Research Track | User Modeling and Recommendation

Cold-start Bundle Recommendation via Popularity-based Coalescence and Curriculum Heating

Personal website

Hyunsik Jeon[1] Jong-eun Lee[2] Jeongin Yun[2] U Kang[2]

hyjeon@ucsd.edu kjayjay40@snu.ac.kr yji00828@snu.ac.kr ukang@snu.ac.kr

[1]UC San Diego [2]Seoul National University

(1) Summary

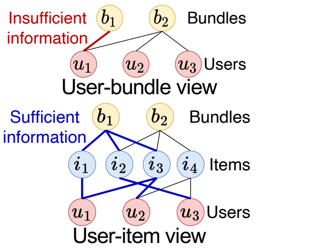
- ***Problem***: Recommend new bundles to users in a cold-start scenario
- ***Main idea***: Propose ***CoHeat***, which leverages popularity-based coalescence and curriculum heating for cold-start bundle recommendation
- ***Homepage***: https://github.com/snudatalab/CoHeat
- ***Oral presentation***: May 17, 2024, 13:00 – 13:15 (West Ballroom)

(2) Problem Definition

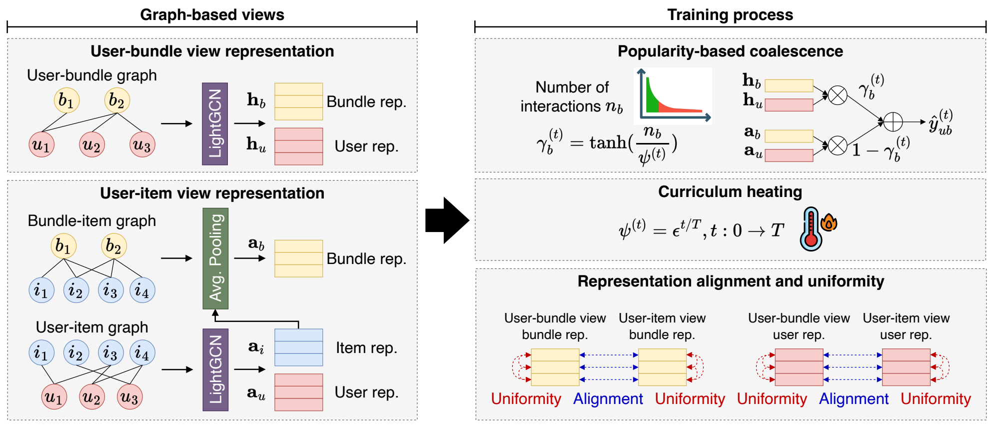
- ***Given***:
  - Sets of users $\mathcal{U}$, bundles $\mathcal{B}$, and items $\mathcal{I}$
  - User-bundle, user-item, and bundle-item interactions
- ***Goal***: Recommend k bundles to each user $u \in \mathcal{U}$, with a focus on accurately recommending cold-start bundles
- ***Main challenge***: Predict the relationship between a user u and a cold bundle b in the absence of any historical interactions of b

(3) Motivation

- Existing methods depend highly on historical information though user-bundle interactions are extremely sparse
- For unpopular bundles, user-item view is more informative than user-bundle view



(4) Proposed Method (CoHeat)



(5) Evaluation

- ***Datasets***:

Table 1: Summary of three real-world datasets where "dens." denotes the density of a matrix.

Dataset	Users	Bundles	Items	User-bundle (dens.)	User-item (dens.)	Bundle-item (dens.)	Avg. size of bundle
Youshu[1]	8,039	4,771	32,770	51,377 (0.13%)	138,515 (0.05%)	176,667 (0.11%)	37.03
NetEase[1]	18,528	22,864	123,628	302,303 (0.07%)	1,128,065 (0.05%)	1,778,838 (0.06%)	77.80
iFashion[1]	53,897	27,694	42,563	1,679,708 (0.11%)	2,290,645 (0.10%)	106,916 (0.01%)	3.86

- ***Comparison with cold-start & warm-start methods***

Table 2: Performance comparison of CoHeat and baseline cold-start methods on three real-world datasets.

Model	Youshu						NetEase						iFashion					
	Recall@20			nDCG@20			Recall@20			nDCG@20			Recall@20			nDCG@20		
	Cold	*Warm*	*All*	*Cold*	*Warm*	*All*	*Cold*	*Warm*	*All*	*Cold*	*Warm*	*All*	*Cold*	*Warm*	*All*	*Cold*	*Warm*	*All*
DropoutNet [51]	.0022	.0336	.0148	.0007	.0153	.0055	.0028	.0154	.0046	.0015	.0078	.0024	.0009	.0060	.0039	.0008	.0045	.0027
CB2CF [2]	.0012	.0258	.0028	.0007	.0208	.0021	.0016	.0049	.0027	.0006	.0027	.0014	.0009	.0057	.0066	.0006	.0043	.0048
Heater [73]	.0016	.1753	.0541	.0007	.0826	.0286	.0021	.0125	.0102	.0010	.0064	.0054	.0015	.0217	.0123	.0010	.0151	.0083
GAR-CF [11]	.0015	.1688	.0529	.0011	.0726	.0317	.0010	.0063	.0014	.0005	.0035	.0008	.0013	.0203	.0090	.0013	.0143	.0055
GAR-GNN [11]	.0013	.0835	.0358	.0006	.0569	.0178	.0009	.0056	.0027	.0003	.0030	.0012	.0065	.0172	.0126	.0030	.0107	.0087
CVAR [70]	.0008	.1958	.0829	.0002	.1112	.0533	.0002	.0308	.0156	.0001	.0154	.0084	.0007	.0220	.0125	.0004	.0152	.0084
CLCRec [58]	.0137	.0626	.0367	.0087	.0317	.0194	.0136	.0407	.0259	.0075	.0215	.0138	.0053	.0203	.0126	.0043	.0135	.0085
CCFCRec [72]	.0044	.1554	.0702	.0022	.0798	.0425	.0007	.0265	.0130	.0004	.0128	.0068	.0005	.0439	.0252	.0003	.0304	.0172
CoHeat (ours)	**.0183**	**.2804**	**.1247**	**.0105**	**.1646**	**.0833**	**.0191**	**.0847**	**.0453**	**.0093**	**.0455**	**.0264**	**.0170**	**.1156**	**.0658**	**.0096**	**.0876**	**.0504**

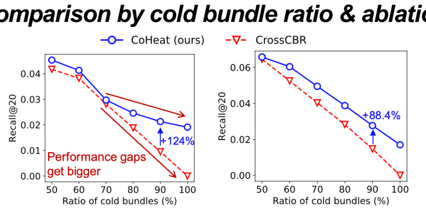
CoHeat outperforms baseline cold-start methods on all settings

Table 3: Performance comparison of CoHeat and baseline warm-start methods on three real-world datasets.

Model	Youshu		NetEase		iFashion	
	Recall @20	nDCG @20	Recall @20	nDCG @20	Recall @20	nDCG @20
MFBPR [42]	.1959	.1117	.0355	.0181	.0752	.0542
LightGCN [23]	.2286	.1344	.0496	.0254	.0837	.0612
SGL [59]	.2568	.1527	.0687	.0368	.0933	.0690
SimGCL [62]	.2691	.1593	.0710	.0377	.0919	.0677
LightGCL [5]	.2712	.1607	.0722	.0388	.0943	.0686
DAM [12]	.2082	.1198	.0411	.0210	.0629	.0450
BundleNet [17]	.1895	.1125	.0391	.0201	.0626	.0447
BGCN [8, 9]	.2347	.1345	.0491	.0258	.0733	.0531
CrossCBR [35]	.2776	.1641	.0791	.0433	.1133	.0875
CoHeat (ours)	**.2804**	**.1646**	**.0847**	**.0455**	**.1156**	**.0876**

CoHeat shows comparable performance with the SOTA method (CrossCBR) on warm settings

- ***Comparison by cold bundle ratio & ablation study***



(a) NetEase (b) iFashion

Figure 5: Performance comparison by cold bundle ratio.

The performance gap gets bigger as the cold bundle ratio increases

Table 4: Ablation study of CoHeat in cold-start scenario which is our main target.

Model	Youshu		NetEase		iFashion	
	Recall @20	nDCG @20	Recall @20	nDCG @20	Recall @20	nDCG @20
CoHeat-*PC*	.0000	.0000	.0000	.0000	.0000	.0000
CoHeat-*CH-Ant*	.0177	.0087	.0176	.0087	.0164	.0093
CoHeat-*CH-Fix*	.0180	.0092	.0182	.0090	.0164	.0092
CoHeat-*AU*	.0069	.0031	.0029	.0013	.0013	.0005
CoHeat (ours)	**.0183**	**.0105**	**.0191**	**.0093**	**.0170**	**.0096**

All main ideas help improve the performance