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RPITN: REVIEW BASED PREFERENCE INVARIANCE TRANSFER NETWORK FOR CROSS-DOMAIN RECOMMENDATION

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ABSTRACT

Cross-domain recommendation is an effective way to cope with the cold-start problem in recommendation systems. Knowledge of the current, particularly reviews, is taken into account to improve user/item embedding to reduce the negative transfer that occurs during mapping processes across the source and target domains. Traditional approaches, on the other hand, typically apply review information from the source and target domain independently without consideration of user preference divergence. In this paper, we propose a novel Review-based Preference Invariance Transfer Network (RPITN) to minimize negative transfer by combining reviews from two domains. We first build a review preference invariance (RPI) embedding procedure to express user/item review correlations between two domains. Then, to improve the generalization ability of user/item embedding and prevent negative transfer across domains, we carefully insert RPI into the embedding learning and mapping process. Extensive experiments on real-world datasets demonstrate the superiority of RPITN compared with other recommendation methods.

Index Terms— cross-domain recommendation, deep learning, review side information, variational auto-encoder

1. INTRODUCTION

By precisely hitting their preferences, the personalized recommendation can assist users in achieving efficient and convenient business experiences. Traditional recommendation systems typically use a collaborative filtering model (CFM) to determine users' preferences, which is based primarily on historical user feedback. CFM-based approaches, on the other hand, become less efficient when new users come because there is no historical data to rely on. This cold-start issue has long been a problem for recommendation system, and it has spawned a variety of solutions [1, 2].

In recent years, the cross-domain recommendation (CDR) is an efficient method to handle this problem by leveraging relatively richer information from a dense historical-data domain to improve recommendation performance in a sparsity domain [3, 4]. The main concept of CDR is to create links by means of transferring certain consistent factors, such as consistent content [5, 6], common users/items embedding [7, 8, 9] or similar rating pattern [10, 11] across domains.

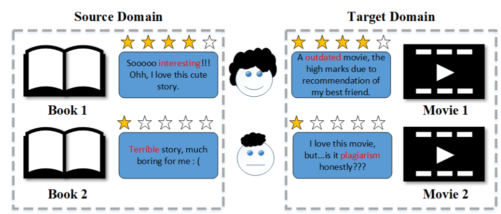

Fig. 1. One user may have the same ratings on different items, however, this user may provide different reviews for these items, which can be utilized to improve the representation of users/items.

To minimize the domain difference, a transfer mapping scheme is applied to project embedding from the source domain to the target. Meanwhile, multi-task learning [4] or transfer learning frameworks [12] is usually adopted to map embedding and build the bridge across domains. As a result, a significant difficulty in the CDR system is developing a stable and efficient representation of consistent characteristics that can have a favorable effect on increasing recommendation performance for cold-start consumers.

In our study, we focus on the scheme of how to reduce negative transfer during user/item embedding learning in CDR for cold-start user problems. Usually, side information is added to help obtain positive transfer across domains. However, traditional approaches treat reviews in source and target domain separately, which is more likely to introduce negative transfer because a user might assign the same ratings but represent different preferences in their reviews like Fig. 1. We think that information in dual domains should not be applied separately but taken into account together to extract review preference invariance. In general, we aim to exploit user/item reviews of both the source domain and target domain together and extract latent factors that can properly represent the invariance of review preference. Furthermore,

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we also need to properly design a strategy to obtain optimized user/item embeddings and reduce negative transfer during the mapping process based on review preference invariance.

In this paper, we propose a novel cross-domain framework for cold-start users via fusing and transferring review-based user preference invariance, named Review-based Preference Invariance Transfer Network (RPITN). To represent review preference invariance, we collect a pair of reviews from dual domains and treated them as representations of the review preference of one user/item in two domains. Inspired by multi-view data fusion framework [13], we select a Connective Model Variational Auto-encoder (CM_VAE) to extract latent embedding of multi-view reviews. Since the encoder module in CM_VAE can process dual-domain reviews as a whole input, it explicitly considers the correlation between two reviews. After that, it learns the review embeddings from the source domain and target domain separately. Thus, by concatenating two embeddings together, this latent vector could indicate review preference called review preference invariance (RPI) embedding. To optimize user/item embedding, we modify the traditional review involved user/item embeddings by replacing single domain reviews with RPI embeddings to achieve more consistent embeddings. Moreover, to reduce negative transfer during the mapping process, we propose an RPI involving multi-layers perceptron to further enhance accuracy by adding user preference invariance. Here, we summarize our key contributions as follows:

- We propose a review-based preference invariance transfer network in cross-domain recommendation (RPITN) for cold-start users to reduce negative transfer problems which exist in most traditional CDRs by exploiting review preference invariance.
- We propose a multi-modal fusion scheme to represent review preference invariance and involve it in both the embedding and mapping process, which not only indicates review preference invariance across domains but also optimizes single domain embedding representation.
- Extensive experiments on the Amazon dataset demonstrate that RPITN significantly outperforms the existing state-of-the-art methods.

2. RELATED WORK

From the perspective of selecting consistency factor to build a bridge between source and target domain, existing cross-domain approaches can be classified into three groups including rating pattern-based transfer [10, 11], content-based transfer [5, 6] and embedding-based transfer [7, 8, 14].

Rating pattern-based transfer mainly handles the cross-domain problem by transferring independent knowledge. CLFM [10] proposed to alleviate the sparsity problems by involving both discriminative and similarity information of rating patterns shared across domains. In contrast to *Rating pattern-based transfer*, *Content-based transfer* bridges two domains mainly by sharing the same content or metadata features, e.g., Winoto [5] proposed to make a recommendation based on related items‘ behaviors from different domains. Then, sahebi [6] further improves recommendation accuracy by introducing indicator features based on metadata features. To this end, the most efficient and popular approach to building a bridge across dual domains by user/item embeddings such as He [8] proposed NCF to achieve high non-linearities by replacing traditional matrix factorization-based module with a neural network-based collaborative filtering method. Then, GA-DTCDR [7] is proposed to improve the recommendation accuracy by considering user-item, user-user, and item-item relationships.

However, these works still have drawbacks. They ignore the latent correlation among dual domains from user reviews. Therefore, we hope to utilize users' reviews to find the latent correlation when transferring users/items embedding across domains. In other words, this latent correlation also can be used to improve the performance of the representation of user/item and to reduce negative transfer.

3. THE FRAMEWORK

The overall structure of RPITN is illustrated in Fig. 2, which consists of three modules: 1) Review Preference Invariance Embedding module, which extracts user preference invariance based on item/user reviews. Different from traditional approaches that exploit review data from the source domain and target domain separately, in our method, we take reviews from dual domains as a whole and try to indicate review preference invariance by representing divergence between reviews; 2) User/Item Embedding module, which learns user/item embeddings by employing variational Autoencoder in source and target domain separately. We highlight that we improve the generalization ability of user/item embeddings by adding review preference invariance embeddings obtained from the first module; 3) User Embedding Transfer module, which maps user embeddings from the source domain to the target domain by employing a multi-layer perceptron. To reduce negative transfer, we carefully design a network architecture to involve the user-aspect preference invariance indicator. We describe detailed information about these modules in the following parts.

3.1. Review Preference Invariance Embedding

This module learns review preference based on reviews from user and item aspects respectively. To avoid learning preferences in a single domain, our work treats reviews from source and target domains as a whole by learning a connected review embedding. To this end, we employ a connective mode

Framework.png ..

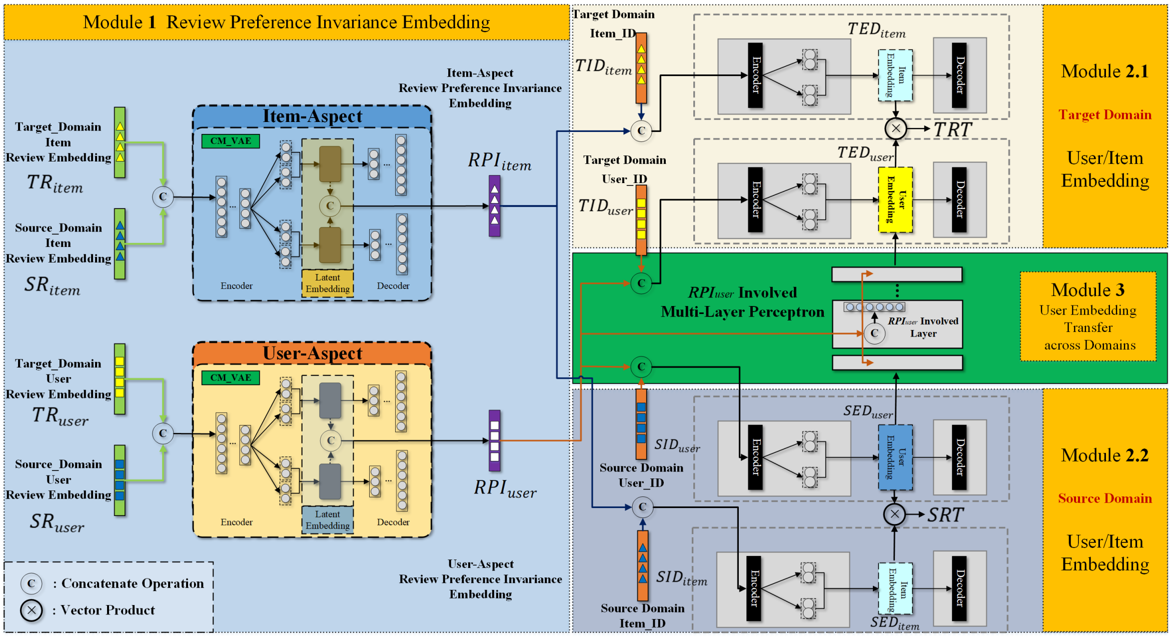

Fig. 2. Framework of the RPITN for cross-domain recommendation.

VAE (CM_VAE) network to learn latent embeddings of reviews from the source domain and target domain simultaneously. Firstly, a pair of reviews of the user or item is encoded by the classic GLove [18] model and then concatenated as one input vector into the CM_VAE. Then, CM_VAE learns to review embeddings of source and target domain respectively. Inspired by [19], reviews from two domains could be considered as describing user/item preference from two views. CM_VAE could learn both consistent and inconsistent representation by applying shared encoders but separate decoders. Although review embeddings of dual domains are represented separately in traditional ways, by concatenating them together, the output embedding could indicate both consistency and divergence of two domains, which is more likely to describe review preference to a better extent than those approaches only consider reviews in a single domain.

Here, we extend two connective mode multi-view variational auto-encoders (CM_VAEs) to learn RPI from the user and item aspect, respectively, as shown in the bottom and the top of Fig. 2, which concatenates two reviews from different domains together as its input. The loss function of this module is as follows, which includes two parts, i.e., user-aspect and item-aspect:

$$\begin{aligned} L_{user\_RPI} = &\sum_{user}(SR_{user} - (SR_{user} \mathbin{\hat{+}} TR_{user}))^2 \\ &+ \sum_{user}(TR_{user} - (TR_{user} \mathbin{\hat{+}} SR_{user}))^2 \\ &+ \sum_{user} L_{KL}^{(RPI_{user})}, \end{aligned} \tag{1}$$

where SR_{user} denotes review in source domain and TR_{user} denotes review in target domain, $(SR_{user} \mathbin{\hat{+}} TR_{user})$ denotes reconstructed SR_{user} like the latent embedding in Fig. 2. $(TR_{user} + SR_{user})$ denotes reconstructed TR_{user}. $L_{KL}^{(RPI_{user})}$ represents the KL divergence loss of this user-aspect module. The L_{Item_RPI} is applied by the same way like Eq. 1.

3.2. User/Item Embedding

This module is used to generate the embeddings of item and user based on the guiding of user transfer embedding illustrated in the next subsections. The input of this module is the features of the user and the item extracted by the rating. The classic auto-encoder model is used to generate the embeddings of user and item. Here, if the item and user have a clear link, their embeddings should have a big similar, vice versa. Based on this assumption, we propose the following loss function:

$$L_{IU} = -\frac{1}{M}\sum_{i=1}^{M}\log(\frac{exp(f_i.f_{user}^T)}{\sum_{j=1}^{M} exp(f_j.f_{user}^T)}), \tag{2}$$

where f_i/f_j represents the item's embedding. f_{user} represents the user's embedding. f^T represents the feature's transpose. M is the number of training samples. We compute the correlation between item and user and maximize it in the training step. The goal is to reduce the difference between item and user if they have a clear link. Meanwhile, to strengthen the representation of item/user. We introduce the user's review information. It means that $f_{user} =$

Table 1. Comparison with baselines and star-of-the-art methods on "Movie & Books" dataset. The best results are in bold.

		RMSE					MAE				
dim	η	PMF[15]	EMCDR[16]	DFM[17]	R-DFM[17]	RPITN	PMF[15]	EMCDR[16]	DFM[17]	R-DFM[17]	RPITN
$\kappa = 10$	0.1	1.30075	1.74911	1.17392	1.14724	**1.10918**	1.02345	1.22424	0.98398	0.98137	**0.93817**
	0.3	1.41632	1.83695	1.14146	1.12639	**1.08737**	1.05842	1.43348	0.97519	0.97115	**0.93602**
	0.6	2.17091	1.85097	1.25995	1.18447	**1.14687**	1.69007	1.36908	1.01574	0.99128	**0.94078**
	0.9	4.27398	4.47282	1.39174	1.27449	**1.20048**	4.13896	3.69859	1.08803	1.04326	**0.97106**
$\kappa = 20$	0.1	1.35810	1.77673	1.21610	1.16313	**1.10808**	1.03631	1.18158	1.00436	0.95790	**0.93559**
	0.3	1.51737	1.65462	1.16166	1.12986	**1.09663**	1.16117	1.24337	0.96752	0.94106	**0.93116**
	0.6	2.26729	1.88589	1.25973	1.19664	**1.16253**	1.82912	1.41387	1.02023	1.00293	**0.95007**
	0.9	4.26979	4.58698	1.42658	1.28538	**1.23596**	4.10066	4.33543	1.20378	1.04222	**1.01781**
$\kappa = 30$	0.1	1.50769	1.67298	1.21564	1.15497	**1.10082**	1.16268	1.05211	1.00361	0.96576	**0.93447**
	0.3	1.77529	1.92915	1.19924	1.11230	**1.09099**	1.39659	1.49877	1.01381	0.96207	**0.91445**
	0.6	2.70412	2.03941	1.26994	1.20350	**1.16422**	2.27566	1.56151	1.07067	1.02230	**0.95352**
	0.9	4.27761	4.73295	1.30066	1.28610	**1.19875**	4.14310	4.34437	1.12047	1.07675	**0.97956**
$\kappa = 50$	0.1	1.66773	1.68250	1.18658	1.16289	**1.10630**	1.32912	1.23140	1.01399	0.98963	**0.93526**
	0.3	1.92449	1.86939	1.13722	1.13123	**1.09584**	1.56077	1.55195	0.97843	0.95711	**0.91636**
	0.6	2.93285	2.17629	1.23182	1.20274	**1.16765**	2.55155	1.69173	1.04570	1.02945	**0.95422**
	0.9	4.27331	5.75454	1.31262	1.25625	**1.19218**	4.13743	4.63301	1.10239	1.04378	**0.98346**

$[f_{user}; RPI_{user}]$.

To improve the correlation between item and user, we propose the embedding losses of source domain L_{SED} and target domain L_{TED} respectively, as illustrated in Fig. 2 module 2.2 and module 2.1. The source domain embedding loss consists of four aspects, i.e., the reconstruct loss of user/item ID, the rate score estimation loss, the L_{IU} and the KL divergence loss of source domain described as following:

$$\begin{aligned} L_{SED} = &\sum_{user}(SID_{user} - (SID_{user} \hat{+} RPI_{user}))^2 \\ &+ \sum_{item}(SID_{item} - (SID_{item} \hat{+} RPI_{item}))^2 \\ &+ \sum_{user,item}(SRT_{user,item} - (SED_{user} \hat{\times} SED_{item}^T)) \\ &+ \sum_{user,item} L_{IU}^{Source} + L_{KL}^{SED}, \end{aligned} \tag{3}$$

where the first two components are user/item reconstruction loss, the third component is rate score estimation loss, and L_{IU}^{Source} denotes L_{IU} of the source domain as in Eq. 2. L_{KL}^{SED} is KL divergence of the source domain. The L_{TED} is applied the same way.

3.3. User Embedding Transfer

The module is the key part of this work. The goal is to fuse the user's information from source and target domains based on the user's review information. Similar to study [16, 17], we utilize multi-layers perceptron (MLP) to transfer user embedding from the auxiliary domain to make a recommendation in the sparse target domain. To reduce the negative transfer during the mapping process, we inject user-aspect review preference invariance into each layer of MLP, named RPI-involved multi-layers perceptron, the loss function is as follows:

$$L_{trans} = \sum_{user}(TED_{user} - (SED_{user} \hat{+} RPI_{user}))^2, \tag{4}$$

To train our model efficiently, we minimize the following loss function:

$$\begin{aligned} L = &\gamma\, L_{user\_RPI} + (1-\gamma)\, L_{item\_RPI} \\ &+ L_{SED} + L_{TED} + L_{trans}, \end{aligned} \tag{5}$$

The classic *Adam* optimizer is used to handle the optimization problem.

4. EXPERIMENTS

4.1. Dataset and Evaluation Metrics

We conduct experiments using the Amazon dataset, which contains 142.8 million reviews, metadata, and links from May 1996 to July 2014 [20]. The dataset's details are listed in Table. 3. The ablation experiments are carried out using the same dataset. We use *RMSE* and *MAE* to show the findings of our experiment.

4.2. Implementation Details

We use grid search to find the best setting of parameters γ as 0.8, and the regularization parameter λ is set as 0.01. The training batchsize is set as 256, and Learning rate is set as 0.0001. The number of layer for each neural network is set 4 follows prior works [16, 17]. The cold ratio η is set from $\{0.1, 0.3, 0.6, 0.9\}$, the dimension κ of user/item embedding is set from $\{10, 20, 30, 50\}$.

4.3. Compared with State-Of-The-Art Methods

Some classic recommendation methods are selected as comparison methods. The related experimental results are shown in Table. 1. From these experimental results, we can find that RPITN achieves superior performance over traditional baselines. Specifically, RPITN has improvement over RC-DFM about 6.79% on *RMSE* and 9.02% on *MAE* when dim κ set

Table 2. The impact of each component of our proposal on "Movie & Books" dataset. The best results are in bold.

		RMSE				**MAE**			
dim	η	RPITN_Basic	RIMFCDR_R	RIMFCDR_RIP	RPITN	RPITN_Basic	RIMFCDR_R	RIMFCDR_RIP	RPITN
$\kappa = 10$	0.1	1.17071	1.12567	1.12529	**1.10918**	0.98260	0.95821	0.95809	**0.93817**
	0.3	1.12869	1.11824	1.09008	**1.08737**	0.97383	0.95696	0.94893	**0.93602**
	0.6	1.17720	1.16454	1.15874	**1.14687**	0.98335	0.97644	0.96591	**0.94078**
	0.9	1.26903	1.24835	1.22016	**1.20048**	1.06732	1.03407	1.02323	**0.97106**
$\kappa = 20$	0.1	1.16845	1.13808	1.12353	**1.10808**	0.99086	0.94258	0.94020	**0.93559**
	0.3	1.15176	1.12878	1.12116	**1.09663**	0.98997	0.93853	0.93410	**0.93116**
	0.6	1.21305	1.17113	1.16648	**1.16253**	1.01228	0.98029	0.97587	**0.95007**
	0.9	1.26090	1.25129	1.24469	**1.23596**	1.04663	1.03674	1.03527	**1.01781**
$\kappa = 30$	0.1	1.16793	1.16546	1.16005	**1.10082**	0.99389	0.98284	0.97500	**0.93447**
	0.3	1.12827	1.11762	1.10950	**1.09099**	0.96633	0.96195	0.95346	**0.91445**
	0.6	1.19202	1.18791	1.17146	**1.16422**	1.01809	0.99664	0.97865	**0.95352**
	0.9	1.28173	1.24558	1.22432	**1.19875**	1.07586	1.04069	1.03614	**0.97956**
$\kappa = 50$	0.1	1.14762	1.14193	1.13369	**1.10630**	0.97573	0.97295	0.96625	**0.93526**
	0.3	1.13412	1.11908	1.10686	**1.09584**	0.97002	0.96533	0.94451	**0.91636**
	0.6	1.20728	1.18494	1.17813	**1.16765**	1.01460	1.00430	0.98770	**0.95422**
	0.9	1.22968	1.21168	1.19527	**1.19218**	1.02456	1.02103	1.01360	**0.98346**

Table 3. Statistics of the datasets

Datasets	*#Overlap_users*	*#Users*	*#Items*	*#Ratings*	#Density
Movie	527	27,822	12,287	779,376	0.23%
Book		2,764	814	59,581	2.64%

as 30 and cold ratio η is 0.6, which confirms the superior of RPITN.

When the cold ratio η is 0.1, the performance of DFM, R-DFM, and RPITN suffers from declination. The reason for this is that these models have a complicated structure, making it simple for them to become overfitted, resulting in poor generalization on the test set. To put it another way, our strategy focuses on the relationship between items and users from various domains. The embedding modules for user and item can efficiently fuse cross-domain information and improve user and item embedding representation. The reasonableness of our method is further demonstrated by the final experimental results.

4.4. Ablation Study

To evaluate the efficacy of each component in our proposal, we conduct the following tests, which are carried out in the same setting as comparative trials to ensure a fair comparison. The corresponding experimental results are shown in Table. 2. Here, *RPITN_Basic* means that we only select the rating as the single input. The novel *Review Preference Invariance Embedding module* and the *User Embedding Transfer* are not added to the framework. *RPITN_R* means that the review information is added to the input. Further, *RPITN_RPI* means that the *Review Preference Invariance Embedding module* is be added but using classical MLP as the transfer module. We have the following observations.

- *RPITN_Basic* outperforms PMF and EMCDR significantly in all cold start scenarios, and as well makes a slight improvement over DFM which also only has rating information as input. We also find that *RPITN_Basic* achieves the worse performance in this ablation study. The reason for this is that it overlooks the review information, which causes the framework to neglect the correlation between cross-domain information, resulting in a large disparity in the final feature space between the user and the item.
- *RPITN_R* adds the review side information to improve the recommendation accuracy based on *RPITN_Basic*. *RPITN_R* outperforms slightly over *R-DFM*, which also takes the review side information into account. It further proves the superiority of this algorithm in cross-modal information representation and fusion.
- *RPITN_RPI* is used to find the correlation between reviews from different domains. This latent correlation is used to guide the final feature learning of item/user for the final recommendation. From Table. 2, *RPITN_RPI* achieves the better results than *RPITN_R*. It means that the correlation of reviews is more useful for the cross-domain recommendation. In the future, we'll focus more on finding users' union information from various domains.

In general, our approach focuses on improvement based on review data and the discovery of correlation data among reviews. The performance of these modules is also demonstrated in the related experiments.

5. CONCLUSION AND FUTURE WORK

In this paper, we proposed the RPITN, a review-based preference invariance transfer network for cold-start users in a cross-domain scenario. This is the first attempt to reduce the impact of negative transfer by using review preference invariance in the source and target domains. Furthermore, we developed a multi-modal fusion approach to enhance recommendation accuracy by improving the embedding representation of the user/item. Experiments show that combining single-domain review with multi-review preference invariance and fusing review preference invariance into the embedding learning can improve the final performance of recommendation, which can demonstrate the efficiency of our approach. In the future, we will emphasize merging multi-modal representations efficiently for better recommendation performance.

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