Decentralized Multi-Target Cross-Domain Recommendation for Multi-Organization Collaborations

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ABSTRACT

Recommender Systems (RSs) are operated locally by different organizations in many realistic scenarios. If various organizations can fully share their data and perform computation in a centralized manner, they may significantly improve the accuracy of recommendations. However, collaborations among multiple organizations in enhancing the performance of recommendations are primarily limited due to the difficulty of sharing data and models. To address this challenge, we propose Decentralized Multi-Target Cross-Domain Recommendation (DMTCDR) with Multi-Target Assisted Learning (MTAL) and Assisted AutoEncoder (AAE). Our method can help multiple organizations collaboratively improve their recommendation performance in a decentralized manner without sharing sensitive assets. Consequently, it allows decentralized organizations to collaborate and form a community of shared interest. We conduct extensive experiments to demonstrate that the new method can significantly outperform locally trained RSs and mitigate the cold start problem.

1 INTRODUCTION

Recommender Systems (RSs) have become one of the most popular techniques in web applications in recent years. They can effectively extract helpful information for relevant users, e.g., recommending restaurants, videos, and e-commerce products [1, 2]. However, a long-standing challenge in RSs is the data sparsity problem, that the users usually interact with very few items. To address this issue, researchers have developed the direction of Cross-Domain Recommendation (CDR) to leverage ratings from a source domain where users may have relatively more information to improve the performance of a target domain [3, 4]. A few recent works study Multi-Target Cross-Domain Recommendation (MTCDR), which aims to improve the performance of all domains simultaneously [5, 6]. However, most existing works on this topic require that the data and models of different domains are shared, and the computation must be performed in a centralized manner [5–10]. Since most RSs are built upon users’ sensitive data, e.g., user profiles and usage history, and the model and task information are also proprietary to organizational learners [11], collaborations among various organizations are often restricted by ethical, regulatory, and commercial constraints [4, 12]. Therefore, we propose Decentralized Multi-Target Cross-Domain Recommendation (DMTCDR), which aims to simultaneously improve the performance of multiple domains in a decentralized manner. As illustrated in Figure 1, our solution provides the keystone for establishing collaborations among multiple organizations to leverage isolated data to improve recommendation performance.

Our method helps different organizations improve their recommendation performance simultaneously without sharing local data, models, and objective functions. In particular, each organization will calculate a set of ‘residuals’ and broadcast these to other organizations. These residuals approximate the fastest direction of reducing the training loss in hindsight. Subsequently, other organizations will fit the residuals using their local data, models, and objective functions and broadcast the fitted values back to each other. Each learner will then assign weights to its peers to approximate the fastest direction of learning. The prediction will be aggregated from the fitted values. The above procedure is repeated until all organizations accomplish a sufficient level of learning. Moreover, our approach can handle explicit or implicit feedback [13], user- or item-based alignment [4], and with or without side information [14]. We perform extensive experiments to demonstrate that our method significantly outperforms locally trained RSs and mitigates the cold start problem. Therefore, our method can integrate decentralized organizations to form a community of shared interest, as shown in Figure 1. Our main contributions are as follows.

- We present a new recommendation framework Decentralized Multi-Target Cross-Domain Recommendation (DMTCDR), which can simultaneously improve the recommendation performance of multiple decentralized organizations without sharing their local data, models, or objective functions.
A natural extension of CDR is Multi-Domain Recommendation (MDR), which aims to improve the overall recommendation performance by incorporating the domain-wise information [7, 10].

Then, Dual-Target CDR (DTCDR) has been proposed to improve MDR, which aims to improve the overall recommendation performance in the target domain and mitigate the cold start problem [4]. Recent CDR methods use the latent factors obtained from a source domain for a target domain [17–21].

We propose a new decentralized learning algorithm named Multi-Target Assisted Learning (MTAL) with a new AutoEncoder-based RS called Assisted AutoEncoder (AAE). Our method exchanges information from various decentralized organizations by fitting pseudo-residuals with local data and models. It also covers broad application scenarios, including explicit or implicit feedback, user- or item-based alignment, and with or without side information.

We conduct extensive experiments and demonstrate that our method can significantly outperform locally trained RSs and mitigates the cold start problem. As a result, our approach can promote collaborations among various organizations to form a community of shared interest.

2 RELATED WORK

Recommender Systems. Recommender Systems (RSs) predict users’ preferences on items and provide personalized recommendations for users [1, 2]. Recommendation approaches are mainly classified into three categories [1, 15], namely collaborative filtering, content-based recommendation, and hybrid systems. Specifically, collaborative filtering learns from user-item interactions, while the content-based recommendation is primarily based on side information. Hybrid systems leverage both user-item interactions and side information. Our proposed method is a hybrid Recommender System (RS) that can leverage user-item interactions, explicit feedback (e.g., user’s previous ratings) or implicit feedback (e.g., browsing history), and side information.

Users usually interact with very few items [16] in most realistic scenarios. To address the data sparsity problem, cross-domain recommendation (CDR) [3] has been proposed to utilize relatively more affluent information from the source domain to improve the recommendation performance in the target domain and mitigate the cold start problem [4]. Recent CDR methods use the latent factors obtained from a source domain for a target domain [17–21].

A natural extension of CDR is Multi-Domain Recommendation (MDR), which aims to improve the overall recommendation performance by incorporating the domain-wise information [7, 10]. Then, Dual-Target CDR (DTCDR) has been proposed to improve the recommendation performance in both the source and target domain [9]. Inspired by MDR and DTCDR, the Multi-Target CDR (MTCDR) aims to improve the recommendation performance in all domains simultaneously [5, 6, 10]. The existing works require centralized training with shared data and models. However, due to various ethical and regulatory constraints, decentralized organizations may not be feasible to share their data and fully collaborate to learn a shared RS. Therefore, we propose Decentralized MTCDR (DMTCDR) to simultaneously improve the performance of multiple decentralized organizations without sharing local data, models, and objective functions.

3 PROBLEM

3.1 Recommender Systems

Let \( U = \{u_1, \ldots, u_m\} \) and \( V = \{v_1, \ldots, v_n\} \) denote respectively the set of users and items, where \( m \) is the number of users and \( n \) is the number of items. We have a user-item interaction or rating matrix \( R \in \mathbb{R}^{m \times n} \), where \( r_{i,j} \in R \) denotes the rating that user \( u_i \) gives to item \( v_j \). The rating matrix \( R \) is sparse as each user will only interact with a few items. A Recommender System \( F(\cdot) \) predicts the unseen rating with all the seen ratings. For instance, collaborative filtering is a well-known example which predicts the unseen rating \( \hat{r}_{i,j} \) given a pair of user and item \( (u_i, v_j) \), i.e., \( \hat{r}_{i,j} = F(u_i, v_j) \).

The hybrid RSs can also incorporate side information such as user profile \( s_{u,i} \in S_u \) and item attributes \( s_{v,j} \in S_v \) that are associated with the

[Figure 1: (a) User-Aligned (b) Item-Aligned Decentralized Multi-Target Cross-Domain Recommendation (DMTCDR) for Multi-Organization Collaborations. Decentralized organizations form a community of shared interest by leveraging the predictive power of each other without sharing their local data, model and objective functions.]
We propose Multi-Target Assisted Learning (MTAL) demonstrated as shown in Figure 1. DMTCDR can be categorized based on their implicit feedback, the base model is the popularity estimates, where the number of ratings of each item at the organization is computed its own ‘pseudo residuals’ \( r_{i,j} \). However, our proposed method leverages the common users \( \mathcal{U}^k \) or the common items \( \mathcal{V}^k \) that appear in other sets of users or items in order to resolve the data sparsity problem and improve the recommendation performance of Decentralized Multi-Target Cross-Domain Recommendation (DMTCRD) \( P^k(\cdot) \). The set common users \( \mathcal{U}^k \) and items \( \mathcal{V}^k \) are those shared between a pair of organizations,

\[
\mathcal{U}^k = \{ \mathcal{U}^1 \cap \mathcal{U}^k, \ldots, \mathcal{U}^n \cap \mathcal{U}^k \} \\
\mathcal{V}^k = \{ \mathcal{V}^1 \cap \mathcal{V}^k, \ldots, \mathcal{V}^n \cap \mathcal{V}^k \}.
\]

As shown in Figure 1, DMTCDR can be categorized based on their data alignment. Depending on the application scenario, a user-aligned DMTCDR leverages the common users, while an item-aligned one leverages the common items. The ultimate goal is that DMTCDR \( P^k(\cdot) \) can significantly outperform locally trained RSS \( \hat{P}^k(\cdot) \) for each organization \( k \)

\[
\mathbb{E}( \mathcal{L}( \hat{F}^k(u^k_i, u^k_j), r^k_{i,j}) ) \ll \mathbb{E}( \mathcal{L}( \hat{F}^k(u^k_i, u^k_j), r^k_{i,j}) ),
\]

where the expectation \( \mathbb{E} \) is over test data and \( \mathcal{L}(\cdot) \) is the objective function.

We propose Multi-Target Assisted Learning (MTAL) with Assisted AutoEncoder (AAE) to achieve the above goal for decentralized organizations without sharing local rating matrix \( R^k \), user profiles \( S^k_u \), item attributes \( S^k_v \), models \( F^k(\cdot) \), or objective functions \( L^k(\cdot) \).

## 4 METHOD

### 4.1 Multi-Target Assisted Learning

We propose Multi-Target Assisted Learning (MTAL) demonstrated in Algorithm 1, so that each organization can operate on its own local data, model, and objective function. We describe the learning and prediction procedures in detail.

In the beginning, each organization \( k \) coordinates with other organizations to construct the set of common users \( \mathcal{U}^k \) or items \( \mathcal{V}^k \), depending on whether the system is user-aligned or item-aligned. During the Learning stage, each organization initializes with an unbiased base model \( f^k_0(R^k) = E_u(R^k) \approx B^{-1} \sum_i r^k_{i} \in \mathbb{R}^n \). For explicit feedback, the base model is the average ratings, where \( B \) is the number of ratings of each item at the organization \( k \). For the implicit feedback, the base model is the popularity estimates, where \( B \) is the number of users at the organization \( k \). Each organization computes its own ‘pseudo residuals’ \( r^k_{i,j} \) and broadcast its common residuals \( r^k_{i,j} \) to another organization \( l \) at every assistance round \( t \), where

\[
r^k_{i,j} = -\frac{\partial L_{k}(f^k_{t-1}(R^k), R^k)}{\partial f^k_{t-1}(R^k)} - r^k_{i,j}, i \in \mathcal{U}^k \cup \mathcal{U}^l.
\]

\( L^k(\cdot) \) is the overarching loss function used by organization \( k \), and \( f^k_{t-1}(R^k) \) is the output from the previous assistance round. Here, the superscript of \( f^{i,j} \) means the organization \( i \) transmits the residuals to the organization \( j \), or the organization \( j \) receives from the organization \( i \). In Figure 2, we let \( r^{1:K,k} \) denote all the residual of organization \( k \) from organizations from 1 to \( K \).

Then, each organization aggregates its own residuals together with the received common residuals from other organizations into ‘pseudo targets’ \( \hat{R}^k_t = \{ r^{1,k}, \ldots, r^{K,k} \} \) in \( \mathbb{R}^m \times n \). Note that \( \hat{R}^k_t \) is a sparse matrix of size \( m \times n \). The dimension of items increases from \( n_k \) to \( n \), because the received common residuals from other organizations introduce unobserved targets of items. Next, each organization will fit a local model \( f^k_t \) with the pseudo targets \( \hat{R}^k_t \) and the local loss function \( L^k(\cdot) \). Each organization will then broadcast the common predicted outputs \( r^{1:K,k}_t \) to organizations from 1 to \( K \).

\[
f^k_t = \arg\min_{\eta} f^k(R^k, \hat{R}^k_t),
\]

\[
r^{kl}_{i,j} = f^k(R^k), r^{kl}_{i,j} = \{ r^{kl}_{i,j}, i \in \mathcal{U}^k \cup \mathcal{U}^l \}.
\]

Subsequently, each organization can train suitable gradient assistance weights \( \eta_k \) to aggregate received outputs and gradient assisted learning rate \( \eta_k \) in minimizing the overarching loss,

\[
\eta_k = \arg\min_{\eta_k} \sum_{j=1}^{K} \sum_{w_{jk}} w_{jk} \eta_k \sum_{j=1}^{K} \sum_{w_{jk}} w_{jk} \eta_k,
\]

where \( P_K = \{ w \in \mathbb{R}^K : \sum_{k=1}^{K} w_{jk} = 1, w_{jk} \geq 0 \} \) denotes the probability simplex. Finally, the output of organization \( k \) at round \( t \) denoted as \( f^k_t(R^k) \) is the aggregation of predicted outputs from all participating organizations and the output from previous round \( f^k_{t-1}(R^k) \), where

\[
f^k_t(R^k) = f^k_t(R^k) + \eta^k \sum_{j=1}^{K} w_{jk} f^k_{t-1}(R^k).
\]
In the Prediction stage, each organization will predict outputs from their local models $f^k_t$ for all assistance rounds from 1 to $T$. The predicted results will be broadcast to other organizations, which will aggregate them with local assistance weights $w_{1:T}$ and gradient assisted learning rate $\eta_{1:T}$, to eventually produce an overarching prediction $F^T(x)$ which is implicitly operated on $R$. Compared with the Learning stage, the Prediction stage does not require synchronization of each assistance round because we can operate all local models across $T$ rounds before broadcasting the outputs.

**Algorithm 1: MTAL: Multi-Target Assisted Learning**

**Input:** $K$ decentralized organizations, organization $k$ holding rating matrix $R \in \mathbb{R}^{m_k \times n_k}$, local model $f^k(\cdot)$, gradient assistance weights $w_k$, gradient assisted learning rate $\eta_k$, overarching loss function $L_k$, local loss function $l_k$, and the total number of assistance rounds $T$.

**Learning Stage:**
- **Alignment:** Construct the set of common users $U_k$ or items $V_c^k$.
- **Initialization:** Let $t = 0$, and initialize $P_k^0(x) = \mathbb{E}_n(R^k)$ (where $\mathbb{E}_n$ denotes the sample average).
- **for** assistance round $t$ from 1 to $T$ **do**
  - Compute pseudo-residuals $r_{t,k}^{k,k}$ and broadcast common pseudo-residuals $r_{t,k}^{k,l}$ to other organizations.
  - Aggregates pseudo-residuals and construct pseudo-targets $\hat{R}_t^k = \{r_{t,k}^{k,k} \} \in \mathbb{R}^{m_k \times n_k}$
  - Fit local AAE and broadcast the common predicted outputs $\hat{f}_{t,k}^k$ to other organizations.
  - Optimize the gradient assistance weights $w_{t,k}^k = \text{argmin}_{w \in P_M} f_k \left( \sum_{j=1}^{M} w_{j,t,k}^k, \hat{R}_t^k \right)$
  - Line search for the gradient assisted learning rate $\eta_t^k = \text{argmin}_{\eta \in \mathbb{R}} L_k \left( f_{t-1}^k(\hat{R}_t^k) + \eta \sum_{j=1}^{K} w_{j,t,k}^k, \hat{R}_t^k \right)$
- **end**

**Prediction Stage:**
- **Gather predictions** $\hat{r}_{t,k}^{j,k} = f_{t,k}^j(\hat{R}_t^k)$, $t = 1, \ldots , T$ from each organization $j, j = 1, \ldots , K$.
- **Predict with** $F^T(R^k) \triangleq t^{(1)}(\hat{R}_t^k) + \sum_{t=1}^{T} \eta_t^k \sum_{j=1}^{K} w_{j,t,k}^k$.
- **Return** $F^T(R^k)$. 

**Figure 2:** Learning and Prediction stages of Multi-Target Assisted Learning (MTAL). Decentralized organizations collaborate with each other and construct a set of common users or items. The organization $k$ learns local models $f^k_t$ with received pseudo-targets $r_{t,k}^{1:k,k}$ and predicted outputs $\hat{f}_{t,k}^{1:k,k}$ from all the organizations 1 to $K$. 

Equation 1: 
\[
\text{Algorithm 1: MTAL: Multi-Target Assisted Learning}
\]

**Input:** $K$ decentralized organizations, organization $k$ holding rating matrix $R \in \mathbb{R}^{m_k \times n_k}$, local model $f^k(\cdot)$, gradient assistance weights $w_k$, gradient assisted learning rate $\eta_k$, overarching loss function $L_k$, local loss function $l_k$, and the total number of assistance rounds $T$.

**Learning Stage:**
- **Alignment:** Construct the set of common users $U_k$ or items $V_c^k$.
- **Initialization:** Let $t = 0$, and initialize $P_k^0(x) = \mathbb{E}_n(R^k)$ (where $\mathbb{E}_n$ denotes the sample average).
- **for** assistance round $t$ from 1 to $T$ **do**
  - Compute pseudo-residuals $r_{t,k}^{k,k}$ and broadcast common pseudo-residuals $r_{t,k}^{k,l}$ to other organizations.
  - Aggregates pseudo-residuals and construct pseudo-targets $\hat{R}_t^k = \{r_{t,k}^{k,k} \} \in \mathbb{R}^{m_k \times n_k}$
  - Fit local AAE and broadcast the common predicted outputs $\hat{f}_{t,k}^k$ to other organizations.
  - Optimize the gradient assistance weights $w_{t,k}^k = \text{argmin}_{w \in P_M} f_k \left( \sum_{j=1}^{M} w_{j,t,k}^k, \hat{R}_t^k \right)$
  - Line search for the gradient assisted learning rate $\eta_t^k = \text{argmin}_{\eta \in \mathbb{R}} L_k \left( f_{t-1}^k(\hat{R}_t^k) + \eta \sum_{j=1}^{K} w_{j,t,k}^k, \hat{R}_t^k \right)$
- **end**

**Prediction Stage:**
- **Gather predictions** $\hat{r}_{t,k}^{j,k} = f_{t,k}^j(\hat{R}_t^k)$, $t = 1, \ldots , T$ from each organization $j, j = 1, \ldots , K$.
- **Predict with** $F^T(R^k) \triangleq t^{(1)}(\hat{R}_t^k) + \sum_{t=1}^{T} \eta_t^k \sum_{j=1}^{K} w_{j,t,k}^k$.
- **Return** $F^T(R^k)$.
that represents the ratings of user $u^k_i$ giving to all items $d^k_1, \ldots, d^k_n_k$, where $n_k$ is the number of items in organization $k$. The key difference between AE and our proposed AAE is that the output vector of a user-based AAE has the dimension of the total number of items of all organizations, i.e., $\hat{r}^k_i = D(E(r^k_i)) \in \mathbb{R}^n$. Specifically, $n$ is the total number of items across all organizations because our proposed MTAL algorithm requires local RSs to fit the pseudo-targets of all organizations.

We illustrate our proposed AAE in Figure 3. Both the encoder and decoder consist of Fully Connected (FC) layers. We use $\tanh(\cdot)$ as our nonlinear activation function [29, 30]. We adopt Dropout [31] at the encoded space as suggested by [30]. We also consider side information of domain $k$ such as user profile $S^k_u \in \mathbb{R}^{m_u \times d_{u,k}}$ and item attributes $S^k_i \in \mathbb{R}^{n_k \times d_{i,k}}$, where $d_{u,k}$ and $d_{i,k}$ denote the feature dimension of user profile and item attribute at domain $k$, respectively. The dimension of output ratings is much larger than the input ratings because we will fit the pseudo-targets of all organizations with the MTAL algorithm. Our proposed AAE can extend the scope of standard AE for DMTCDR by leveraging our proposed MTAL algorithm.

AAE is designed to generate the ratings of all organizations. Our MTAL algorithm requires that the local RSs can use the rating $r_{i,j}$ of a pair of user and item $(u_i, v_j)$ to predict the ratings $r_{p,q}$ of other pairs of user and item, i.e. $p \neq i$ and $q \neq j$. Recall that classical CF predicts the unseen rating $\hat{r}_{i,j}$ given a single pair of user and item $(u_i, v_j)$. CF takes user-item pairs as the input, which cannot predict other user-item pairs. Thus, it is not suitable to integrate CF with our MTAL algorithm. Fortunately, an AutoEncoder-based RSs takes in all the available ratings of a user $u_i$, i.e. $(r^1_{i,1}, \ldots, r^1_{i,m_1})$ and predicts the ratings of all the unseen items, i.e. $(\hat{r}^1_{i,1}, \ldots, \hat{r}^1_{i,n_k})$. Therefore, AutoEncoder-based RSs are naturally compatible with our proposed MTAL algorithm. In particular, AE treats the rating matrix $R$ as tabular data. The rating matrix’s rows and columns are data samples and feature spaces. Local AutoEncoder-based RSs can be viewed as each organization holding a subset of the feature space. Specifically, user-based AE treats users as data samples and items as feature space, while item-based AE treats items as data samples and users as feature space. It is worth mentioning that the proposed MTAL algorithm is not limited to AutoEncoder-based RSs. Any models that can use the rating $r_{i,j}$ to predict the ratings $r_{p,q}$ are also compatible with the proposed MTAL algorithm.

5 EXPERIMENTS

5.1 Experimental Setup

We conduct experiments with commonly used benchmark datasets, including MovieLens1M (ML1M), Douban, and Amazon datasets [32–34]. We split items of ML1M dataset according to $K = 18$ movie genres, Douban dataset according to ‘book’, ‘movie’ and ‘music’ domains, and Amazon dataset according to ‘Books’, ‘Digital Music’, ‘Movies and TV’, and ‘Video Games’ domains. The side information of ML1M includes users’ age, gender, and occupation, and the side information of Douban is the users’ living place. The summary statistics of each dataset can be found in Table 1. We compare the proposed DMTCDR with three recommendation baselines, including ‘Joint’, MTCDR [35], and ‘Alone’. ‘Joint’ denotes the scenario
Table 1: Summary of statistics of ML1M, Douban, and Amazon datasets. Each dataset contains $m$ users and $n$ items. $d^k_{s,u}$ represents the dimension of the side information.

| Dataset  | $m$  | $n$  | $d^k_{s,u}$ | $M$ | Sparsity  |
|----------|------|------|-------------|-----|-----------|
| ML1M     | 6040 | 3706 | 30          | 18  | 96.0%     |
| Douban   | 2570 | 11361| 35          | 3   | 97.5%     |
| Amazon   | 15628| 6946 | N/A         | 4   | 99.8%     |

where all the data are held by one organization, and the RS is trained in a centralized manner. MTCDR is based on cross-domain Collaborative Filtering, where the embeddings of users or items are shared across multiple organizations. Compared with the proposed DMTCDR, ‘Joint’ and MTCDR require the RS to be trained in a centralized manner. ‘Alone’ denotes the case where organizations train local RSs and thus do not leverage the interaction among multiple organizations.

Apart from learning baselines, we experiment various kinds of backbone recommendation models including the unbiased Base model described in Section 4.1, classical Matrix Factorization (MF) [36], Multi-Layer Perceptron (MLP) [37], Neural Collaborative Filtering (NCF) [37], and AutoEncoder (AE) [29]. It is worth noting that each recommendation baseline requires different backbone recommendation models. In particular, we experiment with ‘Joint’ and ‘Alone’ baselines with all backbone models, MTCDR with backbone models based on collaborative filtering (e.g., MF, MLP, NCF), and DMTCDR with AAE. We use Root Mean Squared Error (RMSE) to evaluate explicit feedback and Normalized Discounted Cumulative Gain at rank position 10 (NDCG@10) to evaluate implicit feedback. ↓ indicates the smaller the better, while ↑ indicates the larger the better.

The ‘Improvement’ is computed from the best result of the ‘Alone’ baseline. We conduct four random experiments with different seeds. The standard errors of results are shown in the figures. Details of the experimental setup and further experimental results can be found in the Appendix.

5.2 Experimental Results

**User alignment.** We demonstrate the experimental results of user-aligned DMTCDR in Tables 2. We illustrate the evaluations of DMTCDR across all assistance rounds and the best result of each baseline in Figure 4. As shown in Tables 2, our proposed method AAE equipped with MTAL significantly outperforms all ‘Alone’ cases for both explicit and implicit feedback with various backbone models and datasets. The results demonstrate that our decentralized framework can improve the recommendation performance of each domain simultaneously without sharing their local data, models, and objective function. Our approach also consistently outperforms the MTCDR baseline. Our method performs competitively with the ‘Joint’ baseline for the ML1M dataset while performing better than the ‘Joint’ baseline for Douban and Amazon datasets. However, it is worth noting that we do not expect our method can consistently outperform the ‘Joint’ and MTCDR baselines. Because ‘Joint’ and MTCDR baselines can be trained in a centralized manner, some more advanced methods may outperform DMTCDR [19, 21]. Our ultimate goal is to demonstrate that it is feasible to improve the local recommendation performance by training RSs in a decentralized manner with the proposed method.

The performance gain of DMTCDR is limited for implicit feedback. This may be due to the binary cross-entropy overarching loss.
used for training implicit feedback, which is less related to the metric than the mean squared error used for training explicit feedback. As illustrated in Figure 4, the performance gap between the ‘Alone’ and ‘Joint’ baseline is small for Douban and Amazon datasets because the domains of the Douban and Amazon datasets are less related than those of the ML1M dataset. In particular, local RSs can achieve satisfactory recommendation performance because they can well characterize the intra-domain interactions when the inter-domain interactions are limited. Furthermore, the results of MTCDR show that simply sharing the embeddings of items cannot effectively characterize the intra- and inter-domain interactions. Our proposed method effectively outperforms the baselines because it trains local RSs and exchanges multiple domains’ predictive power by fitting their pseudo-targets.

**Item alignment.** We demonstrate the results of item-aligned DMTCDR in Table 3. We illustrate the evaluations of item-aligned DMTCDR across all assistance rounds in Figures 5. We randomly split users for item-aligned DMTCDR into $K = 8$ domains, and each domain has roughly the same number of users. The performance gap between the ‘Alone’ and ‘Joint’ baseline is also reduced because the randomly constructed inter-domain interactions are much less meaningful. MTCDR fails to improve the performance of locally trained RSs as it struggles to characterize inter-domain interactions. Our proposed method performs much better than the ‘Alone’ baseline for the item-aligned Douban dataset with explicit feedback. Consequently, DMTCDR can outperform all baselines as it can effectively characterize the intra- and inter-domain interactions.

Table 3: Results of ML1M, Douban, and Amazon datasets with explicit and implicit feedback. Item-aligned DMTCDR improves the performance of locally trained RSs.

| Dataset   | ML1M     | Douban   | Amazon   |
|-----------|----------|----------|----------|
| Metric    | RMSE (↑) | NDCG (↑) | RMSE (↑) | NDCG (↑) | RMSE (↑) | NDCG (↑) |
| Base      | 1.036    | 0.611    | 1.356    | 0.695    | 1.396    | 0.887    |
| Joint     | 0.915    | 0.721    | 1.092    | 0.740    | 1.324    | 0.914    |
| MTCVR     | 0.910    | 0.718    | 1.104    | 0.739    | 1.342    | 0.912    |
| Base      | 1.005    | 0.611    | 1.356    | 0.695    | 1.396    | 0.886    |
| Joint     | 0.921    | 0.709    | 1.092    | 0.740    | 1.324    | 0.912    |
| MTCVR     | 0.921    | 0.678    | 1.092    | 0.740    | 1.324    | 0.912    |
| DMTCDR    | 0.834    | 0.738    | 0.886    | 0.765    | 1.236    | 0.917    |

**Partial alignment.** In our previous experiments, we assume all users or items of various organizations are completely aligned for user-aligned or item-aligned DMTCDR. As mentioned in Equations 1 and 2, the common users or items are shared between a pair of domains. Specifically, two domains can share a subset of their users or items. To study the impact of alignment, we conduct an ablation study of alignment ratio. We assume that all organizations have part of users aligned according to an alignment ratio. We demonstrate the results of partial alignment in Figure 6. It is worth mentioning that when the alignment ratio equals zero, the result is reduced to the best result of the ‘Alone’ baseline. The best result of ‘Alone’ includes all backbone models, but MTCDR and DMTCDR are limited to a subset of backbone models as described in Section 5.1. As a result, MTCDR and DMTCDR may perform worse than the ‘Alone’ baseline when the alignment ratio is small. Our results demonstrate that DMTCDR outperforms MTCVR across all alignment ratios and outperforms the ‘Alone’ baseline when the alignment ratio is large for the Amazon dataset. It indicates that our decentralized recommendation framework is robust enough to improve the performance of partially aligned domains.

**Cold start.** We study the cold start problem by considering the ratio of available users of one organization, denoted as the cold start ratio. We demonstrate our results of ML1M dataset in Figure 7. We choose the ‘Action’ as the cold start organization. The cold start organization only uses the data of available users to train and align with other organizations. However, we will evaluate the performance of the cold start organization against its new users. In this case, the ‘Alone’ baseline only works with the Base and AE backbone models because backbone models based on CF cannot train the embeddings of new users. The MTCDR baseline can also mitigate this issue because the embeddings of new users can be trained with the data from other organizations. Our proposed method can

Figure 5: Results across all assistance rounds. Item-aligned DMTCDR outperforms ‘Alone’ baseline for both explicit and implicit feedback.
The results demonstrate that our method outperforms the 'Alone' baseline with various backbone models. In particular, it improves the performance of all domains simultaneously for both explicit and implicit feedback. It is worth noting that domains with a smaller number of items \(n_k\) have less domain-wise improvement because the local loss functions are not reweighted according to the number of items of each domain. By reweighting the local loss functions according to the number of items of each domain, we may achieve a more fair improvement in recommendation performance over all domains.

**Privacy enhancement.** Our proposed algorithm allows different domains to improve their recommendation performance without sharing local data, models, or objective functions. We consider this requirement a bottom line for protecting the privacy of DMTCDR. Nevertheless, we are aware that it is possible to apply further privacy enhancement techniques such as Differential Privacy (DP) [38] and Interval Privacy (IP) [39] by adding noises to the transmitted residuals [23]. We demonstrate the results of privacy-enhanced MTAL in Table 5, labeled as MTAL_{DP} and MTAL_{IP}. The results show that privacy-enhanced MTAL can still outperform the 'Alone' baseline and thus improve the local recommendation performance under privacy constraints.

### 6 CONCLUSION

In this work, we present a new recommendation framework Decentralized Multi-Target Cross-Domain Recommendation (DMTCDR), which can simultaneously improve the recommendation performance of multiple decentralized organizations without sharing sensitive assets. Our proposed solution consists of a new decentralized learning algorithm named Multi-Target Assisted Learning (MTAL) and a new AutoEncoder-based RS called Assisted AutoEncoder (AAE). Our method covers broad application scenarios, including promoting collaborations among various organizations to form a community of shared interest.
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APPENDIX

A LIMITATIONS AND FUTURE WORK

Our proposed work extends and applies Assisted Learning (AL) for Decentralized Multi-Target Cross-Domain Recommendation (DMTCDR) with Multi-Target Assisted Learning (MTAL) and Assisted AutoEncoder (AAE). The results show that our method can outperform baselines in most scenarios. However, obtaining a dominant advantage over all existing works can be challenging. First, we can further improve the performance with hyperparameter searching methods in practice [40]. Second, we only discover AAE as one candidate backbone model for MTAL. The performance may be improved with more advanced backbone models such as graph-based RSs [41] as long as they are compatible with MTAL. Furthermore, the domain-wise results show that the improvement over locally trained RS is not fair enough across various domains. Finally, we do not focus on preserving privacy because AL still lacks a comprehensive analysis on this subject. Instead, we focus on decentralized computation without sharing local data, models, or objective functions. Furthermore, we also conduct experiments with privacy-enhancing techniques. Nonetheless, it is desirable to study the privacy aspect of DMTCDR further.

B EXPERIMENTAL SETUP

We train on 90% of the available data for all datasets and test on the remaining. We set negative implicit feedback when the ratings are below 3.5. Since the original Douban and Amazon datasets contain extremely sparse entries, we use users and items with more than 20 associated ratings. We demonstrate the model architecture of backbone models used in our experiments in Table 6. Details of hyper-parameters are included in Tables 7.

Table 6: The model architecture of models used in our experiments. The size embeddings of MF and NCF is 128. The Fully Connected (FC) neural networks used in MLP and NCF have four layers of size [128, 64, 32, 16]. Our proposed AAE has a two-layer encoder of size [n_k or m_k, 256, 128] and a two-layer decoder of size [128, 256, n or m].

| Model | Architecture |
|-------|--------------|
| MF    | 128          |
| MLP   | [128, 64, 32, 16] |
| NCF   | [128, 64, 32, 16] |
| AAE   | [n_k or m_k, 256, 128], [128, 256, n or m] |

C EXPERIMENTAL RESULTS

C.1 Ablation studies

We conduct an ablation study of the gradient assisted learning rate η_k of three datasets. As demonstrated in Table 8, η_k represents a constant gradient assisted learning rate for all domains, and the optimization of gradient assistance weights w_k is disabled. In particular, the weighted average becomes an unweighted average of outputs. We observe that the optimization of η_k for explicit feedback may result in overfitting due to a very large η_k. A moderate η_k produce better results than a large η_k. In practice, a more reliable solution to determine η_k is to use a validation set. We use the best choice of the gradient assisted learning rate η_k to perform the ablation study of gradient assistance weights w_k. As demonstrated in Table 8, the impact of optimizing w_k is not significant in terms of recommendation performance. It is worth noting that previous work shows that w_k is beneficial against adversarial training [23].

Table 7: Hyperparameters used for training local models, gradient assistance weights w_m, and gradient assisted learning rates η_m.

| Dataset   | ML1M | Douban | Amazon |
|-----------|------|--------|--------|
|            |      |        |        |
| Local      |      |        |        |
| Batch size | 500  | 100    | 500    |
| Epoch      | 20   |        |        |
| Optimizer  | Adam |        |        |
| Learning rate | 1.0E-03 |      |        |
| Weight decay | 5.0E-04 |    |        |
| Optimize   |      |        |        |
| η_k, w_k   |      |        |        |
| Batch size | Full |        |        |
| Optimizer  | L-BFGS |    |        |
| Learning rate | 1 |    |        |
| Assistance rounds | 10 |    |        |

C.2 Partial alignment

In Figure 8 and 9, we demonstrate the results of partial alignment for ML1M and Douban datasets. The results demonstrate that DMTCDR performs worse than MTCDR for the ML1M dataset with explicit feedback when the alignment ratio is small. It may be because the chosen gradient assisted learning rate is not optimal for the small alignment ratio. Our method outperforms MTCDR in other experiments. The performance improvement of alignment converges at a small alignment ratio for the ML1M dataset with explicit feedback and Douban dataset with explicit feedback. Meanwhile, the result of the Douban dataset with implicit feedback continues to improve when the alignment ratio increases. Consequently, the results demonstrate that DMTCDR performs better at a large alignment ratio while potentially converging at a small one.

C.3 Cold start

In Figure 10 and 11, we demonstrate the results of cold start for Douban and Amazon datasets. We choose the ‘Book’ as the cold start organization for the Douban dataset and the ‘Books’ as the cold start organization for the Amazon dataset, respectively. The cold start organization only uses the data of available users to
DMTCR outperforms MTCDR and ‘Alone’ baselines when the alignment ratio increases.

Figure 9: Results of partial alignment with Douban dataset. DMTCDR outperforms MTCDR and ‘Alone’ baselines when the alignment ratio increases.

Figure 10: Results of cold start with Douban dataset. ‘Book’ is the cold start domain. DMTCDR outperforms MTCDR and ‘Alone’ baselines when the cold start ratio increases.

Figure 11: Results of cold start with Amazon dataset. ‘Books’ is the cold start domain. DMTCDR outperforms MTCDR and ‘Alone’ baselines when the cold start ratio increases.

DMTCR performs worse than MTCDR for the Amazon dataset with explicit feedback when the cold start ratio is small. It may be because the performance of the Base model, used as the initial state of DMTCDR, is poor when the cold start ratio is small. However, the performance of DMTCDR continues to improve when the cold start ratio increases. Consequently, the results demonstrate that DMTCDR performs better at a large cold start ratio while potentially performing worse than MTCDR at a small cold start ratio.

C.4 Domain-wise improvement

In Tables 9 and 10, we demonstrate the results of each domain of user-aligned datasets. The results show that DMTCDR improves the performance of all domains simultaneously. The results of DMTCDR for the Amazon dataset (‘Digital Music’) with explicit feedback perform worse than its corresponding ‘Alone’ baseline. It may be because the performance of the AE is poor as the number of items of ‘Digital Music’ is much smaller than that of other domains. Nonetheless, DMTCDR outperforms ‘Alone’ baselines in other scenarios.

Table 9: Domain-wise results of Douban dataset.

| Domain | Book | Movie | Music |
|--------|------|-------|-------|
| \(n_k\) | 1134 | 9500  | 727   |
| RMSE(↓) |  |  |  |
| Alone | Base | 0.811 | 0.908 | 0.855 |
| MF | 0.847 | 1.059 | 0.963 |
| MLP | 0.817 | 0.905 | 0.860 |
| NCF | 0.847 | 0.907 | 0.879 |
| AE | 0.857 | 0.907 | 0.910 |
| DMTCDR | AAE | 0.800 | 0.859 | 0.843 |
| Improvement | 1.3% | 5.1% | 1.4% |
| NDCG(↑) |  |  |  |
| Alone | Base | 0.846 | 0.770 | 0.843 |
| MF | 0.858 | 0.850 | 0.853 |
| MLP | 0.861 | 0.868 | 0.858 |
| NCF | 0.861 | 0.868 | 0.858 |
| AE | 0.860 | 0.865 | 0.858 |
| DMTCDR | AAE | 0.862 | 0.873 | 0.859 |
| Improvement | 0.0% | 0.6% | 0.1% |

Table 10: Domain-wise results of Amazon dataset.

| Domain | Books | Digital Music | Movies and TV | Video Games |
|--------|-------|---------------|---------------|-------------|
| \(n_k\) | 2241  | 343           | 3178          | 1184        |
| RMSE(↓) |  |  |  |  |
| Alone | Base | 1.632 | 1.388 | 1.339 | 1.483 |
| MF | 2.125 | 3.802 | 1.348 | 2.225 |
| MLP | 1.487 | 1.173 | 1.254 | 1.362 |
| NCF | 1.488 | 1.178 | 1.250 | 1.360 |
| AE | 1.504 | 2.767 | 1.359 | 1.588 |
| DMTCDR | AAE | 1.406 | 1.237 | 1.144 | 1.247 |
| Improvement | 5.4% | -5.5% | 8.5% | 8.3% |
| NDCG(↑) |  |  |  |  |
| Alone | Base | 0.856 | 0.906 | 0.859 | 0.832 |
| MF | 0.857 | 0.906 | 0.862 | 0.832 |
| MLP | 0.859 | 0.906 | 0.866 | 0.833 |
| NCF | 0.859 | 0.906 | 0.866 | 0.833 |
| AE | 0.860 | 0.906 | 0.866 | 0.832 |
| DMTCDR | AAE | 0.860 | 0.906 | 0.867 | 0.833 |
| Improvement | 0.1% | 0.0% | 0.1% | 0.0% |