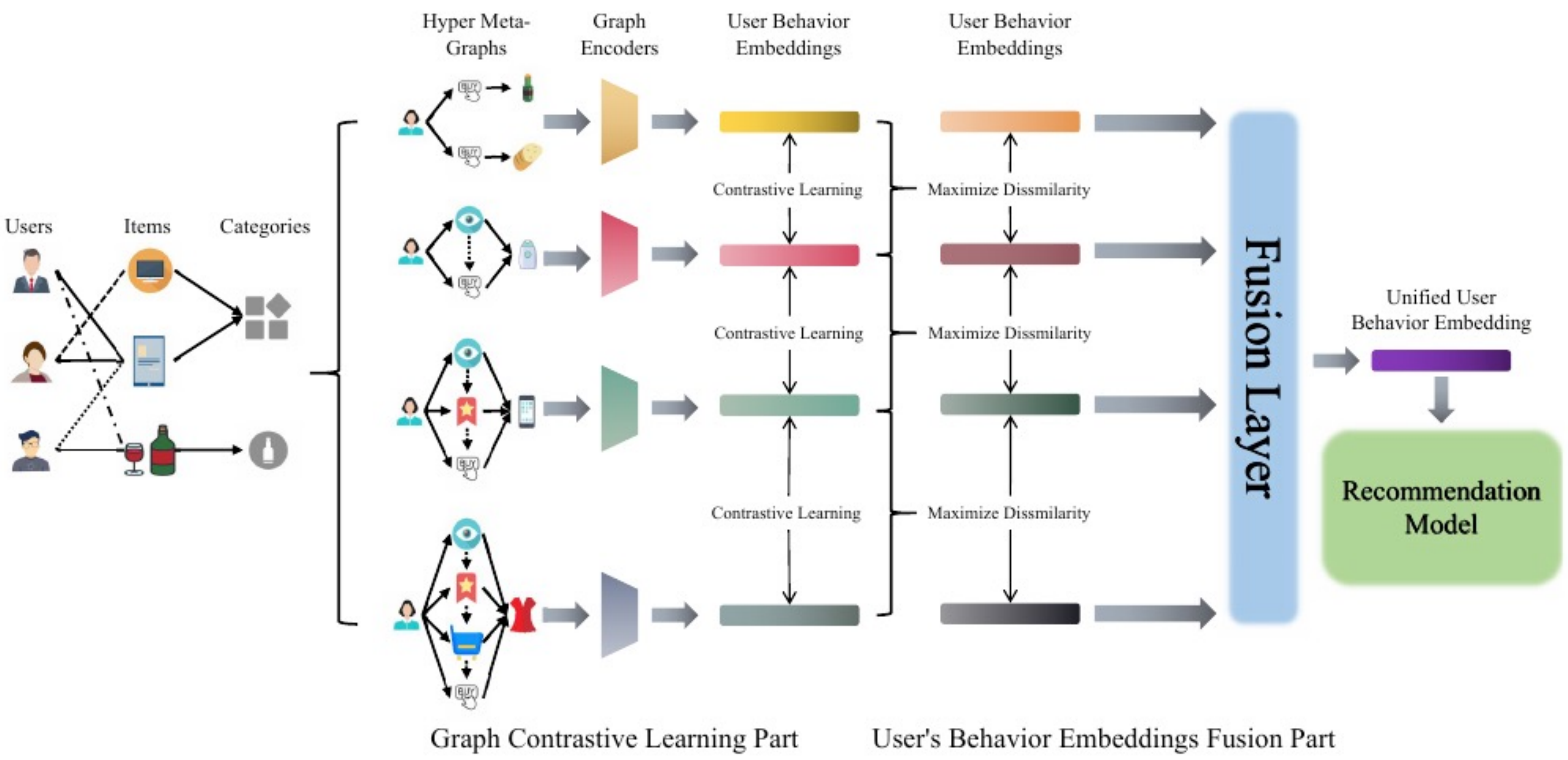


Figure 1: (a) Meta-paths of a user in the recommendation system denotes the user's different behaviors. (b) A hyper meta-path constructed by previous meta-paths denotes the user's behavior pattern when he is purchasing a smartphone.

Framework


Users
Items
Categories
Hyper Meta-Graphs
Graph Encoders
User Behavior Embeddings
User Behavior Embeddings
Contrastive Learning
Contrastive Learning
Contrastive Learning
Maximize Dissmilarity
Maximize Dissmilarity
Maximize Dissmilarity
Fusion Layer
Unified User Behavior Embedding
Recommendation Model
Graph Contrastive Learning Part
User's Behavior Embeddings Fusion Part

Datasets

TABLE I
STATISTICS OF DATASETS

Dataset	Taobao	Tmall
#users	48946	9368
#items	1500839	302722
#pv (percentage)	7723217 (85.17%)	1510303 (92.14%)
#fav (percentage)	436715 (4.82%)	102419 (6.25%)
#cart (percentage)	527221 (5.81%)	24557 (1.50%)
#buy (percentage)	380877 (4.20%)	104360 (6.37%)
#total	9068030	1639220
#ave_pv	157.79	161.22
#ave_fav	8.92	10.93
#ave_cart	10.77	2.62
#ave_buy	7.78	11.14
#ave_total	185.27	174.98

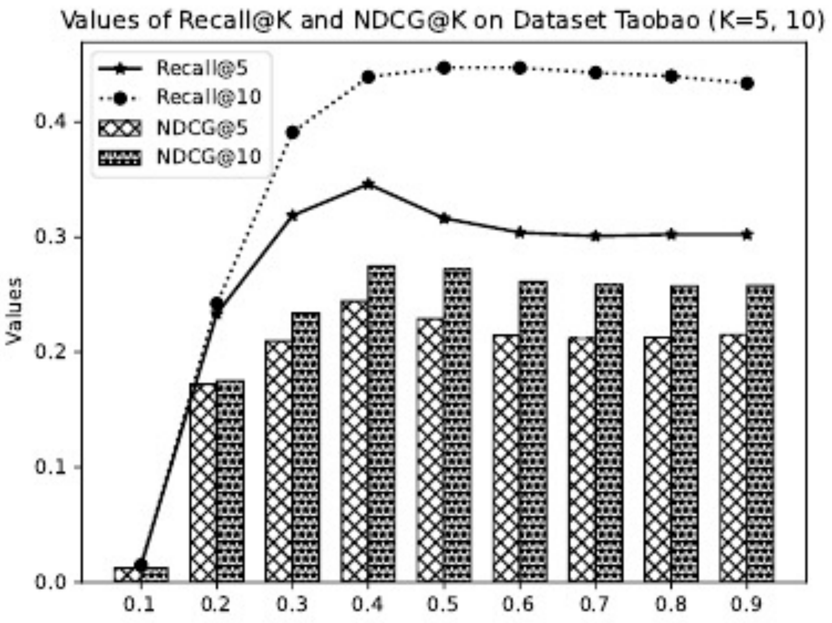
- **Taobao**[1]: The researchers from Alibaba Group randomly selected about 1 million users who have behaviors including click, purchase, adding item to shopping cart and item favoring during November 25 to December 03, 2017. The dataset is organized in a very similar form to MovieLens-20M, i.e., each line represents a specific user-item interaction, which consists of user ID, item ID, item's category ID, behavior type and timestamp, separated by commas.
- **Tmall**[2]: The dataset contains anonymized users' shopping logs in the past 6 months before and on the *Double 11* day,and the label information indicating whether they are repeated buyers. Due to privacy issue, data is sampled in a biased way, so the statistical result on this data set would deviate from the actual of Tmall.com. But it will not affect the applicability of the solution. It is organized in a similar form to Taobao.

Comparison Experiments

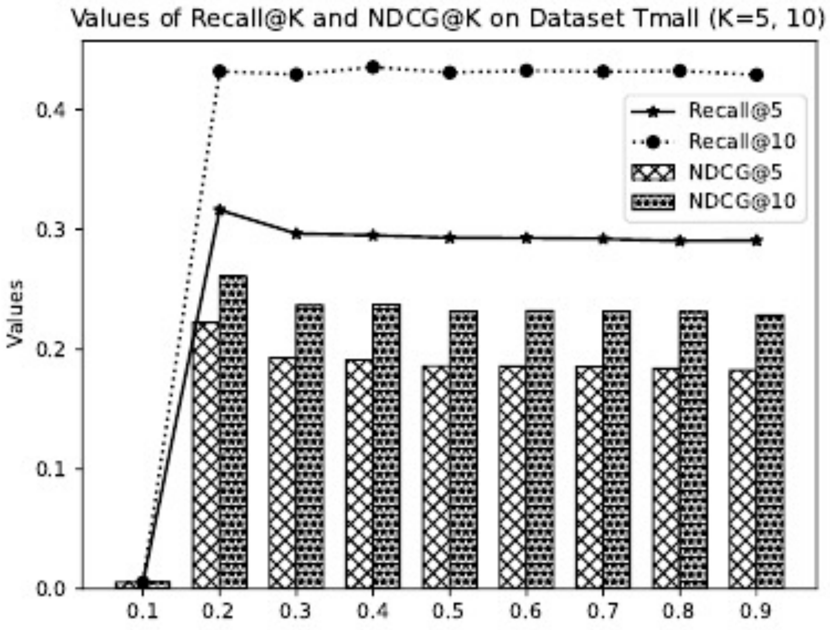
TABLE II
COMPARISON EXPERIMENT RESULTS OF HMG-CR AND BASELINES

Dataset	Taobao				Tmall			
Methods \ Metrics	Recall@5	Recall@10	NDCG@5	NDCG@10	Recall@5	Recall@10	NDCG@5	NDCG@10
GCN	0.2577	0.3589	0.1842	0.2167	0.2544	0.3775	0.1763	0.2163
GraphSAGE	0.2751	0.3826	0.1965	0.2312	0.2588	0.3695	0.1813	0.2170
GAT	0.2782	0.3921	0.1972	0.2339	0.2561	0.3735	0.1777	0.2158
RGCN	0.2714	0.3767	0.1946	0.2285	0.2725	0.4144	0.1749	0.2215
NMTR	0.2215	0.3781	0.1513	0.2012	0.2780	0.4230	0.1798	0.2265
EHCF	0.2882	0.4166	0.1945	0.2359	0.2451	0.4115	0.1581	0.2113
HMG-CR(SG)	0.3050	0.4417	0.2162	0.2608	0.2943	0.4329	0.1863	0.2321
HMG-CR(GCN)	0.3039	0.4441	0.2154	0.2613	0.2954	0.4332	0.1869	0.2324
HMG-CR(GAT)	0.3460	0.4390	0.2443	0.2746	0.3163	0.4320	0.2224	0.2604
HMG-CR(GIN)	0.3141	0.3627	0.2029	0.2191	**0.3547**	0.4313	**0.2642**	**0.2891**
HMG-CR(TAG)	**0.3588**	**0.4464**	**0.2639**	**0.2926**	0.2964	**0.4350**	0.1902	0.2359
Improvement	24.50%	7.15%	33.82%	24.04%	27.59%	2.84%	45.73%	27.64%

Contrastive Learning Tasks vs. Recommendation tasks



(a)



(b)

- Graph contrastive learning brings improvement to HMG-CR
- Graph contrastive learning tasks and recommendation tasks should have a relatively balanced significance during HMG-CR training.

Graph Encoder Studies

HMG-CR(SG)	0.3050	0.4417	0.2162	0.2608	0.2943	0.4329	0.1863	0.2321
HMG-CR(GCN)	0.3039	0.4441	0.2154	0.2613	0.2954	0.4332	0.1869	0.2324
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HMG-CR(TAG)	**0.3588**	**0.4464**	**0.2639**	**0.2926**	0.2964	**0.4350**	0.1902	0.2359

TABLE III
SUPPLEMENTARY EXPERIMENT RESULTS OF GIN AND TAG

Dataset	Taobao				Tmall			
Metrics / Methods	Recall@5	Recall@10	NDCG@5	NDCG@10	Recall@5	Recall@10	NDCG@5	NDCG@10
GIN	0.2682	0.3779	0.1892	0.2246	0.2817	0.4236	0.1878	0.2340
TAG	0.2784	0.3863	0.1994	0.2342	0.2845	0.4235	0.1869	0.2323
HMG-CR(GIN)	0.3141	0.3627	0.2029	0.2191	**0.3547**	0.4313	**0.2642**	**0.2891**
HMG-CR(TAG)	**0.3588**	**0.4464**	**0.2639**	**0.2926**	0.2964	**0.4350**	0.1902	0.2359

Fusion Layer Studies

TABLE IV
PERFORMANCES OF HMG-CR(GAT) WITH DIFFERENT FUSION LAYERS ON BOTH DATASETS
($\beta = 0.4$ FOR DATASET TAOBAO AND $\beta = 0.2$ FOR DATASET TMALL)

Dataset	Taobao				Tmall			
Fusion \ Metrics	Recall@5	Recall@10	NDCG@5	NDCG@10	Recall@5	Recall@10	NDCG@5	NDCG@10
MEAN	**0.3460**	0.4390	**0.2443**	**0.2746**	**0.3163**	0.4320	**0.2224**	**0.2604**
SUM	0.3012	**0.4427**	0.2118	0.2580	0.2939	0.4345	0.1879	0.2343
MLP	0.3024	0.4344	0.2150	0.2579	0.2946	**0.4349**	0.1873	0.2336
PNLF	0.3046	0.4363	0.2157	0.2586	0.2944	0.4344	0.1865	0.2327

- HMG-CR with linear fusion layer achieves better performances
- There are mapping layers in MLP and PNLF. Mapping layers may disturb the user behavior pattern obtained in the space in which the graph contrastive learning was conducted

Thanks for your listening!