

CoNet: Collaborative Cross Networks for Cross-Domain Recommendation

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Abstract

The cross-domain recommendation technique is an effective way of alleviating the data sparsity in recommender systems by leveraging the knowledge from relevant domains. Transfer learning is a class of algorithms underlying these techniques. In this paper, we propose a novel transfer learning approach for cross-domain recommendation by using neural networks as the base model. We assume that hidden layers in two base networks are connected by cross mappings, leading to the collaborative cross networks (CoNet). CoNet enables dual knowledge transfer across domains by introducing cross connections from one base network to another and vice versa. CoNet is achieved in multi-layer feedforward networks by adding dual connections and joint loss functions, which can be trained efficiently by back-propagation. The proposed model is evaluated on two real-world datasets and it outperforms baseline models by relative improvements of 3.56% in MRR and 8.94% in NDCG, respectively.

1 Introduction

Collaborative filtering (CF) approaches, which model the preference of users on items based on their past interactions such as product ratings, are the corner stone for recommender systems. Matrix factorization (MF) is a class of CF methods which learn user latent factors and item latent factors by factorizing their interaction matrix [Salakhutdinov and Mnih, 2007; Koren *et al.*, 2009]. Neural collaborative filtering is another class of CF methods which use neural networks to learn the complex user-item interaction function [Dziugaite and Roy, 2015; Cheng *et al.*, 2016; He *et al.*, 2017]. Neural networks have the ability to learn highly nonlinear function, which is suitable to learn the complex user-item interaction. Both traditional matrix factorization and neural collaborative filtering, however, suffer from the cold-start and data sparsity issues.

One effective solution is to transfer the knowledge from relevant domains and the cross-domain recommendation techniques address such problems [Berkovsky *et al.*, 2007; Li *et al.*, 2009; Pan *et al.*, 2011; Cantador *et al.*, 2015]. In real

life, a user typically participates several systems to acquire different information services. For example, the user installs applications in an app store and reads news from a website. It brings us an opportunity to improve the recommendation performance in the target service (or all services) by learning across domains. Following the above example, we can represent the app installation feedback using a binary matrix where the entries indicate whether a user has installed an app. Similarly, we use another binary matrix to indicate whether a user has read a news article. Typically these two matrices are highly sparse, and it is beneficial to learn them simultaneously. This idea is sharpened into the collective matrix factorization (CMF) [Singh and Gordon, 2008] approach which jointly factorizes these two matrices by sharing the user latent factors. It combines CF on a target domain and another CF on an auxiliary domain, and enables knowledge transfer learning [Pan *et al.*, 2008; Zhang and Yang, 2017]. CMF, however, is a shallow model and has the difficulty in learning the complex user-item interaction function [Dziugaite and Roy, 2015; He *et al.*, 2017]. Moreover, its knowledge sharing is only limited in the level of user latent factors.

Motivated by benefitting from both knowledge transfer learning and learning interaction function, we propose a novel transfer learning approach for cross-domain recommendation using neural networks as the base model. Though neural CF approaches are proposed for single domain recommendation [He *et al.*, 2017; Yang *et al.*, 2017a], there are few related works to study knowledge transfer learning for cross-domain recommendation using neural networks. On the other hand, neural networks have been used as the base model in natural language processing [Collobert and Weston, 2008; Yang *et al.*, 2017b] and computer vision [Yosinski *et al.*, 2014; Misra *et al.*, 2016; Doersch and Zisserman, 2017]. We explore how to use a neural network as the base model for each domain and enable the knowledge transfer on the entire network across domains. Then a few questions and challenges are raised: 1) What to transfer/share between these individual networks for each domain? 2) How to transfer/share during the learning of these individual networks for each domain? and 3) How is the performance compared with single domain learning and shallow models?

This paper aims at answering these questions. The usual transfer learning approach is to train a base network and then copy its first several layers to the corresponding first layers of

a target network with fine-tuning or parameter frozen [Yosinski *et al.*, 2014]. This way of transferring has possibly two weak points. Firstly, the shared-layer assumption is strong in practice as we find that it does not work well on real-world cross-domain datasets. Secondly, the knowledge transfer happens in one direction, i.e., only from source to target. Instead, we assume that hidden layers in two base networks are connected by dual mappings, which do not require them to be identical. We enable dual knowledge transfer across domains by introducing cross connections from one base network to another and vice versa, letting them benefit from each other. These ideas are sharpened into the proposed collaborative cross networks (CoNet). CoNet is achieved in simple multi-layer feedforward networks by using dual shortcut connections and joint loss functions, which can be trained efficiently by back-propagation.

This paper is organized as follows. We firstly introduce the preliminaries in Section 2.1 and 2.2. In Section 2.3, we introduce the cross connections to enable knowledge transfer between source and target networks. We propose a novel transfer learning approach, collaborative cross networks (CoNet) in Section 2.4, for cross-domain recommendation. In Section 3, we experimentally show the benefits of both knowledge transfer learning and neural approaches for improving the recommendation performance in terms of ranking metrics. We conclude the paper in Section 4.

2 Collaborative Cross Networks

We first give the notation and describe the problem setting (section 2.1). We also review a multi-layer feedforward neural network as the base model (section 2.2). Then, we propose the CoNet in Section 2.4 by following the introduction of the cross connections unit in Section 2.3. Finally, we describe the learning process from implicit feedback and the optimization of the joint loss in Section 2.5.

2.1 Notation

We are given two domains, a source domain \mathcal{S} (e.g., news recommendation) and a target domain \mathcal{T} (e.g., app recommendation). As a running example, we let app recommendation be the target domain and news recommendation be the source domain. The set of users in both domains are shared, denoted by \mathcal{U} (of size m). Denote the set of items in \mathcal{S} and \mathcal{T} by \mathcal{I}_S and \mathcal{I}_T (of size n_S and n_T), respectively. Each domain corresponds to collaborative filtering for implicit feedback [Pan *et al.*, 2008; Hu *et al.*, 2008]. For the target domain, let a binary matrix $\mathbf{R}_T \in \mathbb{R}^{m \times n_T}$ describe user-app installing interactions, where an entry $r_{ui} \in \{0, 1\}$ is 1 (observed entries) if user u has an interaction with app i and 0 (unobserved) otherwise. Similarly, for the source domain, let another binary matrix $\mathbf{R}_S \in \mathbb{R}^{m \times n_S}$ describe user-news reading interactions, where the entry $r_{uj} \in \{0, 1\}$ is 1 if user u has an interaction with news j and 0 otherwise. Usually the interaction matrix is very sparse since a user only consumed a very small subset of all items.

Similarly for the task of item recommendation, each user is only interested in identifying top-N items. The items are ranked by their predicted scores $\hat{r}_{ui} = f(u, i | \Theta)$, where f is

the interaction function and Θ are model parameters. Neural networks are used to parameterize function f and learn it from interactions:

$$f(\mathbf{x}_{ui} | \mathbf{P}, \mathbf{Q}, \theta_f) = \phi_o(\phi_L(\dots(\phi_1(\mathbf{x}_{ui}))\dots)), \quad (1)$$

where the input $\mathbf{x}_{ui} = [\mathbf{P}^T \mathbf{x}_u, \mathbf{Q}^T \mathbf{x}_i]$ is merged from projections of user and item and the projections are based on their one-hot encodings $\mathbf{x}_u \in \{0, 1\}^m$, $\mathbf{x}_i \in \{0, 1\}^n$ and embedding matrices $\mathbf{P} \in \mathbb{R}^{m \times d}$, $\mathbf{Q} \in \mathbb{R}^{n \times d}$. The output and hidden layers are computed by ϕ_o and $\{\phi_l\}$ in a multilayer feedforward neural network (FFNN).

In our transfer learning approach for cross-domain recommendation, each domain is modelled by a neural network and these networks are jointly learned to improve the performance via mutual knowledge transfer. We review the base network in the following subsection before introducing our model.

2.2 Base Network

We adopt a FFNN as the base network to parameterize the interaction function (see Eq.(1)). The base network is similar to the Deep model in [Cheng *et al.*, 2016] and the MLP model in [He *et al.*, 2017]. The base network, as shown in Figure 1 (the gray part or the blue part), consists of four modules with the information flow from the input (u, i) to the output \hat{r}_{ui} : 1) **Input**: $(u, i) \rightarrow \mathbf{x}_u, \mathbf{x}_i$. This module encodes user-item interaction indices. We adopt the one-hot encoding. It takes user u and item i , and maps them into one-hot encodings $\mathbf{x}_u \in \{0, 1\}^m$ and $\mathbf{x}_i \in \{0, 1\}^n$ where only the element corresponding to that index is 1 and all others are 0. 2) **Embedding**: $\mathbf{x}_u, \mathbf{x}_i \rightarrow \mathbf{x}_{ui}$. This module embeds one-hot encodings into continuous representations and then merges them as $\mathbf{x}_{ui} = [\mathbf{P}^T \mathbf{x}_u, \mathbf{Q}^T \mathbf{x}_i]$ to be the input of following hidden layers. 3) **Hidden layers**: $\mathbf{x}_{ui} \rightsquigarrow \mathbf{z}_{ui}$. This module takes the continuous representations from the embedding module and then transforms, through multi-hop say L , to a final latent representation $\mathbf{z}_{ui} = \phi_L(\dots(\phi_1(\mathbf{x}_{ui}))\dots)$. This module consists of multiple hidden layers. 4) **Output**: $\mathbf{z}_{ui} \rightarrow \hat{r}_{ui}$. This module predicts the score \hat{r}_{ui} for the given user-item pair based on the representation \mathbf{z}_{ui} from the last layer of multi-hop module. Since we focus on one-class collaborative filtering, the output is the probability that the input pair is a positive interaction. This can be achieved by a classification layer $\hat{r}_{ui} = \phi_o(\mathbf{z}_{ui}) = 1/(1 + \exp(-\mathbf{h}^T \mathbf{z}_{ui}))$, where \mathbf{h} is the parameter.

2.3 Cross Connections Unit

In this section, we present a novel soft-sharing approach for transferring knowledge for cross-domain recommendation. It relaxes the hard-sharing assumption [Yosinski *et al.*, 2014] and is motivated by the cross-stitch networks [Misra *et al.*, 2016].

Cross-stitch Networks. Given two activation maps a_A and a_B from the l -th layer for two tasks A and B , cross-stitch convolutional networks [Misra *et al.*, 2016] learn linear combinations \tilde{a}_A, \tilde{a}_B of both the input activations and feed these combinations as input to the next layers' filters:

$$\tilde{a}_A^{ij} = \alpha_S a_A^{ij} + \alpha_D a_B^{ij}, \text{ and } \tilde{a}_B^{ij} = \alpha_S a_B^{ij} + \alpha_D a_A^{ij},$$

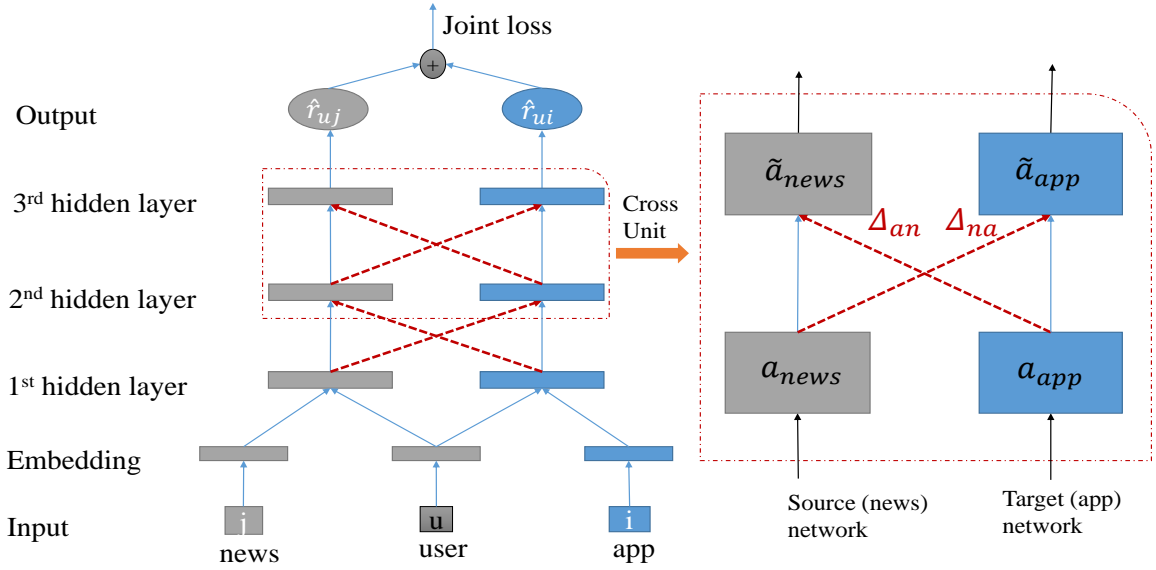


Figure 1: The proposed collaborative cross networks (CoNet) model (a version of three hidden layers and two cross units). We adopt a multilayer feedforward neural network as the base model (grey or blue part). The red dotted lines indicate the cross connections which enable the dual knowledge transfer across domains (a cross unit illustrated in the dotted rectangle box on the right part).

where parameter α_D controls information shared from the other network, α_S controls information from the task-specific network, and (i, j) is the location in the activation map.

We now introduce the cross connections unit to enable dual knowledge transfer, as shown in Figure 1 (the dotted rectangle box). Similarly to the cross-stitch network, the target network receives information from the source network and vice versa. In detail, let \mathbf{a}_{app} be the representations of the l -th hidden layer and $\tilde{\mathbf{a}}_{app}$ be the $l + 1$ -th in the app network, respectively. Similarly, they are \mathbf{a}_{news} and $\tilde{\mathbf{a}}_{news}$ in the news network. Since two domains are relevant by shared users, we assume that $\tilde{\mathbf{a}}_{app}$ and $\tilde{\mathbf{a}}_{news}$ are also relevant such that they are connected by cross mappings:

$$\tilde{\mathbf{a}}_{app} = \mathbf{a}_{app} + \Delta_{na}, \text{ and } \tilde{\mathbf{a}}_{news} = \mathbf{a}_{news} + \Delta_{an}, \quad (2)$$

where Δ_{na} carries the information from news network to app network and Δ_{an} from app to news, respectively (embodied in Eq.(4)). Thus, the app network only needs to learn representations \mathbf{a}_{app} by reference to the residual mappings Δ_{na} from the news network. Similarly, the news network only needs to learn representations \mathbf{a}_{news} by reference to the residual mappings Δ_{an} from the app network. That is, the knowledge transfer happens in two directions, from source to target and from target to source. We enable dual knowledge transfer across domains and let them benefit from each other.

Though our model is a bit similar to cross-stitch convolutional networks in the sense of soft-sharing, they are different in several ways. Firstly, cross-stitch networks cannot process the case that the dimensions of contiguous layers are different. In other words, it assumes that the activations in contiguous layers are in the *same vector space* which is not the case in typical multi-layer feedforward neural networks. Secondly, it assumes that the representations from other networks

are *equally important* with weights being all the same scalar α_D . Some features, however, are more useful and predictive and it should be learned attentively from data. Thirdly, it assumes that the representations from other networks are *all useful* since it transfers activations from every location in a dense way. Instead, our model can be extended to learn the sparse structure on the task relationship matrices which are defined in Eq. (8), with the help of the existing sparsity-induced regularization. As we will see in the experiments (see Table 2), the sparse structure is helpful for better performance.

2.4 The CoNet Model

In this section, we propose the collaborative cross network model by adding cross connection units (described in the above section 2.3) and joint loss to multi-layer feedforward neural networks.

We decompose the model parameters into two parts, task-shared and task-specific: $\Theta_{app} = \{\mathbf{P}\} \cup \{\mathbf{Q}_{app}, \theta_{f_{app}}\}$ and $\Theta_{news} = \{\mathbf{P}\} \cup \{\mathbf{Q}_{news}, \theta_{f_{news}}\}$, where \mathbf{P} is the user embedding matrix and \mathbf{Q} are the item embedding matrices with the subscript specifying the domain. We stack the cross connections units on the top of the shared user embeddings as shown in Figure 1. Denote by \mathbf{W}^l the weight matrix connecting from the l -th to the $l + 1$ -th layer (we ignore biases for simplicity), and by \mathbf{H}^l the linear projection underlying the corresponding cross connections. Then two base networks are coupled by cross connections:

$$\mathbf{a}_{app}^{l+1} = \sigma(\mathbf{W}_{app}^l \mathbf{a}_{app}^l + \mathbf{H}^l \mathbf{a}_{news}^l), \quad (3a)$$

$$\mathbf{a}_{news}^{l+1} = \sigma(\mathbf{W}_{news}^l \mathbf{a}_{news}^l + \mathbf{H}^l \mathbf{a}_{app}^l), \quad (3b)$$

where the function $\sigma(\cdot)$ is the widely used rectified activation (ReLU) [Nair and Hinton, 2010]. We can see that \mathbf{a}_{app}^{l+1} receives two information flows: one is from the transform gate controlled by \mathbf{W}_{app}^l and one is from the transfer gate controlled by \mathbf{H}^l (similarly for \mathbf{a}_{news}^{l+1}). Comparing with Eq. (2), the cross mappings are achieved by the transfer gate:

$$\Delta_{na} \triangleq \mathbf{H}^l \mathbf{a}_{news}^l, \text{ and } \Delta_{an} \triangleq \mathbf{H}^l \mathbf{a}_{app}^l. \quad (4)$$

We call \mathbf{H}^l the task relationship matrix since it learns to control how much sharing is needed. Dimensions of two contiguous hidden layers in a typical feedforward network are different, and so \mathbf{H}^l can help achieve this.¹

2.5 Model Learning

Due to the nature of the implicit feedback and the task of item recommendation, the squared loss $(\hat{r}_{ui} - r_{ui})^2$ may be not suitable since it is usually for rating prediction. Instead, we adopt the cross-entropy loss:

$$\mathcal{L}_0 = - \sum_{(u,i) \in \mathbf{R}^+ \cup \mathbf{R}^-} r_{ui} \log \hat{r}_{ui} + (1 - r_{ui}) \log (1 - \hat{r}_{ui}), \quad (5)$$

where \mathbf{R}^+ and \mathbf{R}^- are the observed interaction matrix and randomly sampled negative pairs, respectively. This objective function has probabilistic interpretation and is the negative logarithm likelihood of the following likelihood function:

$$L(\Theta | \mathbf{R}^+ \cup \mathbf{R}^-) = \prod_{(u,i) \in \mathbf{R}^+} \hat{r}_{ui} \prod_{(u,i) \in \mathbf{R}^-} (1 - \hat{r}_{ui}), \quad (6)$$

where parameters are $\Theta = \{\mathbf{P}, \mathbf{Q}, \theta_f\}$. This objective function can be optimized by stochastic gradient descent (SGD) and its variants like adaptive moment method (Adam) [Kingma and Ba, 2015]. Typical deep learning library like TensorFlow² provides automatic differentiation.

Now we define the joint loss function, leading to the proposed CoNet model which can be trained efficiently by back-propagation.

Instantiating the *base loss* (\mathcal{L}_0) described in Eq. (5) by the *loss of app* (\mathcal{L}_{app}) and *loss of news* (\mathcal{L}_{news}) recommendation, the objective function for the CoNet model is their weighted sum:

$$\mathcal{L}(\Theta) = \alpha \mathcal{L}_{app}(\Theta_{app}) + (1 - \alpha) \mathcal{L}_{news}(\Theta_{news}), \quad (7)$$

where model parameters $\Theta = \Theta_{app} \cup \Theta_{news} \cup \{\mathbf{H}^l\}$, and the nonnegative hyperparameter α is the weight of target domain (there is no knowledge transfer if it is one). Each training iteration loops each domain once and joint training is done by back-propagation using mini-batch stochastic optimization.

Sparse Variant. As we can see, the task relationship matrices $\{\mathbf{H}^l\}$ are crucial to the proposed CoNet model. We further enforce these matrices to have some structure. We may expect that the representations coming from other domains are sparse and selective. This corresponds to enforce a sparse

¹To reduce model parameters, we use the same linear transformation \mathbf{H}^l for \mathbf{H}_{app}^l and \mathbf{H}_{news}^l . We omit the case in which cross connections skip layers including that the source and target networks have different architectures.

²<https://www.tensorflow.org>

Table 1: Datasets and Statistics.

Dataset	#user	Target Domain			Source Domain		
		#item	#interact	density	#item	#interact	density
Mobile	23,111	14,348	1,164,394	0.351%	29,921	617,146	0.089%
Amazon	80,763	93,799	1,323,101	0.017%	35,896	963,373	0.033%

prior on the structure³ and can be achieved by penalizing the task relationship matrix $\{\mathbf{H}^l\}$ via some regularization. It may help the individual network to learn intrinsic representations for itself and other tasks. In other words, $\{\mathbf{H}^l\}$ adaptively controls when to transfer. We adopt the widely used sparsity-induced regularization—Lasso and its variant. In detail, denote by $r \times p$ the size of matrix \mathbf{H}^l (usually $r = p/2$). That is, \mathbf{H}^l linearly transforms representations $\mathbf{a}_{news}^l \in \mathbb{R}^p$ in the news network and the result (residual mappings) is as part of the input to the next layer $\mathbf{a}_{app}^{l+1} \in \mathbb{R}^r$ in the app network (see Eq.(3) and Eq.(4)). Denote by $\mathbf{h}_j \in \mathbb{R}^r$ and h_{ij} the j -th column and the (i, j) entries of \mathbf{H}^l , respectively. To induce overall sparsity, we impose the ℓ_1 -norm penalty on the entries $\{h_{ij}\}$ of \mathbf{H}^l :

$$\Omega(\mathbf{H}^l)_{lasso} = \lambda_{lasso} \sum_i \sum_j |h_{ij}|. \quad (8)$$

This corresponds to the lasso regularization [Tibshirani, 1996]. We call this sparse version as the CoNet-lasso model.

3 Experiment

We conduct thorough experiments to evaluate the proposed models. We show their superior ranking accuracy over the state-of-the-art recommendation algorithms in a wide range baselines and demonstrate the effectiveness of the lasso versions which enforce prior structure to select representations (section 3.2). Furthermore, we conduct investigation on sensitivity to hyperparameters (section 3.3). We analyze optimization performance (section 3.4) to help understand the proposed models.

3.1 Experimental Setup

We begin the experiments by introducing the datasets, evaluation protocol, comparing baselines, and implementation details.

Dataset We evaluate on two real-world cross-domain datasets. The first dataset, **Mobile**⁴, is provided by a large internet company. The information contains logs of user reading news, the history of app installation, and some meta-data such as news publisher and user gender collected in one month in the US. The dataset we used contains 1,164,394 user-app installations and 617,146 user-news reading records. There are 23,111 shared users, 14,348 apps, and 29,921 news articles. We aim to improve the app recommendation by transferring knowledge from relevant news reading domain. The second dataset is a public **Amazon** dataset⁵, which has been widely used to evaluate the performance of collaborative filtering approaches. We use the two largest categories,

³Low-rank ($\mathbf{H} = \mathbf{U}^T \mathbf{V}$) structure is left for future work.

⁴An anonymous version can be released later.

⁵<http://snap.stanford.edu/data/web-Amazon.html>

Table 2: Comparison Results of Different Methods on Two Datasets.

Dataset	Metric	BPRMF	CMF	FM	MLP	CoNet	CoNet-lasso	ours vs. best
Mobile	HR	.6175	.7879	.7812	.8405	.8480	.8547	1.69%
	NDCG	.4891	.5740	.5875	.6615	.6754	.6802	2.83%
	MRR	.4489	.5067	.5265	.6210	.6373	.6431	3.56%
Amazon	HR	.4723	.3712	.3685	.5014	.5167	.5338	6.45%
	NDCG	.3016	.2378	.2307	.3143	.3261	.3424	8.94%
	MRR	.2971	.1966	.1884	.3113	.3163	.3351	7.65%

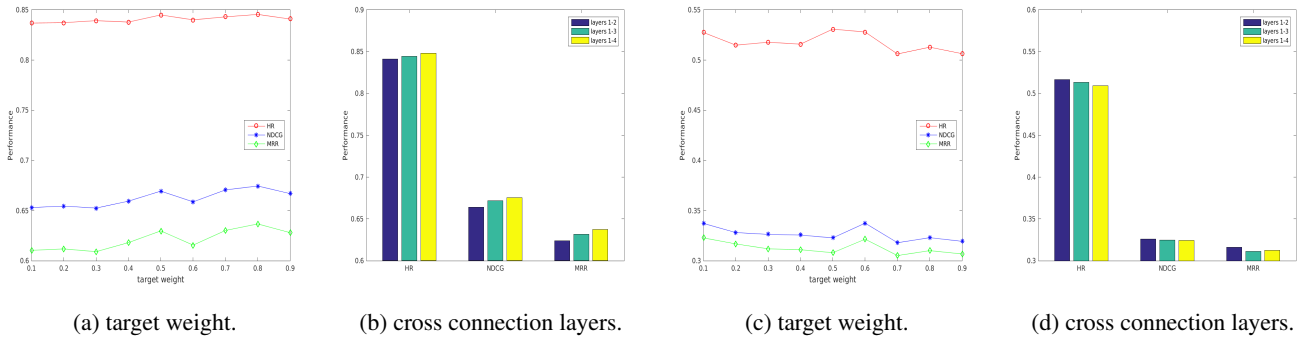


Figure 2: Analysis of the target weight and layers of performing cross connections on two datasets. (a)(b): Mobile. (c)(d): Amazon.

Books and Movies & TV, as the cross-domain. We convert the ratings of 4-5 as positive samples. The dataset we used contains 1,323,101 user-book ratings and 963,373 user-movie ratings. There are 80,763 shared users, 93,799 books, and 35,896 movies. We aim to improve the book recommendation by transferring knowledge from relevant movie watching domain. The statistics are summarized in Table 1.

Evaluation Protocol For item recommendation task, the leave-one-out (LOO) evaluation is widely used and we follow the protocol in [He *et al.*, 2017]. That is, we reserve one interaction as the test item for each user. We follow the common strategy which randomly samples 99 (negative) items that are not interacted by the user and then evaluate how well the recommender can rank the test item against these negative ones. Since we aim at top-N item recommendation, the typical evaluation metrics are hit ratio (HR), normalized discounted cumulative gain (NDCG), and mean reciprocal rank (MRR), where the ranked list is cut off at $N=10$. HR intuitively measures whether the reserved test item is present on the top-N list, while NDCG and MRR also account for the hit position. A higher value indicates better performance.

Baseline We compare our proposed models with different kinds of baselines:

- BPRMF: Bayesian personalized ranking [Rendle *et al.*, 2009] is a state-of-the-art traditional CF approach which matches the degree of users and items using simple dot product. It is a shallow model and learns on a single domain.
- MLP: Multilayer perceptron [He *et al.*, 2017] is a state-of-the-art neural CF approach which learns user-item interaction function using neural networks. It is a deep model and learns on a single domain.

- FM: Factorization machine [Rendle, 2012] is a state-of-the-art cross-domain approach which applies factorization on the merged domains (aligning by the shared users). It is a shallow model and learns on the merged domains.
- CMF: Collective matrix factorization [Singh and Gordon, 2008] is a state-of-the-art multi-task learning approach which jointly factorizes the matrices of individual domains. It is a shallow model and jointly learns on two domains.

Implementation For BPRMF, we use LightFM’s implementation⁶ which is a popular CF library. For FM, we use the official libFM implementation⁷. For MLP, we use the code released by its authors⁸. For CMF, we use a Python version reference to the original Matlab code⁹. Our methods are implemented using TensorFlow. Parameters are randomly initialized from Gaussian $\mathcal{N}(0, 0.01^2)$. The optimizer is Adam with initial learning rate 0.001. The size of mini batch is 128. The ratio of negative sampling is 1. As for the design of network structure, we adopt a tower pattern, halving the layer size for each successive higher layer. Specifically, the configuration of hidden layers in the base network is $[64 \rightarrow 32 \rightarrow 16 \rightarrow 8]$. This is also the network configuration of the MLP model. Actually, the basic structure of the base model is the same with MLP. Based on the general setting, we determine hyper-parameters by randomly sampling one interaction per user as the validation set.

⁶<https://github.com/lyst/lightfm>

⁷<http://www.libfm.org>

⁸https://github.com/hexiangnan/neural_collaborative_filtering

⁹<http://www.cs.cmu.edu/~ajit/cmf/>

3.2 Comparing Different Approaches

In this section, we report the recommendation performance of different methods and discuss the results. Table 2 shows the results of different methods. We can see that our proposed neural models are better than both the base network (MLP) trained independently¹⁰ and the shallow models (CMF and FM) learned using two domains information.

On Mobile, our best model achieves 3.56% improvements in terms of MRR comparing with the best baseline MLP, (it is also the base model), showing the benefits of knowledge transfer. Our model improves 22.13% and 26.90% in terms of MRR comparing with FM and CMF, showing the effectiveness of neural approaches. Together, our neural models consistently give better performance than other existing methods. Within our models (CoNet-lasso vs CoNet), enforcing sparse structure on the task relationship matrices are useful.¹¹

On Amazon, our best model achieves 8.94% improvements in terms of NDCG comparing with the best baseline MLP, showing the benefits of knowledge transfer. Compared to the BPRMF, the inferior performance of CMF and FM shows the difficulty in transferring knowledge between Amazon Books and Amazon Movies & TV, but our models also achieve good results. Within our models, enforcing sparse structure on the task relationship matrices are also useful.

3.3 Sensitivity Analysis

We analyze the sensitivity to the task weights, the layers of performing cross connections, the lasso penalty of sparsity. Some results are only shown on Mobile due to space limit and we give the corresponding conclusions on Amazon.

Figure 2a and Figure 2c show the performance varying with the target weight α in Eq.(7) (target domain: app recommendation). The performance achieves good results at 0.8 on Mobile, and it is 0.6 on Amazon. Figure 2b and Figure 2d show the performance varying with the layers of performing residual/cross connections. We find that performing all layers contributes to the performance improvements on Mobile, and it is performing 1-2 layers on Amazon. When adding sparse regularization, performing 1-3 layers achieves good results on Amazon (not shown).

Figure 3a shows the performance varying with the lasso penalty of sparsity enforcing on the task relationship matrices. For CoNet-lasso, the performance achieves good results at 0.1, and it is 1.0 on Amazon (not shown).

3.4 Optimization Performance

Figure 3b shows the training loss (averaged over all training examples) varying with each optimization iteration on Cheeta. Results on Amazon show the same trend and thus we ignore them due to space limitation. First, we can see that with more iterations, the training losses of CoNet and CoNet-lasso models gradually decrease and the recommendation performance is improved. The most effective updates are occurred

¹⁰Pre-training an MLP on source domain and then transferring use embeddings to target domain as warm-up did not achieve much improvement. It shows the necessity of dual knowledge transfer.

¹¹Dropout technique and ℓ_2 norm penalty did not achieve these improvements. It shows the necessity of selecting representatons.

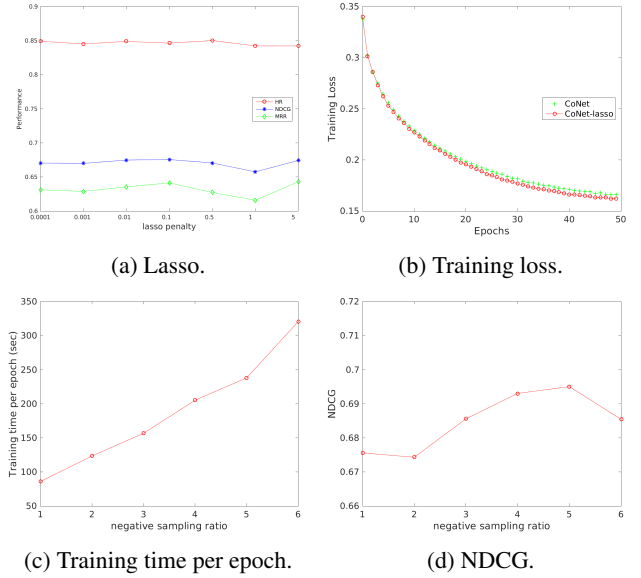


Figure 3: (a): Impact of lasso penalty; (b): Training loss; (c)(d): optimization time and performance w.r.t. negative sampling ratio on Mobile.

in the first 15 iterations, and performance gradually improves until 30 iterations. With more iterations beyond 40, CoNet slowly degrades recommendation performance while CoNet-lasso is more stable.

To illustrate the impact of negative sampling for optimizing our methods, we show the performance of the CoNet-lasso model w.r.t. different negative sampling ratios in Figure 3c and Figure 3d on Mobile (NegativeSamplingRatio = #NegativeSamples / #PositiveSamples). Results on Amazon show the same trend and thus we ignore them due to space limitation. It can be clearly seen that one negative sample per positive sample is usually insufficient to achieve optimal performance, and sampling more negative instances is beneficial. The optimal sampling ratio is around 3 to 5. Though we can get better performance by setting ratio as four, we fix negative sampling ratio as one being the same with baselines, for fairness. The training time (an Nvidia TITAN Xp GPU) grows approximately linear with the negative sampling ratio.

4 Conclusions

We proposed a novel approach to perform knowledge transfer learning for cross-domain recommendation via collaborative cross networks (CoNet). By cross connection units, CoNet enables dual knowledge transfer across domains where the information flows from source domain to the target domain and vice versa. Thus, the sparse target user-item interaction matrix can be reconstructed with the knowledge guidance from the source domain. We further improve the generalization by enforcing a sparse prior structure to select representations from other domain. Experiments show the effectiveness of our models. The breakdown of the performance improvement by cold users and others will be worth investigating.

References

- [Berkovsky *et al.*, 2007] Shlomo Berkovsky, Tsvi Kuflik, and Francesco Ricci. Cross-domain mediation in collaborative filtering. In *International Conference on User Modeling*, pages 355–359. Springer, 2007.
- [Cantador *et al.*, 2015] Iván Cantador, Ignacio Fernández-Tobías, Shlomo Berkovsky, and Paolo Cremonesi. Cross-domain recommender systems. In *Recommender Systems Handbook*, pages 919–959. Springer, 2015.
- [Cheng *et al.*, 2016] Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishikesh Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, et al. Wide & deep learning for recommender systems. In *Proceedings of the 1st Workshop on Deep Learning for Recommender Systems*, pages 7–10. ACM, 2016.
- [Collobert and Weston, 2008] Ronan Collobert and Jason Weston. A unified architecture for natural language processing: Deep neural networks with multitask learning. In *Proceedings of the 25th international conference on Machine learning*, pages 160–167. ACM, 2008.
- [Doersch and Zisserman, 2017] Carl Doersch and Andrew Zisserman. Multi-task self-supervised visual learning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 2051–2060, 2017.
- [Dziugaite and Roy, 2015] Gintare Karolina Dziugaite and Daniel M Roy. Neural network matrix factorization. *arXiv preprint arXiv:1511.06443*, 2015.
- [He *et al.*, 2017] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. Neural collaborative filtering. In *Proceedings of the 26th International Conference on World Wide Web*, pages 173–182. International World Wide Web Conferences Steering Committee, 2017.
- [Hu *et al.*, 2008] Yifan Hu, Yehuda Koren, and Chris Volinsky. Collaborative filtering for implicit feedback datasets. In *Data Mining, 2008. ICDM'08. Eighth IEEE International Conference on*, pages 263–272. Ieee, 2008.
- [Kingma and Ba, 2015] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *International Conference on Learning Representations*, 2015.
- [Koren *et al.*, 2009] Yehuda Koren, Robert Bell, and Chris Volinsky. Matrix factorization techniques for recommender systems. *Computer*, 42(8), 2009.
- [Li *et al.*, 2009] Bin Li, Qiang Yang, and Xiangyang Xue. Can movies and books collaborate?: cross-domain collaborative filtering for sparsity reduction. In *Proceedings of the 21st international joint conference on Artificial intelligence*, pages 2052–2057. Morgan Kaufmann Publishers Inc., 2009.
- [Misra *et al.*, 2016] Ishan Misra, Abhinav Shrivastava, Abhinav Gupta, and Martial Hebert. Cross-stitch networks for multi-task learning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3994–4003, 2016.
- [Nair and Hinton, 2010] Vinod Nair and Geoffrey E Hinton. Rectified linear units improve restricted boltzmann machines. In *Proceedings of the 27th international conference on machine learning (ICML-10)*, pages 807–814, 2010.
- [Pan *et al.*, 2008] Rong Pan, Yunhong Zhou, Bin Cao, Nathan N Liu, Rajan Lukose, Martin Scholz, and Qiang Yang. One-class collaborative filtering. In *Data Mining, 2008. ICDM'08. Eighth IEEE International Conference on*, pages 502–511. IEEE, 2008.
- [Pan *et al.*, 2011] Weike Pan, Nathan N Liu, Evan W Xiang, and Qiang Yang. Transfer learning to predict missing ratings via heterogeneous user feedbacks. In *Proceedings of the Twenty-Second international joint conference on Artificial Intelligence-Volume Volume Three*, pages 2318–2323. AAAI Press, 2011.
- [Rendle *et al.*, 2009] Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. Bpr: Bayesian personalized ranking from implicit feedback. In *Proceedings of the twenty-fifth conference on uncertainty in artificial intelligence*, pages 452–461. AUAI Press, 2009.
- [Rendle, 2012] Steffen Rendle. Factorization machines with libfm. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 3(3):57, 2012.
- [Salakhutdinov and Mnih, 2007] Ruslan Salakhutdinov and Andriy Mnih. Probabilistic matrix factorization. In *NIPS*, 2007.
- [Singh and Gordon, 2008] Ajit P Singh and Geoffrey J Gordon. Relational learning via collective matrix factorization. In *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 650–658. ACM, 2008.
- [Tibshirani, 1996] Robert Tibshirani. Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, pages 267–288, 1996.
- [Yang *et al.*, 2017a] Carl Yang, Lanxiao Bai, Chao Zhang, Quan Yuan, and Jiawei Han. Bridging collaborative filtering and semi-supervised learning: A neural approach for poi recommendation. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1245–1254. ACM, 2017.
- [Yang *et al.*, 2017b] Zhilin Yang, Ruslan Salakhutdinov, and William W Cohen. Transfer learning for sequence tagging with hierarchical recurrent networks. *International Conference on Learning Representations*, 2017.
- [Yosinski *et al.*, 2014] Jason Yosinski, Jeff Clune, Yoshua Bengio, and Hod Lipson. How transferable are features in deep neural networks? In *Advances in neural information processing systems*, pages 3320–3328, 2014.
- [Zhang and Yang, 2017] Yu Zhang and Qiang Yang. A survey on multi-task learning. *arXiv preprint arXiv:1707.08114*, 2017.