Personalized Transfer of User Preferences for Cross-domain Recommendation

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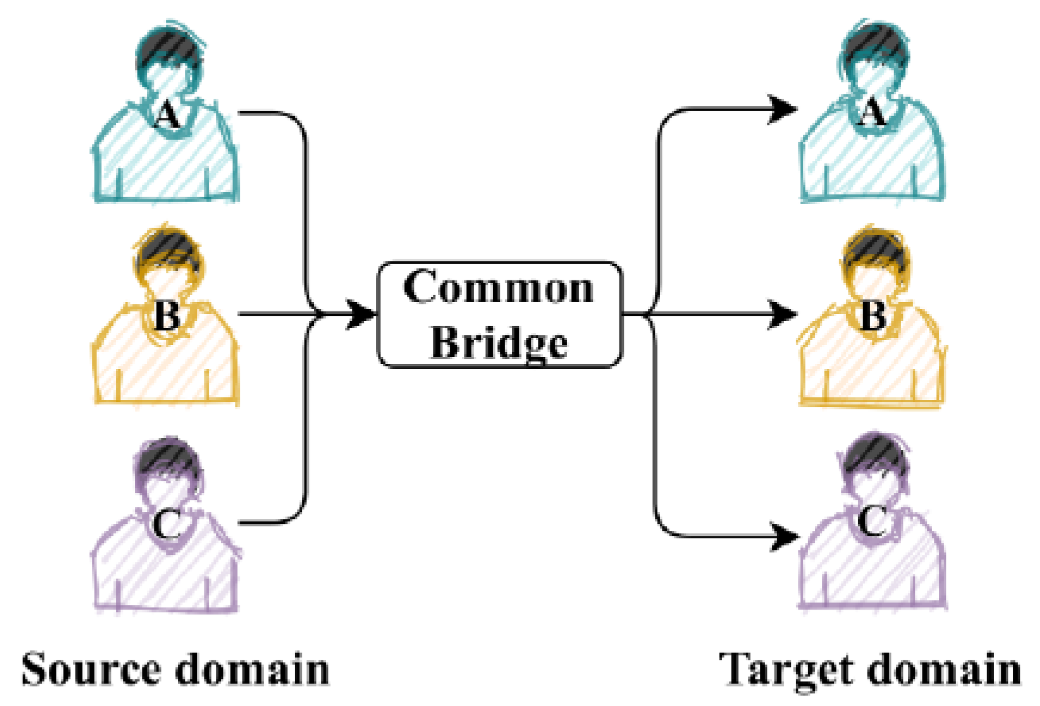
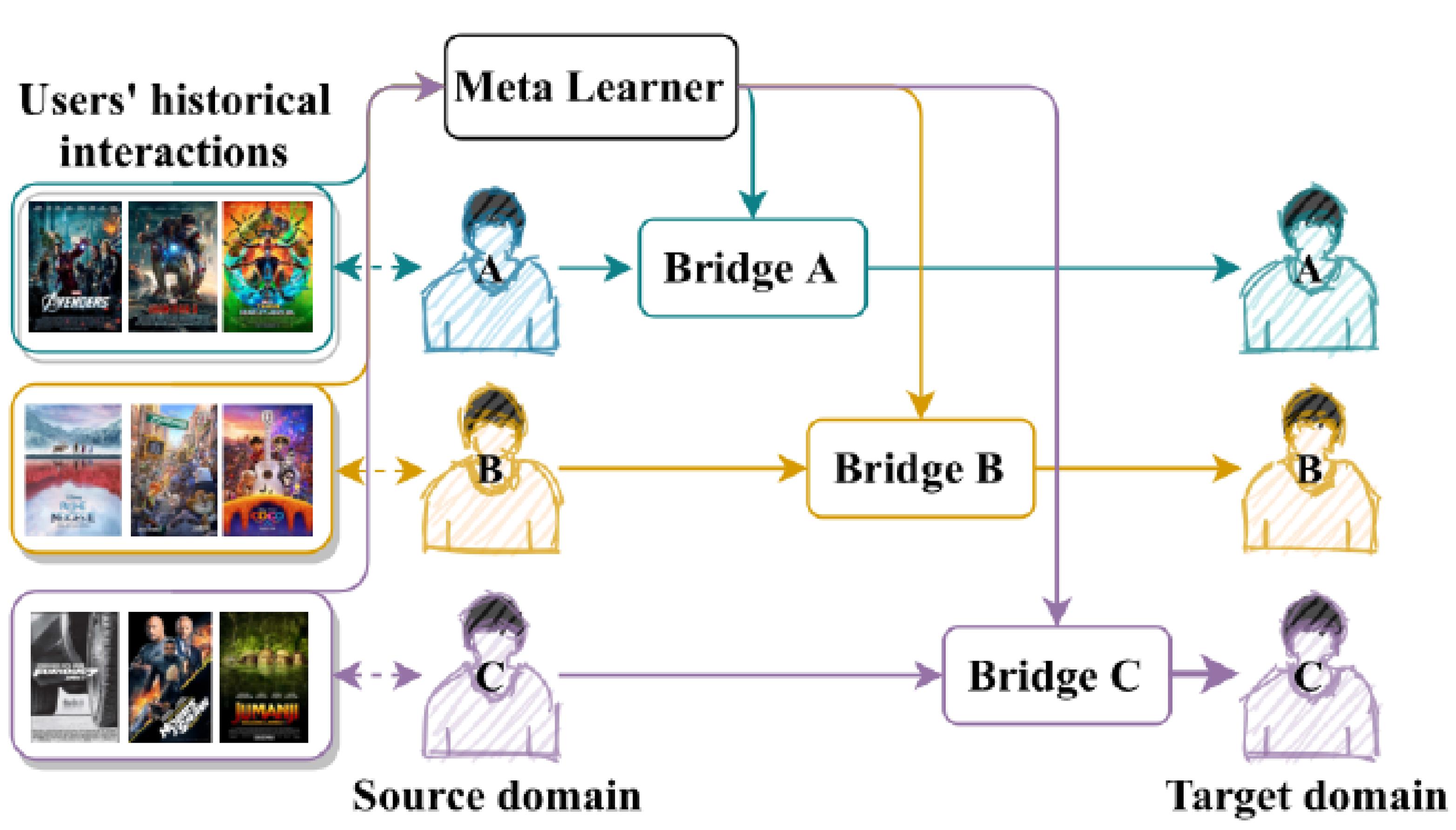
Introduction

Cold-start problem is still a very challenging problem in recommender systems. Fortunately, the interactions of the cold-start users in the auxiliary source domain can help cold-start recommendations in the target domain. How to transfer user's preferences from the source domain to the target domain, is the key issue in Cross-domain Recommendation (CDR) which is a promising solution to deal with the cold-start problem.



(a)



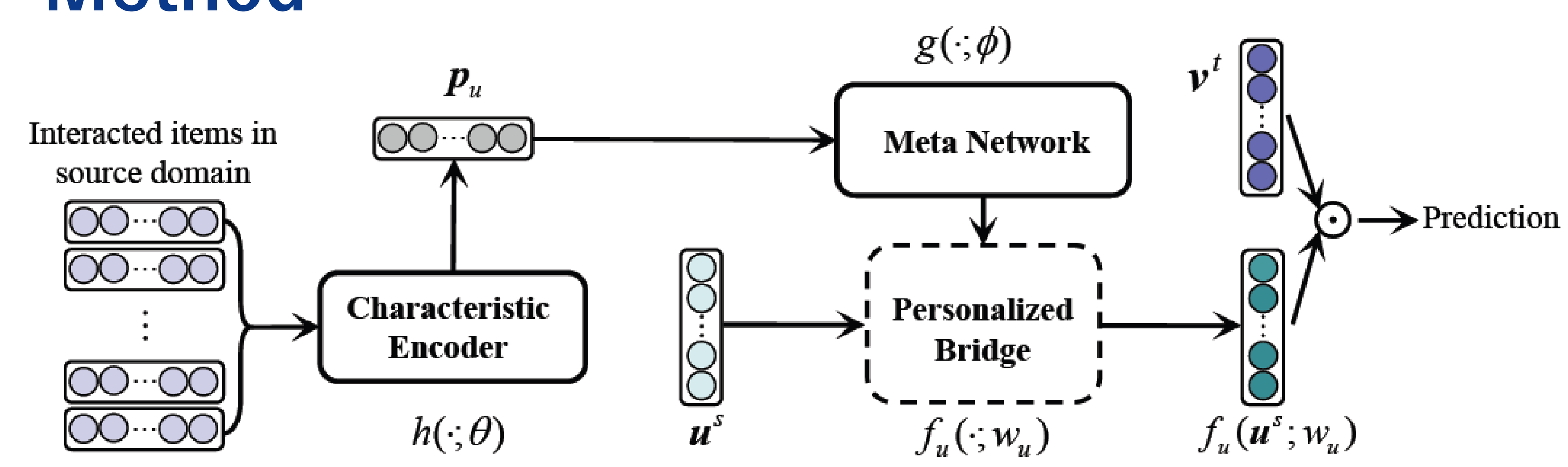
(b)

To achieve preference transfer, many existing CDR methods assume that all users share the same relationships between user preferences in the source domain and the target domain, and learn a common preference bridge shared by all users, as shown in Figure (a).

In practice, due to individual differences, the complex relationships between the user preferences of the source and target domains vary from user to user. Hence, it is hard for a single bridge to capture such complicated and various relationships, which may degrade these CDR methods' performance. To alleviate the drawback, it is necessary to use personalized bridges to model various relationships between user preferences in different domains. In other words, the process of preference transfer should be personalized.

Along this line, we propose a novel framework named Personalized Transfer of User Preferences for Cross-domain Recommendation (PTUPCDR) as shown in Figure (b). Specifically, a meta network fed with users' characteristic embeddings is learned to generate personalized bridge functions to achieve personalized transfer of preferences for each user. To learn the meta network stably, we employ a task-oriented optimization procedure. With the meta-generated personalized bridge function, the user's preference embedding in the source domain can be transformed into the target domain, and the transformed user preference embedding can be utilized as the initial embedding for the cold-start user in the target domain.

Method



- Characteristic Encoder: $p_{u_i} = \sum_{v_j^s \in \mathcal{S}_{u_i}} a_j v_j^s,$ $\quad a_j' = h(v_j;\theta),$ $\quad a_j = \frac{\exp(a_j')}{\sum_{v_l^s \in \mathcal{S}_{u_i}} \exp(a_l')},$
- Meta Network: $w_{u_i} = g(p_{u_i};\phi),$
- Personalized Bridge Function: $f_{u_i}(\cdot;w_{u_i}),$
- Transformed User's Embeddings: $\hat{u}_i^t = f_{u_i}(u_i^s;w_{u_i})$
- Task-oriented Optimization:

$$\min_{\theta,\phi} \frac{1}{|\mathcal{R}_o^t|} \sum_{r_{ij} \in \mathcal{R}_o^t} (r_{ij} - f_{u_i}(u_i^s;w_{u_i})v_j)^2$$

Experiments

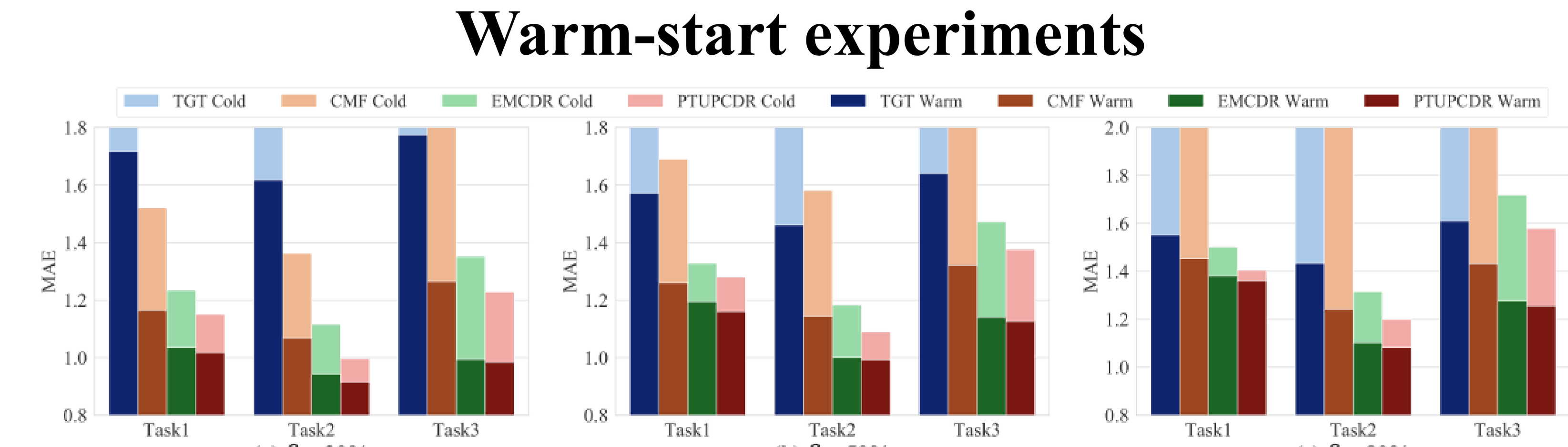
Datasets

CDR Tasks	Domain Source	Domain Target	Item Source	Item Target	User Overlap	User Source	User Target	Rating Source	Rating Target
Task1	Movie	Music	50,052	64,443	18,031	123,960	75,258	1,697,533	1,097,592
Task2	Book	Movie	367,982	50,052	37,388	603,668	123,960	8,898,041	1,697,533
Task3	Book	Music	367,982	64,443	16,738	603,668	75,258	8,898,041	1,097,592

Main experiments

	β	*Metric*	TGT	CMF	DCDCSR	SSCDR	EMCDR	PTUPCDR	Improve
Task1	20%	*MAE*	4.4803	1.5209	1.4918	1.3017	1.2350	**1.1504***	6.86%
		RMSE	5.1580	2.0158	1.9210	1.6579	1.5515	**1.5195**	2.06%
	50%	*MAE*	4.4989	1.6893	1.8144	1.3762	1.3277	**1.2804***	3.57%
		RMSE	5.1736	2.2271	2.3439	1.7477	1.6644	**1.6380**	1.59%
	80%	*MAE*	4.5020	2.4186	2.7194	1.5046	1.5008	**1.4049***	6.39%
		RMSE	5.1891	3.0936	3.3065	1.9229	1.8771	**1.8234***	2.86%
Task2	20%	*MAE*	4.1831	1.3632	1.3971	1.2390	1.1162	**0.9970***	10.68%
		RMSE	4.7536	1.7918	1.7346	1.6526	1.4120	**1.3317***	5.69%
	50%	*MAE*	4.2288	1.5813	1.6731	1.2137	1.1832	**1.0894***	7.93%
		RMSE	4.7920	2.0886	2.0551	1.5602	1.4981	**1.4395***	3.91%
	80%	*MAE*	4.2123	2.1577	2.3618	1.3172	1.3156	**1.1999***	8.80%
		RMSE	4.8149	2.6777	2.7702	1.7024	1.6433	**1.5916***	3.15%
Task3	20%	*MAE*	4.4873	1.8284	1.8411	1.5414	1.3524	**1.2286***	9.15%
		RMSE	5.1672	2.3829	2.2955	1.9283	1.6737	**1.6085***	3.90%
	50%	*MAE*	4.5073	2.1282	2.1736	1.4739	1.4723	**1.3764***	6.51%
		RMSE	5.1727	2.7275	2.6771	1.8441	1.8000	**1.7447***	3.07%
	80%	*MAE*	4.5204	3.0130	3.1405	1.6414	1.7191	**1.5784***	3.84%
		RMSE	5.2308	3.6948	3.5842	2.1403	2.1119	**2.0510***	2.88%

Warm-start experiments



Generalization experiments