Deep Transfer Tensor Factorization for Multi-View Learning

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Abstract—This paper studies the data sparsity problem in multi-view learning. To solve data sparsity problem in multiview ratings, we propose a generic architecture of deep transfer tensor factorization (DTTF) by integrating deep learning and cross-domain tensor factorization, where the side information is embedded to provide effective compensation for the tensor sparsity. Then we exhibit instantiation of our architecture by combining stacked denoising autoencoder (SDAE) and CANDE-COMP/ PARAFAC (CP) tensor factorization in both source and target domains, where the side information of both users and items is tightly coupled with the sparse multi-view ratings and the latent factors are learned based on the joint optimization. We tightly couple the multi-view ratings and the side information to improve cross-domain tensor factorization based recommendations. Experimental results on real-world datasets demonstrate that our DTTF schemes outperform state-of-the-art methods on multi-view rating predictions.

Index Terms—multi-view learning, tensor factorization, deep learning, side information

I. INTRODUCTION

With the data explosion in recent years, recommender systems are becoming increasingly attractive. Traditional singleview recommender systems typically operate on twodimensional (2D) user-item ratings. In single-view recommender systems, there are two primary categories of recommendation algorithms: content-based methods and collaborative filtering (CF) based methods, where matrix factorization is effective in learning effective latent factors for users and items [1]. However, they cannot work well for multi-view recommender systems that contain multiple view-specific ratings.

With the emergence of multi-modal or multi-aspect data, multi-view recommendation becomes more and more important. The list of applications ranges from social network analysis to brain data analysis, and from web mining and information retrieval to healthcare analytic [2], such as online e-commerce websites and traveling portals. Figure 1 shows an example in TripAdvisor, where customers can rate hotels by using multiple view such as value, service, atmosphere, food and overall, and meanwhile the information of customers and hotels is also provided.

Prior multi-view techniques can be briefly classified into three categories: heuristic neighborhood-based approaches [3], aggregation-based approaches [4], and model-based approaches [5]. Heuristic neighborhood-based approaches attempt to use various multi-view similarity metrics to collect the neighbors of a targeted user, and then estimate unknown



Fig. 1. Multi-view ratings and the side information from TripAdvisor

ratings based on the known ratings of those neighbors [3], [6]. Aggregation-based approaches aim to build a mapping to aggregate multiple view-specific ratings by assuming that there is a certain relation between the overall rating and other viewspecific ratings [4]. Model-based approaches learn a predictive model by leveraging the observed multi-criteria ratings and then employing the model to execute prediction [5].

Tensor factorization is a milestone of model-based techniques and many tensor factorization based techniques have been developed for multi-view recommender systems [7]– [10]. Nevertheless, prior techniques suffer from the tensor sparsity problem. That being said, when the rating tensor is very sparse in real applications, the performance drops significantly. To overcome this problem in multi-view ratings, we attempt to 1) incorporate the *side information* (or the auxiliary information) into the ratings to exploit prior features [11]–[14] and 2) transfer or learn knowledge from relevant domains for crossdomain recommendations.

In this paper, we propose a generic architecture of deep

transfer tensor factorization (DTTF) by integrating deep learning and cross-domain tensor factorization, where the side information is embedded to provide effective compensation for the tensor sparsity. Then we exhibit instantiation of our architecture by combining stacked denoising autoencoder (SDAE) and CANDECOMP/PARAFAC (CP) tensor factorization in both source and target domains, where the side information of both users and items is tightly coupled with the sparse multi-view ratings and the latent factors are learned based on the joint optimization. The contribution of this paper can be summarized as follows

- To solve data sparsity problem in multi-view ratings, we propose a generic architecture to integrate deep structure and cross-domain tensor factorization;
- We present DTTF where cross-domain CP tensor factorization is combined with four SDAEs in different domains for users and items;
- We tightly couple the multi-view ratings and the side information to improve cross-domain tensor factorization based recommendations.

II. RELATED WORK

Multi-view learning (MTL) is an emerging direction in machine learning which considers learning with multiple views to improve the generalization performance. [15] develop a multi-view label embedding (MVLE) model by exploiting the multi-view correlations. Nonlinear relationships usually exist in real-world datasets, which have not been considered by most existing methods. In order to address these challenges, a novel model which simultaneously performs multi-view clustering task and learns similarity relationships in kernel spaces is proposed [16]. In order to overcome the two limitations [17] propose a multi-task multi-view clustering algorithm in heterogeneous situations based on Locally Linear Embedding (LLE) and Laplacian Eigenmaps (LE) methods (L3EM2VC). Comparing with existing methods that separately cope with each view [18] propose a supervised multi-view feature learning framework to handle diverse views with a unified perception. The proposed approach is compared to different state-of-the-art Radiomics and multi-view solutions, on different public multi-view datasets as well as on Radiomics datasets [19]. [20] present a unified multi-view deep learning framework to capture brain abnormalities associated with seizures based on multi-channel scalp EEG signals. A novel deep multi-view clustering model is proposed by uncovering the hierarchical semantics of the input data in a layer-wise way [21]. The restricted Boltzmann machine (RBM) and extensions are rarely used in the field of multi-view learning [22].

Matrix factorization has been widely used in single-view recommender systems to solve the problem of personal information overload [1]. To mitigate the cold start and data sparsity, it is inevitable for matrix factorization models to exploit additional side information. Singh et al. [23] have integrated the side information into matrix factorization to learn effective latent factors from sparse ratings, and shown an improved performance. Deep learning based matrix factorization is designed to mitigate sparse ratings. A collaborative deep learning based on Bayesian SDAE is proposed in [13] that attempts to incorporate the side information but only learns latent representations for items. Deep collaborative filtering is proposed based on marginalized denoising autoencoder to learn latent representations for both items and users [24]. An alternative mode of incorporating the side information is investigated in [11], which considers 2D ratings and the side information in deep structure. Deep transfer structure shares cross-domain information via hidden connections [25] or learn a common network via domain separation network. Different from these scenarios, we study multi-view recommendations via 3D tensor factorization instead.

Multi-view recommendation has been studied over decades and can be briefly grouped into three categories: heuristic neighborhood-based approaches [26], aggregation-based approaches [4], and model-based approaches [5]. Tensor factorization is a milestone of model-based techniques.

Heuristic neighborhood-based approaches attempt to use various multi-view similarity metrics to collect the user neighbors and then predict based on known ratings of those neighbors. Different techniques are proposed to find the best neighbors, including a multi-dimensional distance metric [3], a preference lattice based on user view preferences [27], and multiview Euclidean distance [6]. Aggregation-based approaches build a mapping to aggregate multiple view-specific ratings for prediction by assuming that there is a certain relation between overall ratings and individual ratings. Lakiotaki et al. [4] proposes a utility additive method to aggregate the marginal user' preferences on the given criteria. Jannach et al. [28] uses a support vector regression to learn relative importance of viewspecific ratings and then combines regression models for users and items to predict unknown ratings. A view chain-based method is presented in [29] to aggregate the multi-dimensional ratings for recommendations by considering the dependence among multiple view ratings. The empirical results of the comparative analysis of their performance are presented [30]. Since outputs of expert systems directly dependent on input signals; interventions to the inputs coherently cause failures on productions of such systems. [31] examine shilling attack strategies against multi-criteria preference collections, how to extend well-known attack scenarios against these systems, and propose an alternative attacking scheme. [32] introduce a tensor factorization method to handle three-dimensional useritem- criterion rating data. [33] propose a utility-based multicriteria recommendation algorithm, in which [33] learn the user expectations by different learningto-rank methods. The resulting compressed vectors constitute latent multi-criteria ratings that [34] use for the recommendation purposes via standard multi-criteria recommendation methods. [35] propose a novel multi-criteria collaborative filtering model based on deep learning. The personalized recommendation technology can establish user files through the user's behavior and other information, and automatically recommend the items that best match the user's preferences, thus effectively reducing the information overload problem. Based on this [36] study the personalized recommendation algorithm based on user preferences in mobile e-commerce.

Model-based approaches aim to learn a predictive model and then employ the model to estimate the ratings. Many techniques have been proposed for recommendations, including a probabilistic mixture algorithm [5], an adaptive neurofuzzy inference and self-organizing map clustering [37], and a multi-linear singular value decomposition [38]. Tensor factorization is a milestone of model-based approaches and various methods have been developed for wide applications [2]. A tensor factorization based ranking is presented in [39] to predict personalized tags for users. A high-order singular value decomposition (HOSVD) method is used in [7] to deal with contextual information for context-aware recommendations, where the limitation is that it primarily works for categorical context variables. Rendle et al. [40] proposes a factorization machine method by extending HOSVD. And Zhang et al. [41] presents tensor singular value decomposition (t-SVD) that can perfectly recover a tensor with low tubal-rank under the certain tensor standard incoherent condition. Based on classic matrix factorization, Bhargava et al. [9] tackles context-aware collaborative recommendation by tensor while Yao et al. [10] presents an application in point-of-interest recommendations. Chen et al. [42] proposes deep tensor factorization to integrate deep representation learning and tensor factorization for multiview recommendations.

In this paper, we integrate tensor factorization and deep structure to incorporate the side information, and link tensor factorization in source domain with that in the target domain.

III. PRELIMINARY AND OVERVIEW

This paper aim to cope with the multi-view recommendation problem, similar to some existing works [3], [43]. Generally, multi-view recommender systems refer to the systems that leverage multiple categories of ratings based on various specific view in addition to the overall user-item ratings to implement recommendation tasks. Figure 2 shows an example of a 3D user-item-view rating tensor R, where each user rates on various view of a given item, and the mark "?" means unobserved ratings. And the rating tensor is extremely sparse with I users, J items, L view in this paper. Each rating r_{iil} in the tensor \mathbf{R} corresponds to user *i* rates on the view *l* of item *j*. Given the sparse third-order user-item-view rating tensor **R**, the side information matrix **M** for users and **N** for items, the goal is to learn user latent factors U, item latent factors V and view latent factors C, and then predict the unobserved ratings in R.

Given 3D *user-item-view* ratings, tensor factorization is to map users, items, and view into a joint latent factor space so that the users' preferences on specific view of items can be formulated as the inner products of corresponding latent factor vectors in the space. The CP is widely used as a tensor factorization paradigm due to its key advantage of linear



Fig. 2. Rating tensor



Fig. 3. The CP tensor factorization

complexity. We adopt the CP to decompose the rating tensor in this work.

Figure 3 shows the CP tensor factorization, where a *user-item-view* rating tensor $\mathbf{R} \in \mathbb{R}^{I*J*L}$ can be decomposed into a sum of rank-one tensors across the whole set of users. So, we have

$$\arg\min_{\mathbf{U},\mathbf{V},\mathbf{C}} I \|\mathbf{R} - \mathbf{U} \otimes \mathbf{V} \otimes \mathbf{C}\|^2$$
(1)

where $\mathbf{U} \in \mathbb{R}^{I \times K}$, $\mathbf{V} \in \mathbb{R}^{J \times K}$ and $\mathbf{C} \in \mathbb{R}^{L \times K}$ represent the latent factor matrix for users, items and view, respectively; K is the dimension of latent factor space; and the operator \otimes detnotes the outer product of latent factor vectors in the corresponding matrix.

In this paper, we attempt to propose a novel architecture to combine deep structure and cross-domain CP tensor factorization, where deep structure deals with either only the side information or both the ratings and the side information, and tensor factorization deals with the 3D *user-item-view* ratings.

Four deep structures are designed for users and items in both source and target domains, where the side information of users (or items) is involved as an input, and the transformation of ratings are either taken as one more input or not included (dashed line). The effective latent representation is learned by jointly optimizing deep network and latent factors from tensor factorization. The tightly coupled side information provides a



Fig. 4. The structure of the proposed DTTF

compensation for tensor factorization, so the proposed DTTF could mitigate the tensor sparsity problem.

For convenient description, define by \mathcal{D}_s the source domain and \mathcal{D}_t the target domain. And the domain indices are denoted as $d \in \{s, t\}$. In a recommendation setting, the user-item-view matrix $\mathbf{R}_d \in \mathbb{R}^{I_d \times J_d \times L}$ can be decomposed as a sum of rank1 tensors across all users. So, we have

$$\arg\min_{\mathbf{U}_{d},\mathbf{V}_{d},\mathbf{C}}\left\|\mathbf{R}_{d}-\mathbf{U}_{d}\otimes\mathbf{V}_{d}\otimes\mathbf{C}\right\|^{2},$$
(2)

where $\mathbf{U}_d \in \mathbb{R}^{I_d \times K}$, $\mathbf{V}_d \in \mathbb{R}^{J_d \times K}$ and $\mathbf{C} \in \mathbb{R}^{L \times K}$ represent the latent factor matrix for users, items and view, respectively; K is the dimension of latent factor space; and \otimes denotes the outer product of latent factor vectors in the corresponding matrix. The source domain \mathcal{D}_s is connected with the target domain \mathcal{D}_t via common latent factors \mathbf{C} .

IV. DEEP TRANSFER TENSOR FACTORIZATION

In this section, DTTF instantiation is presented in detail based on the generic architecture.

A. DTTF Scheme

The specific DTTF scheme is composed of several components: a SDAE for users, a SDAE for items and tensor factorization in both domains, as shown in Figure 4. In DTTF, the SDAE only takes the side information as the sole input, similar to [44], where the multi-view ratings are not considered. Considering the SDAE for users in Figure 4 , the representation $h_{d,l}^{(u)}$ at each hidden layer and the output at layer $L^{(u)}$ can be obtained as

$$\mathbf{h}_{d,l}^{(u)} = g \left(\mathbf{W}_{d,l}^{(u)} \mathbf{h}_{d,l-1}^{(u)} + \mathbf{b}_{d,l}^{(u)} \right) \hat{\mathbf{p}}_{d,i}^{(u)} = f \left(\mathbf{W}_{d,L^{(u)}}^{(u)} \mathbf{h}_{d,L^{(u)}}^{(u)} + \mathbf{b}_{d,L^{(u)}}^{(u)} \right),$$
(3)

where $l \in \{1, 2, \dots, L_d^{(u)} - 1\}; g(\cdot)$ and $f(\cdot)$ are activation functions for the hidden and output layers. The corrupted side information $\tilde{\mathbf{p}}_{d,i}^{(u)}$ is the input to the first layer, $\mathbf{h}_{d,r}^{(u_i)}$ denotes deep representations from the middle layer and $\hat{\mathbf{p}}_{d,i}^{(u)}$ denotes the output of the users' SDAE. Similar results can be obtained for the items' SDAE by replacing (u) with (v).

As observed in Figure 4, the users' SDAE takes as input the side information of users to learn the latent representation $\mathbf{h}_{d,r}^{(u_i)}$ that is used to compensate latent factor vectors $\mathbf{u}_{d,i}$ in tensor factorization. And the items' SDAE takes as input the side information of items to learn latent representation $\mathbf{h}_{d,r}^{(v_j)}$ that is used to compensate the latent factor vectors $\mathbf{v}_{d,j}$ in tensor factorization.

1) Loss Function: DTTF learns users' latent factors, items' latent factors and view latent factors through the following objective function

$$\min_{Q} \mathcal{J} = \mathcal{L}_t + \mathcal{L}_r + \mathcal{L}_a + \lambda f_{reg} \tag{4}$$

where the overall loss function \mathcal{J} consists of four components: the loss of tensor factorization \mathcal{L}_t , the reconstruction cost of the side information \mathcal{L}_r , the approximation error between deep representation and latent factors \mathcal{L}_a , and the regularization term f_{reg} that prevent overfitting.

The first term \mathcal{L}_t denotes the loss of factorization on a sparse rating tensor

$$\min_{\boldsymbol{\theta}_t} \mathcal{L}_t = \sum_{d \in (s,t)} \left\| \mathbf{I}_{\mathbf{d}} \odot (\mathbf{R}_{\mathbf{d}} - \mathbf{U}_{\mathbf{d}} \otimes \mathbf{V}_{\mathbf{d}} \otimes \mathbf{C}) \right\|^2, \quad (5)$$

where $\theta_t = {\mathbf{U}_d, \mathbf{V}_d, \mathbf{C}}$; the binary tensor \mathbf{I}_d is an indicator of sparsity, in which each element indicates whether the corresponding rating is observed (= 1) or not (= 0); \otimes means the outer product of latent factor vectors in the corresponding matrix; and \odot is the element-wise production.

Secondly, the reconstruction cost of the side information for both users and items can be expressed as

$$\min_{\theta_r} \mathcal{L}_r = \sum_d \left[\alpha_d \sum_i \left(\mathbf{p}_{d,i}^{(u)} - \hat{\mathbf{p}}_{d,i}^{(u)} \right)^2 + \beta_d \sum_j \left(\mathbf{p}_{d,j}^{(v)} - \hat{\mathbf{p}}_{d,j}^{(v)} \right)^2 \right]$$
(6)

where $\theta_r = \{\mathbf{W}_d^u, \mathbf{b}_d^u, \mathbf{W}_d^v, \mathbf{b}_d^v\}, \alpha_d \text{ and } \beta_d \text{ are penalty parameters.}$

Furthermore, the approximation error between deep representation and latent factor vectors for both users and items can be expressed as

$$\min_{\theta_a} \mathcal{L}_a = \sum_d \left[\rho_d \sum_i \left(\mathbf{u}_{d,i} - \mathbf{h}_{d,r}^{(u_i)} \right)^2 + \gamma_d \sum_j \left(\mathbf{v}_{d,j} - \mathbf{h}_{d,r}^{(v_j)} \right)^2 \right]$$
(7)

where $\boldsymbol{\theta}_a = \left\{ \mathbf{U}_d, \mathbf{V}_d, \mathbf{W}_d^{(u)}, \mathbf{b}_d^{(u)}, \mathbf{W}_d^{(v)}, \mathbf{b}_d^{(v)} \right\}, \rho_d \text{ and } \gamma_d$ are penalty parameters.

The last term denotes the regularization term f_{reg} as

$$f_{reg} = \sum_{d} \left(\sum_{i} \|\mathbf{u}_{d,i}\|^{2} + \sum_{j} \|\mathbf{v}_{d,j}\|^{2} \right) + \sum_{d} \left(\left\| \mathbf{W}_{d}^{(u)} \right\|^{2} + \left\| \mathbf{W}_{d}^{(v)} \right\|^{2} + \left\| \mathbf{b}_{d}^{(u)} \right\|^{2} + \left\| \mathbf{b}_{d}^{(v)} \right\|^{2} \right),$$
(8)

and the overall $\Theta = \theta_t \cup \theta_r \cup \theta_a$ in (4).

2) *Optimization:* To solve this problem, the alternative optimization algorithm is considered by utilizing the following three-step procedure.

Step I: Given all weights \mathbf{W}_d and biases \mathbf{b}_d , the gradients of \mathcal{J} in (4) with respect to $\mathbf{u}_{d,i}, \mathbf{v}_{d,j}$, can be obtained as

$$\frac{\partial \mathcal{J}}{\partial \mathbf{u}_{d,i}} = -\sum_{j} \sum_{l} \mathcal{I}_{d,ijl} \left(r_{d,ijl} - \mathbf{u}_{d,i} \mathbf{v}_{d,j} \mathbf{c}_{l} \right) \left(\mathbf{v}_{d,j} \mathbf{c}_{l} \right)
+ \rho_{d} \left(\mathbf{u}_{d,i} - \mathbf{h}_{d,r}^{(u_{i})} \right) + \lambda \mathbf{u}_{d,i}
\frac{\partial \mathcal{J}}{\partial \mathbf{v}_{d,j}} = -\sum_{i} \sum_{l} \mathcal{I}_{d,ijl} \left(r_{d,ijl} - \mathbf{u}_{d,i} \mathbf{v}_{d,j} \mathbf{c}_{l} \right) \left(\mathbf{u}_{d,i} \mathbf{c}_{l} \right)
+ \gamma_{d} \left(\mathbf{v}_{d,j} - \mathbf{h}_{d,r}^{(v_{j})} \right) + \lambda \mathbf{v}_{d,j}$$
(9)

Step II: Fixed the users' latent factors \mathbf{U}_d and the items' latent factors $\mathbf{V}_d, d \in \{s, t\}$, the common latent factors $\mathbf{C}(\mathbf{c}_l)$ can be updated by

$$\frac{\partial \mathcal{J}}{\partial \mathbf{c}_{l}} = -\sum_{d} \sum_{i} \sum_{j} \mathcal{I}_{d,ijl} \left(r_{d,ijl} - \mathbf{u}_{d,i} \mathbf{v}_{d,j} \mathbf{c}_{l} \right) \left(\mathbf{u}_{d,i} \mathbf{v}_{d,j} \right) \\
+ \lambda \mathbf{c}_{l},$$
(10)

where the binary $\mathcal{I}_{d,ijl}$ indicates whether the corresponding rating is observed (=1) or not (=0).

Step III: Fixed the latent factors \mathbf{U}, \mathbf{V} and \mathbf{C} , all weights \mathbf{W} and biases \mathbf{b} of both SDAEs can be learned by backpropagation with stochastic gradient decent (SGD) method

$$\frac{\partial \mathcal{J}}{\partial \mathbf{W}_{d}^{(u)}} = -\rho_{d} \sum_{i} \left(\mathbf{u}_{d,i} - \mathbf{h}_{d,r}^{(u_{i})} \right) \frac{\partial \mathbf{h}_{d,r}^{(u_{i})}}{\partial \mathbf{W}_{d}^{(u)}}
+ \alpha_{d} \sum_{i} \left(\mathbf{p}_{d,i}^{(u)} - \hat{\mathbf{p}}_{d,i}^{(u)} \right) \frac{\partial \hat{\mathbf{p}}_{d,i}^{(u)}}{\partial \mathbf{W}_{d}^{(u)}} + \lambda \mathbf{W}_{d}^{(u)}
\frac{\partial \mathcal{J}}{\partial \mathbf{W}_{d}^{(v)}} = -\gamma_{d} \sum_{j} \left(\mathbf{v}_{d,j} - \mathbf{h}_{d,r}^{(v_{j})} \right) \frac{\partial \mathbf{h}_{d,r}^{(v_{j})}}{\partial \mathbf{W}_{d}^{(v)}}
+ \beta_{d} \sum_{j} \left(\mathbf{p}_{d,j}^{(v)} - \hat{\mathbf{p}}_{d,j}^{(v)} \right) \frac{\partial \hat{\mathbf{p}}_{d,j}^{(v)}}{\partial \mathbf{W}_{d}^{(v)}} + \lambda \mathbf{W}_{d}^{(v)}$$
(11)

and $\frac{\partial \mathcal{J}}{\partial \mathbf{b}_d^{(w)}}$ and $\frac{\partial \mathcal{J}}{\partial \mathbf{b}_d^{(v)}}$ can be easily obtained by replacing \mathbf{W}_d , with \mathbf{b}_d in (11). Iterate three steps above until convergence.

V. EXPERIMENTS

A. Experiment Setup

To evaluate various algorithms, we use four public datasets, two from TripAdvisor (TA) and two from RateBeer (RB). All these datasets are commonly used for evaluating the performance of recommender systems [28], [45]. They are different datasets without any overlap and independent of each other.

- *TripAdvisor-12M* (*TA-12M*): This dataset contains 181,411 records given by 1,750 users based on 4 view including *value*, *location*, *service*, and *overall* for 3,546 hotels. Each user gave at least 2 ratings. The sparsity level of the dataset is around 99.26%.
- *TripAdvisor-20M (TA-20M)*: This dataset contains 63,945 records given by 2,246 users based on 4 view including *value, location, service,* and *overall* for 3,033 hotels. The sparsity level of the dataset is around 99.76%.
- *RateBeer-30M* (*RB-30M*): This dataset contains 1,326,451 records given by 2,167 users for 3,109 beers based on 5 view including *appearance*, *aroma*, *palate*, *taste* and *overall*. The sparsity level of the dataset is around 96.20%.
- *RateBeer-100M (RB-100M)*: This dataset contains 2,294,766 records given by 1,771 users for 2,627 beers based on 5 view including *appearance*, *aroma*, *palate*, *taste* and *overall*. The sparsity level of the dataset is around 90.13%.

	TA 1014	(-) T	A 2014 (4)	TA 2014 (-) TA 1214 (4)			TA 2014 (-) TA 10014 (4)			TA 100M (-) = TA 20M (+)		
Algorithm	IA12M (s) vs $IA20M$ (t)			IA20M (s) vs $IA12M$ (t)			IA30M (s) vs $IA100M$ (t)			IA100M (s) vs IA30M (t)		
	60%	80%	95%	60%	80%	95%	60%	80%	95%	60%	80%	95%
AFBM	1.219	1.167	1.096	1.178	1.053	1.045	0.787	0.784	0.716	0.950	0.937	0.934
CMF	1.184	1.140	1.130	1.274	1.058	1.038	0.713	0.693	0.653	0.855	0.832	0.810
DCF	1.164	1.094	1.036	1.163	1.069	1.031	0.668	0.643	0.628	0.794	0.772	0.743
HCF	1.128	1.073	1.030	1.089	1.066	1.016	0.653	0.639	0.617	0.761	0.734	0.727
t-SVD	1.181	1.075	1.039	1.151	1.040	0.961	0.620	0.598	0.579	0.671	0.660	0.644
DTF	1.082	1.049	1.029	1.022	1.016	0.869	0.610	0.597	0.578	0.668	0.642	0.632
DTTF	1.037	0.963	0.868	0.930	0.899	0.851	0.604	0.587	0.567	0.660	0.628	0.619

 TABLE I

 Performance comparison of various methods in terms of RMSE.



Fig. 5. Ablation Test Results of DTTF on four datasets.

For TA datasets, the user and item additional matrices are generated similarly as RB datasets. And the length of the resulting binary vector is 106 for users and 134 for items.

In our experiments, five-fold cross validation was applied to each dataset, and we use the root mean squared error (RMSE), the Hit Ratio (HR) and Normalized Discounted Cumulative Gain (NDCG) [46] as the evaluation metric.

B. Baseline

In order to evaluate the performance, we consider the following baselines in our experiments:

- *AFBM*: Aggregation function based method [26] employs a matrix factorization to deal with the observed user-view ratings.
- *CMF*: Collective matrix factorization [23] is a model which simultaneously decomposes the ratings and the side information.HCF: HCF is a hybrid collaborative filtering model [11] which unifies aSDAE model with matrix factorization.
- *DCF*: Deep collaborative filtering [44] is a recommendation model which combines probabilistic matrix factorization with marginalized denoising stacked autoencoders to

achieve recommendation.

- *t-SVD*: Tensor Singular Value Decomposition [41] is a model to generalize MF approaches to higher dimensional multi-view recommendations.
- *DTF*: Deep tensor factorization [42] is a model to integrate deep representation learning and tensor factorization for multi-view recommendations.

C. Comparison Experimental Results

We evaluate our proposed DTTF on four datasets in comparison to state-of-the-art recommendation baselines.

Table I illustrates the performance of all methods in terms of the average RMSE, where the lowest RMSE in each dataset is highlighted in boldface and the second lowest RMSE is highlighted in italic boldface. The proposed DTTF clearly outperform all baselines in terms of RMSE, in which DTTF achieves the *best* performance for all cases.

Specifically, it is observed that HCF, DCF and CMF outperform AFBM in general cases, and DTTF schemes outperform t-SVD, which demonstrates the effectiveness of incorporating the side information in either 2D rating matrix or 3D rating tensor. That DTTF, HCF and DCF outperform CMF indicates that deep structure can acquire better features of the side information. HCF, DCF, CMF and AFBM only consider the correlation between arbitrary two of three dimensions so DTTF and t-SVD outperform these methods. That DTTF, DTF outperform DCF and HCF indicates that tensor factorization methods effectively learn the intrinsic interactions among three dimensions, which are a good fit for multi-view recommender systems. And DTTF outperform DTF which only consider single-domain dataset, validating the effectiveness of crossdomain learning in multi-view recommendations.

D. Ablation Analysis

The comparison results in terms of per evaluation metrics indicate that the proposed DTTF clearly outperform the wellestablished baselines.

To justify the efficiency of our architecture design, a careful ablation study is conducted. Specifically, we remove the knowledge transfer from either DTTF and name it as DTTFwoTrans; we remove the deep structure of side information from DTTF and name it as DTTFwoSideinfo; we remove the tensor factorization component from DTTF and name it as DTTFwoTF.

The test results in terms of RMSE are shown in Figure 5 and a few observations are worth being highlighted as follows: 1) The best performance on each dataset is obtained by the complete DTTF, indicating that each of components contributes to the effectiveness and robustness of the whole model; 2) The RMSE of DTTFwoSideinfo in TA datasets is significantly higher than others, indicating that the incorporation of side information is crucial for the sparsity problem in multi-view recommender systems. 3) The RMSE of DTTFwoTF in RB datasets is significantly higher than others. One reason is that the density of the TA-12M dataset (0.73%) and TA20M dataset (0.23%) is much lower than RB-30M (3.80%) and RB-100M dataset (9.87%). Another possible reason is that RB datasets have a stronger personalization, in which multiview ratings are more valuable than side information for recommendations.

VI. CONCLUSION

DTTF is proposed for cross-domain multi-view recommendation by combining tensor factorization and deep structure in both source and target domains. Private latent factors link with deep structures while view latent factor is taken a bridge between domains, which are learned by jointly optimizing tensor factorization and SDAEs. Experimental results on the real-world datasets show that our proposed approach achieves a superiority compared with state-of-the-art works.

REFERENCES

- [1] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," *Computer*, vol. 8, pp. 30–37, 2009.
- [2] E. E. Papalexakis, C. Faloutsos, and N. D. Sidiropoulos, "Tensors for data mining and data fusion: Models, applications, and scalable algorithms," ACM Transactions on Intelligent Systems and Technology (TIST), vol. 8, no. 2, pp. 1–44, 2016.
- [3] K. Lakiotaki, N. F. Matsatsinis, and A. Tsoukias, "Multicriteria user modeling in recommender systems," *IEEE Intelligent Systems*, vol. 26, no. 2, pp. 64–76, 2011.
- [4] K. Lakiotaki, S. Tsafarakis, and N. Matsatsinis, "Uta-rec: a recommender system based on multiple criteria analysis," in *Proceedings of* the 2008 ACM conference on Recommender systems, 2008, pp. 219–226.
- [5] N. Sahoo, R. Krishnan, G. Duncan, and J. Callan, "Research note—the halo effect in multicomponent ratings and its implications for recommender systems: The case of yahoo! movies," *Information Systems Research*, vol. 23, no. 1, pp. 231–246, 2011.
- [6] A. Mikeli, D. Apostolou, and D. Despotis, "A multi-criteria recommendation method for interval scaled ratings," in 2013 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT), vol. 3. IEEE, 2013, pp. 9–12.
- [7] A. Karatzoglou, X. Amatriain, L. Baltrunas, and N. Oliver, "Multiverse recommendation: n-dimensional tensor factorization for context-aware collaborative filtering," in *Proceedings of the fourth ACM conference on Recommender systems*, 2010, p. 79.
- [8] Z. Chen and D. Wang, "Multi-initialization meta-learning with domain adaptation," in *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2021, pp. 1390–1394.
- [9] P. Bhargava, T. Phan, J. Zhou, and J. Lee, "Who, what, when, and where: Multi-dimensional collaborative recommendations using tensor factorization on sparse user-generated data," in *Proceedings of the 24th international conference on world wide web*, 2015, pp. 130–140.
- [10] L. Yao, Q. Z. Sheng, Y. Qin, X. Wang, A. Shemshadi, and Q. He, "Context-aware point-of-interest recommendation using tensor factorization with social regularization," in *Proceedings of the 38th international* ACM SIGIR conference on research and development in information retrieval, 2015, pp. 1007–1010.
- [11] X. Dong, L. Yu, Z. Wu, Y. Sun, L. Yuan, and F. Zhang, "A hybrid collaborative filtering model with deep structure for recommender systems," in *Proceedings of the AAAI Conference on artificial intelligence*, 2017, pp. 1309–1315.
- [12] Z. Chen, T. Xiao, and K. Kuang, "Ba-gnn: On learning bias-aware graph neural network," in 2022 IEEE 38th International Conference on Data Engineering (ICDE). IEEE, 2022, pp. 3012–3024.
- [13] H. Wang, N. Wang, and D.-Y. Yeung, "Collaborative deep learning for recommender systems," in *Proceedings of the 21th ACM SIGKDD international conference on knowledge discovery and data mining*, 2015, pp. 1235–1244.
- [14] T. Xiao, Z. Chen, D. Wang, and S. Wang, "Learning how to propagate messages in graph neural networks," in *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, 2021, pp. 1894–1903.

- [15] P. Zhu, Q. Hu, Q. Hu, C. Zhang, and Z. Feng, "Multi-view label embedding," *Pattern recognition*, vol. 84, pp. 126–135, 2018.
- [16] S. Huang, Z. Kang, I. W. Tsang, and Z. Xu, "Auto-weighted multi-view clustering via kernelized graph learning," *Pattern Recognition*, vol. 88, pp. 174–184, 2019.
- [17] Y. Zhang, Y. Yang, T. Li, and H. Fujita, "A multitask multiview clustering algorithm in heterogeneous situations based on lle and le," *Knowledge-Based Systems*, vol. 163, pp. 776–786, 2019.
- [18] Z. Chen, J. Ge, H. Zhan, S. Huang, and D. Wang, "Pareto self-supervised training for few-shot learning," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2021, pp. 13663– 13672.
- [19] H. Cao, S. Bernard, R. Sabourin, and L. Heutte, "Random forest dissimilarity based multi-view learning for radiomics application," *Pattern Recognition*, vol. 88, pp. 185–197, 2019.
- [20] Y. Yuan, G. Xun, K. Jia, and A. Zhang, "A multi-view deep learning framework for eeg seizure detection," *IEEE journal of biomedical and health informatics*, vol. 23, no. 1, pp. 83–94, 2018.
- [21] S. Huang, Z. Kang, and Z. Xu, "Auto-weighted multi-view clustering via deep matrix decomposition," *Pattern Recognition*, vol. 97, p. 107015, 2020.
- [22] N. Zhang, S. Ding, T. Sun, H. Liao, L. Wang, and Z. Shi, "Multi-view rbm with posterior consistency and domain adaptation," *Information Sciences*, vol. 516, pp. 142–157, 2020.
- [23] A. P. Singh and G. J. Gordon, "Relational learning via collective matrix factorization," in *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*, 2008, pp. 650– 658.
- [24] S. Gai, F. Zhao, Y. Kang, Z. Chen, D. Wang, and A. Tang, "Deep transfer collaborative filtering for recommender systems," in *PRICAI* 2019: Trends in Artificial Intelligence: 16th Pacific Rim International Conference on Artificial Intelligence, Cuvu, Yanuca Island, Fiji, August 26-30, 2019, Proceedings, Part III 16. Springer, 2019, pp. 515–528.
- [25] G. Hu, Y. Zhang, and Q. Yang, "Mtnet: a neural approach for crossdomain recommendation with unstructured text," *KDD Deep Learning Day*, pp. 1–10, 2018.
- [26] G. Adomavicius and Y. Kwon, "New recommendation techniques for multicriteria rating systems," *IEEE Intelligent Systems*, vol. 22, no. 3, pp. 48–55, 2007.
- [27] Z. Chen, D. Wang, and S. Yin, "Improving cold-start recommendation via multi-prior meta-learning," in Advances in Information Retrieval: 43rd European Conference on IR Research, ECIR 2021, Virtual Event, March 28–April 1, 2021, Proceedings, Part II 43. Springer, 2021, pp. 249–256.
- [28] D. Jannach, Z. Karakaya, and F. Gedikli, "Accuracy improvements for multi-criteria recommender systems," in *Proceedings of the 13th ACM* conference on electronic commerce, 2012, pp. 674–689.
- [29] Y. Zheng, "Criteria chains: a novel multi-criteria recommendation approach," in *Proceedings of the 22nd International Conference on Intelligent User Interfaces*, 2017, pp. 29–33.
- [30] M. Hassan and M. Hamada, "Genetic algorithm approaches for improving prediction accuracy of multi-criteria recommender systems," *International Journal of Computational Intelligence Systems*, vol. 11, no. 1, pp. 146–162, 2018.
- [31] A. M. Turk and A. Bilge, "Robustness analysis of multi-criteria collaborative filtering algorithms against shilling attacks," *Expert Systems with Applications*, vol. 115, pp. 386–402, 2019.
- [32] S. Wang, J. Yang, Z. Chen, H. Yuan, J. Geng, and Z. Hai, "Global and local tensor factorization for multi-criteria recommender system," *Patterns*, vol. 1, no. 2, p. 100023, 2020.
- [33] Y. Zheng, S. Shekhar, A. A. Jose, and S. K. Rai, "Integrating contextawareness and multi-criteria decision making in educational learning," in *Proceedings of the 34th ACM/SIGAPP Symposium on Applied Computing*, 2019, pp. 2453–2460.
- [34] P. Li and A. Tuzhilin, "Latent multi-criteria ratings for recommendations," in *Proceedings of the 13th ACM Conference on Recommender Systems*, 2019, pp. 428–431.
- [35] N. Nassar, A. Jafar, and Y. Rahhal, "A novel deep multi-criteria collaborative filtering model for recommendation system," *Knowledge-Based Systems*, vol. 187, p. 104811, 2020.
- [36] Z. Su, J. Yan, H. Ling, and H. Chen, "Research on personalized recommendation algorithm based on ontological user interest model," *Journal of Computational Information Systems*, vol. 8, no. 1, pp. 169– 181, 2012.

- [37] M. Nilashi, O. bin Ibrahim, and N. Ithnin, "Hybrid recommendation approaches for multi-criteria collaborative filtering," *Expert Systems with Applications*, vol. 41, no. 8, pp. 3879–3900, 2014.
- [38] Q. Li, C. Wang, and G. Geng, "Improving personalized services in mobile commerce by a novel multicriteria rating approach," in *Proceedings* of the 17th international conference on World Wide Web, 2008, pp. 1235–1236.
- [39] S. Rendle, L. Balby Marinho, A. Nanopoulos, and L. Schmidt-Thieme, "Learning optimal ranking with tensor factorization for tag recommendation," in *Proceedings of the 15th ACM SIGKDD international conference* on Knowledge discovery and data mining, 2009, pp. 727–736.
- [40] S. Rendle, Z. Gantner, C. Freudenthaler, and L. Schmidt-Thieme, "Fast context-aware recommendations with factorization machines," in *Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval*, 2011, pp. 635–644.
- [41] Z. Zhang and S. Aeron, "Exact tensor completion using t-svd," *IEEE Transactions on Signal Processing*, vol. 65, no. 6, pp. 1511–1526, 2017.
- [42] Z. Chen, S. Gai, and D. Wang, "Deep tensor factorization for multicriteria recommender systems," in 2019 IEEE International Conference on Big Data (Big Data). IEEE, 2019, pp. 1046–1051.
- [43] D. Jannach, M. Zanker, and M. Fuchs, "Leveraging multi-criteria customer feedback for satisfaction analysis and improved recommendations," *Information Technology & Tourism*, vol. 14, no. 2, pp. 119–149, 2014.
- [44] S. Li, J. Kawale, and Y. Fu, "Deep collaborative filtering via marginalized denoising auto-encoder," in *Proceedings of the 24th ACM international on conference on information and knowledge management*, 2015, pp. 811–820.
- [45] J. McAuley, J. Leskovec, and D. Jurafsky, "Learning attitudes and attributes from multi-aspect reviews," in 2012 IEEE 12th International Conference on Data Mining. IEEE, 2012, pp. 1020–1025.
- [46] X. He, T. Chen, M.-Y. Kan, and X. Chen, "Trirank: Review-aware explainable recommendation by modeling aspects," in *Proceedings of the* 24th ACM international on conference on information and knowledge management, 2015, pp. 1661–1670.