Transfer-Meta Framework for Cross-domain Recommendation to Cold-Start Users

1.Motivation

Cold-start problems are enormous challenges in practical recommender systems.

Cross-domain recommendation (CDR) aims to leverage **rich information** from an **auxiliary (source) domain** to improve the performance of recommender systems in the **target domain**.

CDR is promising to solve cold-start problem.

Mapping-based CDR methods are popular, which learns a mapping function to transform the user representation of source domain to the target domain based on overlapping users. However, these methods **ignore** the **generalization ability of mapping**.

With the advantage of **meta-learning**, we proposed a novel framework **TMCDR**.

2.Method

- Transfer stage: two pre-trained models
- Meta stage: a task-oriented meta network

Algorithm 1 Transfer-Meta framework for CDR (TMCDR)

Input: Given user and item sets of source and target domains, U^s, U^t, V^s, V^t. The overlapping user set U^o. The rating matrix R^s, R^t.
Input: Task-oriented meta network f_θ.
Input: The step size (learning rate) λ, α.
Transfer Stage:

- A pre-trained source model contains $\mathrm{u}^s, \mathrm{v}^s$.
- A pre-trained target model contains $\mathrm{u}^t, \mathrm{v}^t$.

Meta Stage: utilize the source embedding of overlapping users u^s and the target item embedding v^t to optimize the task-oriented meta network f_θ.

(1) randomly initialize θ.
(2) **while** not converge **do**:
(3) sample batch of user groups $\{U_1, ..., U_n\}$ from U^o.
(4) **for** $U_i \in \{U_1, ..., U_n\}$ do:
(5) divide U_i into two disjoint sets U_a, U_b
(6) define two training sets D_a, D_b with U_a, U_b
(7) evaluate loss $\mathcal{L}_\theta$ with D_a
(8) compute updated parameter $\theta' = \theta - \lambda \frac{\partial \mathcal{L}_\theta}{\partial \theta}$
(9) evaluate loss $\mathcal{L}_{\theta'_i}$ with D_b
(10) update $\theta = \theta - \alpha \sum_{U_i \in \{U_1,...,U_n\}} \frac{\partial \mathcal{L}_{\theta'_i}}{\partial \theta}$
(11) **end while**

Test Stage: for a cold-start user u, we use $f_\theta(\mathrm{u}^s)$ as the user embedding for prediction.

3.Experiments

- Dataset: Amazon, Douban
- Metrics: AUC, NDCG@10

Method	AUC	NDCG@10	AUC	NDCG@10
	Scenario1		Scenario2	
CMF	0.6490	0.1696	0.6996	0.2076
BPR	0.7226	0.2182	0.7160	0.2379
ListRank-MF	0.6648	0.1709	0.7232	0.2204
CML	0.6470	0.1408	0.6986	0.2147
CST	0.7240	0.2137	0.7124	0.2324
SSCDR	0.7245	0.0089	0.6745	0.0013
EMCDR_MFori	0.6942	0.1978	0.6511	0.1747
EMCDR_MF	0.7271	0.2103	0.6923	0.1985
TMCDR_MF	**0.7501***	**0.2246***	**0.7253***	**0.2427***
	Scenario3		Scenario4	
CMF	0.7769	0.3066	0.7295	0.2349
BPR	0.7737	0.3065	0.7199	0.2150
ListRank-MF	0.7640	0.2902	0.7409	0.2277
CML	0.8191	**0.3548**	0.7857	0.2647
CST	0.7995	0.2960	0.7842	0.2563
SSCDR	0.7956	0.3080	0.6545	0.1628
EMCDR_MFori	0.7273	0.2284	0.7307	0.1990
EMCDR_MF	0.8011	0.3055	0.7936	0.2670
TMCDR_MF	**0.8282***	0.3334	**0.8056***	**0.2775***
	Scenario5		Scenario6	
CMF	0.8465	0.3420	0.8339	0.3764
BPR	0.8108	0.3283	0.8138	0.3659
ListRank-MF	0.8136	0.3106	0.8191	0.3281
CML	0.8466	0.3409	0.8405	0.3707
CST	0.8524	0.3405	0.8406	0.3742
SSCDR	0.8144	0.2925	0.8317	0.3644
EMCDR_MFori	0.7307	0.1990	0.7627	0.2703
EMCDR_MF	0.8438	0.3322	0.8297	0.3702
TMCDR_MF	**0.8589***	**0.3483***	**0.8442***	**0.3778***

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