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Cognitive-Based Enhanced Accuracy and Relevance in Cross-Domain Recommendations

Luong Vuong Nguyen^{1,*}, Hoang Tran² and Thuy-Trang Pham³

¹Faculty of Artificial Intelligence, FPT University, Danang, Vietnam

²Department of Software Engineering, FPT University, Danang, Vietnam

³Department of Business, FPT University, Danang, Vietnam

*Corresponding Author: Luong Vuong Nguyen. Email: vuongnl3@fe.edu.vn

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ABSTRACT: In the era of information overload, cross-domain recommendations offer a promising solution by leveraging user preferences across domains to improve recommendation accuracy and relevance. This study proposes a novel approach to cross-domain recommendations based on cognitive similarity derived from user-based features. We construct comprehensive user profiles across multiple domains by defining cognitive similarity based on user interaction data, including ratings, reviews, and genre preferences. We employ advanced feature extraction techniques, including TF-IDF for textual data and matrix factorization for latent factors, to quantify similarities in user preferences across domains. These cognitive similarity measures are then used to map user profiles into a common latent space, facilitating the generation of personalized cross-domain recommendations. To visualize the effectiveness of our approach, we use methods such as Multidimensional Scaling (MDS) and heatmaps to depict the cognitive similarity between users across different domains. Additionally, network graphs illustrate the intricate relationships and similarities across user profiles, offering intuitive insights into the recommendation process. The results demonstrate that our cognitive similarity-based approach significantly improves the relevance and diversity of cross-domain recommendations, providing a robust framework for future research and practical applications in personalized recommendation systems.

KEYWORDS: Cognitive similarity; cross-domain recommendations; MDS visualizations; matrix factorization; feature extraction

1 Introduction

The rise of online platforms has significantly transformed the way users interact with information, products, and services across various domains. Whether in entertainment, e-commerce, education, or healthcare, recommendation systems (RS) have become essential to enhancing user experience by helping users navigate the overwhelming amount of available content [1]. These systems typically analyze user preferences within a specific domain (e.g., recommending movies on a streaming platform or books on an e-commerce site). However, users often engage with multiple domains simultaneously, introducing a new challenge for traditional RS, which are limited to domain-specific user interactions [2,3]. To bridge this gap, cross-domain RSs (CDRS) have emerged as a promising approach that leverages user data from one domain (the source domain) to enhance recommendations in another (the target domain).

The motivation for cross-domain recommendations arises from several key observations. First, user preferences are often interrelated across domains. For instance, a user who enjoys action movies might also prefer high-adrenaline books, or someone who frequently purchases fitness equipment may be interested in health-related products or services. Traditional RSs overlook this opportunity by focusing solely on single-domain user behavior, thereby limiting their ability to offer more comprehensive, personalized recommendations. Second, in many cases, the target domain may suffer from data sparsity, meaning there is insufficient user interaction data to accurately predict preferences [4]. By incorporating data from the source domain, CDRS can mitigate this issue, allowing the system to provide more accurate and diverse recommendations [5]. Finally, cross-domain recommendations enhance user engagement and satisfaction by providing a seamless experience across platforms and domains, thereby increasing retention and conversion rates for businesses.

Despite these advantages, several challenges hinder the implementation of effective CDRS [6–8]. The primary challenge is modeling and transferring knowledge between domains, especially when the domains are highly heterogeneous (e.g., movies and books). Traditional collaborative filtering (CF) approaches, successful in single-domain settings, struggle in cross-domain scenarios due to the complexity of aligning user-item interactions across different domains [9]. Additionally, ensuring that the transferred knowledge remains relevant and accurate in the target domain remains a key challenge, as not all user preferences in one domain are applicable in another.

This research addresses these challenges by introducing a novel cognitive similarity-based cross-domain (Cognitive-CDR) recommendation approach. The proposed method leverages cognitive similarity between users in different domains to transfer knowledge from a well-populated source domain to a sparsely populated target domain. Cognitive similarity captures semantic relationships among user preferences across domains, enabling the system to understand and predict user preferences even when direct interactions with items in the target domain are limited. Our approach is designed to overcome the limitations of traditional cross-domain methods by explicitly accounting for the cognitive connections between user behaviors across domains. This is particularly beneficial in cases where user preferences exhibit cross-domain coherence (e.g., users who prefer particular genres of movies and books). Compared with existing cross-domain recommendation methods based on latent-factor alignment, adversarial adaptation, or graph propagation, the proposed Cognitive-CDR introduces a user-centric cognitive similarity framework. Instead of relying solely on latent embedding correspondence, Cognitive-CDR integrates behavioral, semantic, and textual preference signals into a unified cognitive representation. This design provides both effective cross-domain transfer and enhanced interpretability through explicit similarity computation and visualization. The contributions of this study are described as follows.

- Proposes a Cognitive-CDR model that bridges user preferences across domains by leveraging shared cognitive features.
- Develops an algorithm to predict user preferences in a target domain using user interactions from a source domain.
- Uses MDS and heatmaps to visually represent cognitive similarity among users, thereby enhancing interpretability.

The remainder of this manuscript is organized as follows. The next [Section 2](#) details related work on cross-domain methods. The proposed method is described in [Section 3](#). In [Section 4](#), the datasets, settings, and experimental results are presented, including a comparison of the proposed methods and baselines on recommendation accuracy and performance. This section also describes the results of our MDS-based visualization and provides insight into the visualizations. Finally, we conclude the study and outline directions for future work in [Section 5](#).

2 Related Work

CDRS has emerged as a prominent research area, offering solutions for transferring knowledge across domains to enhance the performance of recommendations. This section presents related works, categorized into the following areas: factorization-based models, domain adaptation approaches, adversarial learning methods, graph-based models, and knowledge transfer techniques. Recent advances have increasingly explored foundation-model and contrastive-learning paradigms for cross-domain recommendation [10]. Several studies employ graph contrastive learning to align user representations across domains [11,12], while others leverage large language models and semantic embeddings to improve cross-domain transferability and cold-start performance [13]. Despite their effectiveness, these approaches often rely on complex neural architectures and provide limited interpretability. In contrast, the proposed Cognitive-CDR focuses on explicit cognitive preference modeling and interpretable similarity computation while maintaining competitive recommendation performance.

2.1 Factorization-Based Models

Factorization methods are widely used in cross-domain recommendation systems (CDRS) because they learn compact latent representations that can be shared across domains. A typical multi-domain objective jointly factorizes domain-specific interaction matrices while regularizing shared user representations:

$$\min_{\{\mathbf{U}, \mathbf{V}^{(d)}\}} \sum_{d \in \mathcal{D}} \mathcal{L}^{(d)}(\mathbf{R}^{(d)}, \mathbf{U}\mathbf{V}^{(d)\top}) + \lambda \left(\|\mathbf{U}\|^2 + \sum_d \|\mathbf{V}^{(d)}\|^2 \right) + \Omega_{\text{CD}}, \quad (1)$$

where $\mathbf{U}$ represents shared user factors, $\mathbf{V}^{(d)}$ denotes domain-specific item factors, and Ω_{CD} enforces cross-domain consistency.

Several approaches extend this framework to enhance transfer. Loni et al. [14] apply Factorization Machines (FM) to incorporate side features (e.g., user IDs, item attributes, or domain tags), enabling soft information sharing across domains. Sahu and Dwivedi [15] propose domain-invariant user representations, where a shared latent user space improves generalization for sparse target domains. Study [16] introduce cluster-level latent factorization, transferring knowledge through user/item clusters to improve robustness under sparsity. Zhang et al. [17] further enhance collective matrix factorization by integrating knowledge graphs, which provide semantic relations across domains and strengthen cross-domain transfer.

2.2 Domain Adaptation Approaches

Domain adaptation (DA) reduces the distribution gap between source and target domains, enabling knowledge transfer with minimal negative shift. A general DA objective combines task losses with a distribution-alignment term:

$$\min_{\theta_s, \theta_t} \mathcal{L}_{\text{src}}(\theta_s) + \mathcal{L}_{\text{tgt}}(\theta_t) + \lambda \mathcal{D}(f_s(X_s; \theta_s), f_t(X_t; \theta_t)), \quad (2)$$

where f_s and f_t are representation functions and $\mathcal{D}(\cdot, \cdot)$ measures cross-domain discrepancy (e.g., adversarial alignment, MMD, or CORAL).

Several studies extend this principle for cross-domain recommendation. Kanagawa et al. [18] first apply deep domain adaptation to align latent representations across domains while preserving user privacy. Following on this idea, Tiroshi and Kuflik [19] introduce domain selection, transferring knowledge only from the most relevant source domains to reduce negative transfer. Focusing further on user-level consistency, Zhao et al. [5] align user interest distributions across domains so that semantically similar users remain close

in the shared representation space. Other, Gao et al. [20] address practical deployment issues by proposing privacy-preserving cross-domain recommendation that exchanges representations instead of raw user data. Overall, DA-based CDR methods align latent spaces, select useful source domains, and preserve user privacy. However, they may struggle when user preferences differ significantly across domains or when alignment overly constrains target learning. Our Cognitive-CDR complements DA with cognitive-similarity modeling, domain alignment, and a cross-domain adapter, balancing transferable knowledge with domain-specific signals, which is particularly effective under cold-start and sparse data conditions.

2.3 Adversarial Learning Models

Adversarial objectives help disentangle domain-invariant from domain-specific signals by training encoders to fool a domain discriminator while still optimizing recommendation loss. A typical setup solves

$$\min_{E,R} \max_D \mathcal{L}_{\text{rec}}(R \circ E) + \lambda \mathcal{L}_{\text{adv}}(D(E(\cdot))), \quad (3)$$

where E encodes users/items, R scores user-item pairs, and D predicts domain labels; the adversarial term encourages domain-invariant embeddings. Hao et al. [21] propose adversarial feature translation between domains (with consistency constraints), yielding substantial gains by aligning representational geometry across domains. Similarly, Liu et al. [22] couple adversarial alignment with attention to emphasize transferable user signals, effectively capturing cross-domain preferences while preserving domain-specific nuances.

2.4 Graph-Based Models

Graphs naturally capture higher-order relations among users and items within and across domains. Let each domain $d \in \{\mathcal{A}, \mathcal{B}\}$ be represented as a bipartite graph $\mathcal{G}^{(d)} = (\mathcal{U} \cup \mathcal{I}^{(d)}, \mathcal{E}^{(d)})$ with normalized adjacency $\tilde{\mathbf{A}}^{(d)}$. A L -layer GCN encoder propagates information as

$$\mathbf{H}^{(l+1,d)} = \sigma(\tilde{\mathbf{A}}^{(d)} \mathbf{H}^{(l,d)} \mathbf{W}^{(l)}), \quad \mathbf{Z}^{(d)} = \mathbf{H}^{(L,d)}, \quad (4)$$

where shared weights $\mathbf{W}^{(l)}$ encourage transferable structures across domains. Liu et al. [23] extend this framework with a bi-directional transfer graph model that propagates signals between domains (source $\leftrightarrow$ target), enabling cross-domain diffusion of user-item signals. To further align representations, cross-domain losses can be applied on shared users:

$$\mathcal{L}_{\text{align}} = \sum_{u \in \mathcal{U}_\cap} \|\mathbf{z}_u^{(\mathcal{A})} - \mathbf{z}_u^{(\mathcal{B})}\|_2^2 \quad \text{or} \quad \mathcal{L}_{\text{InfoNCE}}(u) = -\log \frac{\exp(\langle \mathbf{z}_u^{(\mathcal{A})}, \mathbf{z}_u^{(\mathcal{B})} \rangle / \tau)}{\sum_v \exp(\langle \mathbf{z}_u^{(\mathcal{A})}, \mathbf{z}_v^{(\mathcal{B})} \rangle / \tau)}. \quad (5)$$

Beyond user-item graphs, Liu et al. [24] incorporate cross-domain knowledge graphs (KGs) to model semantic relations among items. Items and entities are learned using KG objectives (e.g., DistMult or TransE) and combined with collaborative signals:

$$\max \sum_{(h,r,t) \in \mathcal{T}} \phi(\mathbf{e}_h, \mathbf{r}, \mathbf{e}_t) - \sum_{(h',r,t') \in \mathcal{T}^-} \phi(\mathbf{e}_{h'}, \mathbf{r}, \mathbf{e}_{t'}), \quad \hat{y}_{ui}^{(d)} = g(\mathbf{z}_u^{(d)}, \mathbf{z}_i^{(d)} \oplus \mathbf{e}_i). \quad (6)$$

These graph-based approaches are effective under sparsity and cold-start conditions by exploiting high-order neighborhoods and semantic relations. However, they may incur higher computational cost and require regularization to avoid over-smoothing across domains.

2.5 Knowledge Transfer Method

A central theme in cross-domain recommendation is to transfer user preferences or latent factors learned in a source domain to a target domain while avoiding negative transfer. Zhang et al. [25] formulate transfer in a probabilistic manner by imposing a prior on target latent factors conditioned on source factors, e.g.,

$$p(\mathbf{U}^{(t)} | \mathbf{U}^{(s)}) \propto \exp\left(-\frac{1}{2\sigma^2} \|\mathbf{U}^{(t)} - \mathbf{U}^{(s)}\mathbf{M}\|_F^2\right), \quad (7)$$

which yields a MAP objective with a quadratic coupling term that regularizes the target space toward a mapped source space via $\mathbf{M}$ (learned). In a related vein, Man et al. [26] bridge domains by embedding & mapping: both domains learn their factors, and an explicit linear (or nonlinear) mapping aligns source to target, typically through

$$\min_{\Theta} \mathcal{L}_{src} + \mathcal{L}_{tgt} + \lambda \|\mathbf{U}^{(t)} - \phi(\mathbf{U}^{(s)}, \Theta)\|_F^2, \quad (8)$$

where ϕ captures cross-domain correspondences beyond a simple rotation. To mitigate user heterogeneity, Zhu et al. [27] advocate personalized transfer: each user u , has a transfer weight $\alpha_u \in [0, 1]$ controlling how strongly the source guides the target, e.g.,

$$\min \mathcal{L}_{tgt} + \sum_u \alpha_u \|\mathbf{u}_u^{(t)} - \phi(\mathbf{u}_u^{(s)})\|_2^2 \quad \text{with} \quad \alpha_u = \text{gate}(\text{sparsity}_u, \text{similarity}_u) \quad (9)$$

so that highly sparse or well-aligned users benefit more from transfer, while others rely primarily on target evidence. Complementarily, Tiroshi and Kuflik [19] introduce domain ranking to prioritize which sources to transfer from, selecting a subset $\mathcal{S}^*$ that maximizes estimated relevance/utility to the target:

$$\mathcal{S}^* = \arg \max_{\mathcal{S} \subseteq \mathcal{D}_{src}, |\mathcal{S}|=k} \sum_{d \in \mathcal{S}} \omega(d, \text{tgt}) \cdot \Delta(d \rightarrow \text{tgt}), \quad (10)$$

thereby reducing negative transfer from weakly related domains.

2.6 Content and Tag-Based Models

A complementary line of work transfers knowledge through descriptive signals such as item content, tags, and reviews, allowing semantically similar users or items to align across domains even when interactions are sparse. Let $\mathbf{x}_u$ and $\mathbf{x}_i^{(d)}$ denote user and item content features in domain d . A simple content-aware scoring function is:

$$\hat{y}_{ui}^{(d)} = \langle \mathbf{W}^{(d)} \mathbf{x}_u, \mathbf{Q}^{(d)} \mathbf{x}_i^{(d)} \rangle, \quad (11)$$

where $\mathbf{W}^{(d)}$ and $\mathbf{Q}^{(d)}$ are learnable projections. Cross-domain coupling can be achieved by sharing or aligning content projections across domains.

Several approaches extend this idea. Sahebi and Walker [28] propose segmented content transfer, where users or items are grouped by semantic facets (e.g., genres or topics), and segment-specific models are jointly learned across domains:

$$\min_{\{\Theta_s\}} \sum_s \left(\mathcal{L}_s^{(\mathcal{A})} + \mathcal{L}_s^{(\mathcal{B})} \right) + \lambda \sum_s \|\Theta_s^{(\mathcal{A})} - \Theta_s^{(\mathcal{B})}\|_2^2. \quad (12)$$

This restricts transfer to semantically coherent segments, thereby reducing negative transfer. Tags can also serve as cross-domain bridges. Shi et al. [29] learn tag embeddings $\mathbf{z}_t$ in a user–tag–item graph and incorporate aggregated tag representations into the scoring function:

$$\hat{y}_{ui}^{(d)} = g(\mathbf{p}_u, \mathbf{q}_i^{(d)} \oplus \frac{1}{|T_i^{(d)}|} \sum_{t \in T_i^{(d)}} \mathbf{z}_t), \quad (13)$$

encouraging items with shared tags to align across domains. Finally, review texts provide richer semantic signals. Xin et al. [30] encode reviews into item embeddings $\mathbf{e}_i^{(d)}$ and apply contrastive alignment to match the same items across domains:

$$\mathcal{L}_{\text{CL}} = - \sum_{i \in \mathcal{I}_\cap} \log \frac{\exp(\text{sim}(\mathbf{e}_i^{(A)}, \mathbf{e}_i^{(B)})/\tau)}{\sum_j \exp(\text{sim}(\mathbf{e}_i^{(A)}, \mathbf{e}_j^{(B)})/\tau)}. \quad (14)$$

Such semantic signals help stabilize cross-domain transfer when interaction data is limited.

3 Proposed Method

This section outlines the process of visualizing cross-domain recommendations using cognitive similarity, which involves several steps. These steps include defining cognitive similarity, developing a recommendation algorithm, and visualizing the results.

3.1 User-Based Feature Extraction

In CDRS, the first step is extracting features from user–item interactions to represent user preferences and behaviors across domains (e.g., books and movies). The goal is to construct a feature vector for each user that summarizes their interactions within a domain and enables cross-domain comparison. Let $U = \{u_1, \dots, u_N\}$ denote the set of users and I_d the set of items in domain d . For each user u_i , we build a feature vector $\mathbf{u}_i^d$ that captures interaction characteristics such as ratings, genres, and review keywords. These vectors form the basis for computing cognitive similarity across domains.

- **Average Rating Feature:** For a user u_i in domain d , the average rating feature is calculated as the mean of the user’s ratings for all items I_d they have interacted with.

$$\text{avg_rating}_i^d = \frac{1}{|I_i^d|} \sum_{j \in I_i^d} r_{ij} \quad (15)$$

where I_i^d is the set of items in domain d rated by user u_i . r_{ij} is the rating given by user u_i to item $j \in I_i^d$.

- **Genre Preferences Feature:** Each item $j \in I_d$ belongs to one or more genres from a set of G distinct genres. We define the *genre preference vector* $\mathbf{g}_i^d$ for user u_i in domain d , where each element represents the fraction of items interacted with in a specific genre g_k .

$$\mathbf{g}_i^d = \left[\frac{|I_i^d(g_1)|}{|I_i^d|}, \frac{|I_i^d(g_2)|}{|I_i^d|}, \dots, \frac{|I_i^d(g_G)|}{|I_i^d|} \right] \quad (16)$$

where $|I_i^d(g_k)|$ is the number of items that user u_i has interacted with in genre g_k . G is the total number of distinct genres in the domain d .

- Keywords from Reviews Feature: User reviews are processed to extract keywords or topics reflecting user interests. The *keyword vector* $\mathbf{k}_i^d$ for user u_i in domain d is constructed from the set of keywords W derived from the user's reviews.

$$\mathbf{k}_i^d = [w_1^d, w_2^d, \dots, w_T^d] \quad (17)$$

where w_j^d represents the importance (e.g., TF-IDF weight) of keyword j for user u_i in domain d . T is the total number of keywords considered in domain d .

The complete feature vector $\mathbf{u}_i^d$ for user u_i in domain d combines the extracted features $[\text{avg_rating}_i^d, \mathbf{g}_i^d, \mathbf{k}_i^d]$. This vector includes the *average rating* feature, the genre preference vector, and the *keywords* vector extracted from reviews.

3.2 Cognitive Similarity

Cognitive similarity refers to the degree of similarity between two users' cognitive patterns, preferences, or behaviors across different domains. It is computed by comparing users' feature vectors across domains and quantifying the alignment or overlap between them. Feature alignment does not require learning an additional neural mapping function. Instead, heterogeneous information from different domains is transformed into a common cognitive feature space. Specifically, rating statistics are normalized into comparable scales, genre preferences are represented as probability distributions, and textual reviews are converted into TF-IDF vectors. This unified representation enables direct similarity computation between users originating from different domains while preserving semantic interpretability. This study defines cognitive similarity as follows.

Definition 1: Let $\mathbf{u}_i^{d_1}$ represent the feature vector of user u_i in domain d_1 , and $\mathbf{u}_j^{d_2}$ represent the feature vector of user u_j in domain d_2 . The cognitive similarity between users u_i and u_j across domains d_1 and d_2 , denoted as $S_{ij}^{d_1, d_2}$, can be defined as:

$$S_{ij}^{d_1, d_2} = \frac{\mathbf{u}_i^{d_1} \cdot \mathbf{u}_j^{d_2}}{\|\mathbf{u}_i^{d_1}\| \|\mathbf{u}_j^{d_2}\|}, \quad (18)$$

where $\mathbf{u}_i^{d_1} \cdot \mathbf{u}_j^{d_2}$ is the dot product of the feature vectors of users u_i and u_j from domains d_1 and d_2 , respectively. $\|\mathbf{u}_i^{d_1}\|$ and $\|\mathbf{u}_j^{d_2}\|$ are the Euclidean norms (magnitudes) of the feature vectors $\mathbf{u}_i^{d_1}$ and $\mathbf{u}_j^{d_2}$, respectively. This formula calculates the cosine similarity between the two users' feature vectors, yielding a value between -1 and 1 , where $S_{ij}^{d_1, d_2} = 1$ indicates perfect cognitive similarity, 0 indicates no cognitive similarity, and -1 indicates perfect cognitive dissimilarity.

The cognitive similarity between users across domains is estimated in two steps.

- Feature alignment across domains: Let $\mathbf{u}_i^{d_1}$ and $\mathbf{u}_j^{d_2}$ denote the feature vectors of user u_i in domain d_1 (e.g., Movies) and user u_j in domain d_2 (e.g., Books). Since features may differ across domains, we align them into a shared feature space F (e.g., average rating, genre preferences, and review keywords):

$$\mathbf{u}_i^{d_1} = [f_1^{d_1}(u_i), \dots, f_F^{d_1}(u_i)], \quad \mathbf{u}_j^{d_2} = [f_1^{d_2}(u_j), \dots, f_F^{d_2}(u_j)].$$

Before computing cognitive similarity, domain-specific user features are projected into a shared cognitive representation space. Let $\phi_d : \mathcal{X}_d \rightarrow \mathcal{F}$ denote a feature harmonization function that transforms domain-specific attributes into a common cognitive space $\mathcal{F}$. The transformed user representations are:

$$\mathbf{z}_i^{d_1} = \phi_{d_1}(\mathbf{u}_i^{d_1}), \quad \mathbf{z}_j^{d_2} = \phi_{d_2}(\mathbf{u}_j^{d_2}).$$

The harmonized representations contain comparable dimensions corresponding to normalized rating behavior, preference distributions, and textual-interest features. Cognitive similarity is then computed between $\mathbf{z}_i^{d_1}$ and $\mathbf{z}_j^{d_2}$.

- Cognitive similarity computation: The similarity between users u_i and u_j across domains is computed using cosine similarity from Eq. (18):

$$S_{ij}^{d_1, d_2} = \frac{\mathbf{z}_i^{d_1} \cdot \mathbf{z}_j^{d_2}}{\|\mathbf{z}_i^{d_1}\| \|\mathbf{z}_j^{d_2}\|}.$$

The score ranges from -1 (completely dissimilar) to 1 (perfectly similar). Cosine similarity was selected because it is scale-invariant and robust to differences in feature magnitude across domains. Since cognitive profiles combine ratings, genre distributions, and textual features with heterogeneous ranges, cosine similarity focuses on preference orientation rather than absolute values. Alternative measures such as Euclidean distance, Pearson correlation, and Jaccard similarity were considered; however, cosine similarity offers a favorable balance between computational efficiency, interpretability, and robustness for high-dimensional sparse representations.

Example 1: Assume the feature vectors for user u_i in the Movies domain and user u_j in the Books domain are $\mathbf{u}_i^{\text{Movies}} = [4.2, \mathbf{g}_i^{\text{Movies}}, \mathbf{k}_i^{\text{Movies}}]$, and $\mathbf{u}_j^{\text{Books}} = [4.5, \mathbf{g}_j^{\text{Books}}, \mathbf{k}_j^{\text{Books}}]$, where $\mathbf{g}$ represents genre preferences and $\mathbf{k}$ represents review-keyword features. Following Eq. (18), the cosine similarity $S_{ij}^{\text{Movies, Books}} = \frac{\mathbf{u}_i^{\text{Movies}} \cdot \mathbf{u}_j^{\text{Books}}}{\|\mathbf{u}_i^{\text{Movies}}\| \|\mathbf{u}_j^{\text{Books}}\|}$ measures how similar the two users' preferences are across domains. A higher value indicates stronger cognitive similarity.

3.3 Recommendations Generation

The proposed cross-domain recommendation algorithm exploits cognitive similarity between users to transfer knowledge from a source domain to a target domain, improving recommendation accuracy. It combines user-based collaborative filtering with cross-domain similarity. Although experiments in this study focus on the common two-domain setting (Books and Movies), the proposed formulation is directly applicable to multi-source recommendation scenarios.

- Input: user set $\mathcal{U}$, item sets $\mathcal{I}^{d_1}$ (source) and $\mathcal{I}^{d_2}$ (target), rating matrices $\mathbf{R}^{d_1}$ and $\mathbf{R}^{d_2}$, and cognitive similarity scores $S_{ij}^{d_1, d_2}$ between users across domains.
- Output: a ranked list of recommended items from $\mathcal{I}^{d_2}$ for user u_i .
- Procedure: First, cognitive similarity between the target user u_i and source-domain users is computed using cosine similarity of their feature vectors. Next, ratings for unseen target items are predicted using a weighted sum of ratings from the top- N similar users. Items are then ranked by predicted scores, and the top- N items are returned as recommendations (Algorithm 1).

Algorithm 1: Cross-domain recommendation via cognitive similarity.

Input: User feature matrices $\mathbf{U}_{d_1}$ (source domain), $\mathbf{U}_{d_2}$ (target domain); Rating matrix $\mathbf{R}_{d_1}$; candidate item set $\mathcal{I}_{d_2}$; number of neighbors N

Output: Top- N recommended items $\mathcal{I}_{rec}^{d_2}$ for target user u_i

1 Step 1: Cognitive Similarity Computation

2 **foreach** user $u_j \in \mathbf{U}_{d_1}$ **do**

3 Compute similarity score: $S_{ij}^{d_1, d_2} = \frac{\mathbf{u}_i^{d_2} \cdot \mathbf{u}_j^{d_1}}{\|\mathbf{u}_i^{d_2}\| \|\mathbf{u}_j^{d_1}\|}$ Store $S_{ij}^{d_1, d_2}$;

4 **end**

5 Select the top- N most similar users $\mathcal{N}_i$;

6 Step 2: Rating Prediction

7 **foreach** item $i_k \in \mathcal{I}_{d_2}$ **do**

8 $num \leftarrow 0$;

9 $den \leftarrow 0$;

10 **foreach** $u_j \in \mathcal{N}_i$ **do**

11 $num \leftarrow num + S_{ij}^{d_1, d_2} \cdot r_{j,k}^{d_1}$;

12 $den \leftarrow den + |S_{ij}^{d_1, d_2}|$;

13 **end**

14 Predict rating: $\hat{r}_{i,k}^{d_2} = \frac{num}{den}$

15 **end**

16 Step 3: Recommendation Generation

17 Rank items in $\mathcal{I}_{d_2}$ according to predicted scores $\hat{r}_{i,k}^{d_2}$;

18 Select the top- N ranked items;

19 Return $\mathcal{I}_{rec}^{d_2}$;

The proposed framework can be naturally extended to multiple source domains. Assume a target domain d_t and a set of source domains $\mathcal{D}_s = \{d_1, d_2, \dots, d_m\}$. For each source domain d_k , cognitive similarity scores are computed independently, $S_{ij}^{(d_k, d_t)}$. The final prediction can be obtained through weighted aggregation:

$$\hat{r}_{u,i} = \sum_{k=1}^m \omega_k \hat{r}_{u,i}^{(d_k)},$$

where $\sum_{k=1}^m \omega_k = 1$ and ω_k represents the relevance of source domain d_k to the target domain.

3.4 Multidimensional Scaling Visualization

To visualize cognitive similarity between users across domains, we use Multidimensional Scaling (MDS), a dimensionality-reduction technique that maps high-dimensional user profiles into a two-dimensional space while preserving pairwise distances. Each point in the resulting plot represents a user, and the distance between points reflects their cognitive similarity. First, the cognitive similarity matrix $S_{ij}^{d_1, d_2}$ is converted into a dissimilarity matrix using $D_{ij}^{d_1, d_2} = 1 - S_{ij}^{d_1, d_2}$, where larger values indicate lower similarity. MDS then projects the data into a 2D space by finding coordinates $\mathbf{x}_i \in \mathbb{R}^2$ that best preserve these dissimilarities by minimizing the stress function:

$$\text{Stress}(\mathbf{X}) = \sum_{i,j} \left(D_{ij}^{d_1, d_2} - \|\mathbf{x}_i - \mathbf{x}_j\| \right)^2. \quad (19)$$

The resulting visualization allows us to observe clusters of cognitively similar users, detect outliers, and better understand relationships between users across domains.

4 Experiments

4.1 Datasets

To evaluate the performance of our proposed Cognitive-CDR, we use two subsets of the Amazon Product Reviews dataset: “Books” and “Movies and TV” (the latter is referred to as “Movies”). This dataset is widely used in RS research due to its diverse product offerings, large user base, and high volume of ratings and reviews.

The Books dataset contains 8,898,041 reviews and 22,507,155 ratings, while the Movies dataset includes 1,697,533 reviews and 4,607,047 ratings. Both datasets provide reviews, ratings, and metadata that support feature extraction and cross-domain analysis. Dataset statistics are summarized in Table 1. We retain users with at least five interactions in either domain and binarize interactions (rating ≥ 4 as positive). Following a leave-one-out protocol, the latest interaction is used for testing, the second latest for validation, and the rest for training. For each test instance, 99 negative items are sampled, yielding candidate lists of 100 items. Results are averaged over five random seeds.

Table 1: Statistics of datasets used in experiments.

Domain	Original		After Preprocessing		
	#Reviews	#Ratings	#Users	#Items	#Pos (≥ 4)
Books	8,898,041	22,507,155	$U_{\text{Books}} = 603,668$	$I_{\text{Books}} = 367,982$	$P_{\text{Books}} = 7,203,909$
Movies	1,697,533	4,607,047	$U_{\text{Movies}} = 123,960$	$I_{\text{Movies}} = 50,052$	$P_{\text{Movies}} = 1,289,602$

Note: After preprocessing: Users with ≥ 5 interactions retained; ratings ≥ 4 binarized as positive.

4.2 Settings

Regarding implementation, we set the embedding size to 64, train with Adam ($\text{lr} = 10^{-3}$), batch size 1024, and ℓ_2 regularization tuned over $\{10^{-5}, 10^{-4}, 10^{-3}\}$. We stop on validation NDCG@10 after 10 epochs of patience to avoid overfitting while preserving strong early-rank performance. For each user, we sample 99 negatives to form a size-100 candidate set at test time; the same random seeds are used for negative sampling and parameter initialization. All results are averaged over five seeds, and we report means. We compare the proposed Cognitive-CDR method with the following baselines.

- PopRec: Rank by item popularity in the target domain.
- ItemCF: Item-based CF with cosine similarity.
- BPR-MF [31]: Matrix factorization trained with BPR loss.
- NeuMF [32]: GMF+MLP fusion for implicit feedback.
- NGCF [33]: Graph-based CF over user-item graph.
- LightGCN [34]: Simplified GCN for recommendation.
- CMF [35]: Collective Matrix Factorization for cross-domain.
- CoNet [36]: Cross-connection networks for cross-domain transfer.

For each user u , we sample 99 negative items and combine them with the held-out positive item $\hat{y}_u$ to form a candidate set of 100 items. The model ranks all items, and the position of the true item is denoted by $r_u = \text{rank}_u(\hat{y})$. Let $\mathcal{U}$ be the set of users and $\mathbb{I}\{\cdot\}$ the indicator function. We evaluate top- K recommendation performance ($K \in \{5, 10\}$) using standard metrics: $\text{HR@}K = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \mathbb{I}\{r_u \leq K\}$, $\text{NDCG@}K =$

$\frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \frac{\mathbb{I}\{r_u \leq K\}}{\log_2(1+r_u)}$, $\text{MRR} = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \frac{1}{r_u}$, $\text{MAP@K} = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \frac{\mathbb{I}\{r_u \leq K\}}{r_u}$, and $\text{P@K} = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \frac{1}{K} \mathbb{I}\{r_u \leq K\}$. The experiment scenarios are as follows:

- S1: In-Domain (ID) Train and evaluate within the same domain (Books-only or Movies-only) to measure pure in-domain performance without transfer.
- S2: Cross-Domain (CD) Train on a source domain and evaluate on a target domain for shared users (Books $\rightarrow$ Movies, Movies $\rightarrow$ Books) to test cross-domain knowledge transfer.
- S3: Cold-Start (CS) Evaluate users with no target-domain interactions but available source-domain history.
- S4: Sparsity (SP) Randomly remove $\{20\%, 40\%, 60\%\}$ of training interactions to test robustness under limited data.
- S5: Ablation (AB) Remove key components (e.g., cognitive similarity, adapters, alignment losses) to measure their impact.
- S6: Sensitivity (SN) Vary the cognitive weight $\alpha \in \{0.0, 0.1, 0.3, 0.5, 0.7\}$ to evaluate model stability.

4.3 Experimental Results

To assess statistical significance, we conducted paired t-tests across five independent random seeds. Cognitive-CDR consistently outperformed the strongest baseline methods, and the observed improvements in HR@10 and NDCG@10 were statistically significant ($p < 0.05$). Table 2 summarizes performance across of the S1 experiment scenarios. Across both Books and Movies & TV, the ranking quality improves monotonically as we move from heuristic popularity (PopRec) to memory-based CF (ItemCF), then to latent-factor methods (BPR-MF, NeuMF), and finally to graph-based recommenders (NGCF, LightGCN). This pattern is consistent with the intuition that models capturing higher-order connectivity and more expressive user-item interactions concentrate probability mass at the top of the list, thereby improving HR@10 and NDCG@10. Among the baselines, LightGCN performs best in both domains, reaffirming the effectiveness of lightweight propagation on the user-item graph without heavy transformations.

Table 2: In-domain results on *Books* and *Movies & TV* (Best in **bold**, second best underlined).

Method	Books					Movies & TV				
	HR	NDCG	MRR	MAP	P	HR	NDCG	MRR	MAP	P
PopRec	0.426	0.261	0.198	0.143	0.112	0.448	0.279	0.210	0.153	0.118
ItemCF	0.471	0.295	0.221	0.167	0.128	0.487	0.307	0.228	0.170	0.131
BPR-MF	0.503	0.318	0.239	0.181	0.136	0.512	0.327	0.242	0.183	0.138
NeuMF	0.521	0.331	0.248	0.189	0.141	0.534	0.343	0.254	0.193	0.144
NGCF	0.536	0.343	0.257	0.196	0.146	0.549	0.355	0.262	0.201	0.149
LightGCN	<u>0.552</u>	<u>0.356</u>	<u>0.266</u>	<u>0.205</u>	<u>0.151</u>	<u>0.564</u>	<u>0.366</u>	<u>0.270</u>	<u>0.208</u>	<u>0.153</u>
CMF	0.517	0.329	0.246	0.187	0.140	0.529	0.338	0.250	0.190	0.142
CoNet	0.541	0.349	0.261	0.199	0.148	0.556	0.361	0.267	0.206	0.151
Cognitive-CDR	0.579	0.377	0.283	0.222	0.162	0.591	0.386	0.289	0.228	0.165

Note: HR = HR@10, NDCG = NDCG@10, MAP = MAP@10, and P = Precision@10.

On Books, Cognitive-CDR improves over LightGCN by +0.027 HR@10 (+4.9%), +0.021 NDCG@10 (+5.9%), and +0.017 MRR (+6.4%), with similar gains in MAP@10 and P@10. On Movies & TV, improvements remain consistent: +0.027 HR@10 (+4.8%), +0.020 NDCG@10 (+5.5%), and +0.019 MRR (+7.0%). These gains indicate that Cognitive-CDR promotes the true item to higher positions within the top-10,

improving early-rank accuracy. By incorporating cross-domain cognitive similarity, the model regularizes user representations so that users with similar preferences across domains are placed closer together in the embedding space, benefiting sparse users. Compared with cross-domain baselines such as CMF and CoNet, Cognitive-CDR better balances graph structure and cross-domain alignment, leading to stronger early-rank performance.

Absolute metrics are slightly higher on Movies & TV than on Books for most methods (e.g., HR@10: PopRec 0.448 vs. 0.426; LightGCN 0.564 vs. 0.552; Cognitive-CDR 0.591 vs. 0.579), likely due to differences in interaction density or item popularity. Notably, the largest relative gains appear in MAP@10 and MRR, suggesting that improvements mainly occur at very early ranking positions. Regarding the other experiment scenarios, the following is a detailed on the results:

- **Cross-domain Transfer Scenarios:** Across both directions, Cognitive-CDR outperforms the strongest baseline (CoNet) on all metrics, indicating more effective knowledge transfer between domains (refer Table 3). From *Books* → *Movies*, gains over CoNet are consistent at early ranks: HR@10 increases from 0.559 to 0.596 (+0.037, $\approx +6.6\%$ rel.), NDCG@10 from 0.364 to 0.390 (+0.026, $\approx +7.1\%$), and MRR from 0.270 to 0.292 (+0.022, $\approx +8.2\%$). In the reverse direction *Movies* → *Books*, improvements are similarly strong: HR@10 0.548 → 0.582 (+0.034, $\approx +6.2\%$), NDCG@10 0.354 → 0.380 (+0.026, $\approx +7.3\%$), and MRR 0.264 → 0.286 (+0.022, $\approx +8.3\%$). These consistent lifts, especially in MRR and NDCG, demonstrate that the proposed cognitive alignment facilitates better early rank placement of true items in both transfer directions. Overall, the symmetry of gains suggests the method learns a domain-agnostic user representation that generalizes reliably, rather than relying on idiosyncrasies of a particular source domain.
- **Cold-Start and Sparsity:** Cold-start and sparsity represent two complementary stress tests for recommendation systems. Cold-start evaluates recommendations for users without target-domain interactions, while sparsity tests robustness when training data is reduced. In both settings, Cognitive-CDR consistently outperforms the baselines. As shown in Table 4, the cold-start scenario is particularly challenging because the model must infer preferences solely from the source domain. Cognitive-CDR achieves the best results across all metrics, improving over the strongest baseline CoNet from 0.469 to 0.508 in HR@10 (+8.3%), from 0.296 to 0.322 in NDCG@10 (+8.8%), and from 0.221 to 0.241 in MRR (+9.0%).

The sparsity experiment further confirms the robustness of the proposed method. As interactions are removed, all models degrade, but Cognitive-CDR declines more slowly and maintains a larger margin. Compared with CoNet, HR@10 improves by +0.027, +0.029, and +0.034 at 20%, 40%, and 60% drop rates, respectively. This widening gap suggests that cognitive coupling helps preserve meaningful user representations when interaction data is scarce.

- **Ablation and Sensitivity:** Table 5 shows that removing any cross-domain component reduces performance compared with the full model (NDCG@10 = 0.386).

Removing the cognitive similarity term decreases NDCG@10 to 0.363 (−5.96%), indicating that cognitive user similarity improves the embedding structure. Removing domain alignment further drops performance to 0.355 (−8.03%), highlighting the importance of aligning representations across domains. The largest decline occurs without the cross-domain adapter (NDCG@10 = 0.347, −10.10%), suggesting that modeling domain-specific variations while sharing global structure is critical. Overall, the components complement each other and jointly improve recommendation quality. Sensitivity analysis shows that varying the cognitive weight α produces a shallow inverted-U trend in HR@10, peaking at $\alpha = 0.3$ with 0.579. Compared with $\alpha = 0.0$ (HR@10 = 0.551), performance improves for $\alpha = 0.1, 0.3$, and 0.5 , but slightly declines at $\alpha = 0.7$, suggesting over-regularization when cognitive

coupling becomes too strong. The stable range $\alpha \in [0.3, 0.5]$ indicates that the model is robust to moderate changes in this parameter.

Table 3: Cross-Domain Transfer (CD): *Books* $\rightarrow$ *Movies* and *Movies* $\rightarrow$ *Books* (Best in **bold**, second best underlined).

Method	Books $\rightarrow$ Movies			Movies $\rightarrow$ Books		
	HR@10	NDCG@10	MRR	HR@10	NDCG@10	MRR
CMF	0.525	0.334	0.247	0.513	0.325	0.241
CoNet	<u>0.559</u>	<u>0.364</u>	<u>0.270</u>	<u>0.548</u>	<u>0.354</u>	<u>0.264</u>
Cognitive-CDR	0.596	0.390	0.292	0.582	0.380	0.286

Table 4: Sparsity and cold-start performance comparison (Best in **bold**, second best underlined).

Method	Sparsity on Books (HR@10)			Cold-Start on Target Domain		
	20% Drop	40% Drop	60% Drop	HR@10	NDCG@10	MRR
LightGCN	0.534	0.511	0.476	–	–	–
CMF	–	–	–	0.441	0.275	0.206
CoNet	<u>0.548</u>	<u>0.524</u>	<u>0.487</u>	<u>0.469</u>	<u>0.296</u>	<u>0.221</u>
Cognitive-CDR	0.575	0.553	0.521	0.508	0.322	0.241

Table 5: Ablation and sensitivity analysis of cognitive-CDR (Best in **bold**).

Ablation on Movies (NDCG@10)				
	Full Cognitive-CDR	w/o CogSim	w/o Domain Align	w/o CDR Adapter
	0.386	0.363	0.355	0.347
Sensitivity to α (Books, HR@10)				
α	0.0	0.1	0.3	0.5
HR@10	0.551	0.563	0.579	0.572

4.4 Visualization

To create the visualization in Fig. 1a, we first constructed a similarity matrix in which each cell represents the cognitive similarity between two users. These scores are calculated using cosine similarity in Eq. (18). The output is a 2D scatter plot where each point represents a user, and the distance between points corresponds to the cognitive similarity between those users. Users with similar preferences will appear closer together on the plot. This visualization helps visualize complex relationships in high-dimensional data by projecting them into a lower-dimensional space, making it easier to identify clusters or patterns in user behavior across different domains. Another visualization is shown in Fig. 1b, which illustrates pairwise user similarities. Each cell in the matrix represents the similarity between two users, with higher values (closer to 1) indicating greater similarity. The color intensity reflects the magnitude of the similarity: lighter colors indicate higher similarity, while darker colors indicate lower similarity. Since the matrix is symmetric, the diagonal will always have a similarity of 1 (each user is most similar to themselves). Bright squares or rectangles indicate

the clusters within the matrix where users share a higher similarity. This suggests that these users share similar cognitive preferences, possibly stemming from overlapping interests across both domains. The darker regions represent users with low similarity. These may indicate distinct user preferences across domains or little overlap in their cognitive patterns.

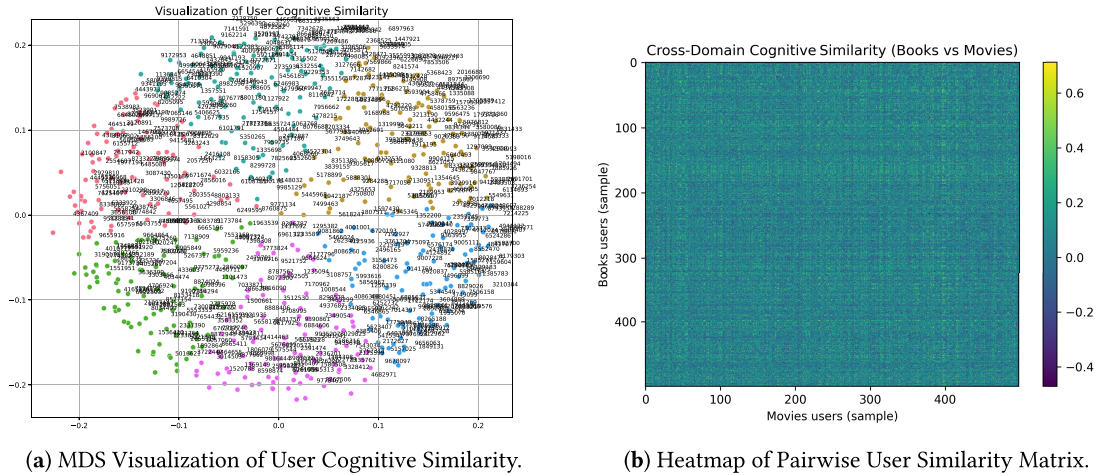


Figure 1: Visualization of user cognitive similarity. (a) shows the relative positions of users based on cognitive similarity, with points closer together indicating more similar users. The axes represent the two dimensions obtained from the MDS projection. (b) The heatmap illustrates pairwise user similarities, where higher values indicate stronger similarity.

4.5 Discussion on Complexity Analysis and Limitations

Let N denote the number of users and F the dimensionality of the cognitive feature space. Computing cognitive similarity requires $O(NF)$ operations per target user. Selecting the top- K neighbors can be done in $O(N \log K)$ using a priority queue. Recommendation generation incurs $O(KM)$ complexity, where M is the number of candidate items. Since user features and similarity matrices can be computed offline, the online recommendation stage remains computationally efficient. Furthermore, similarity computations are naturally parallelizable and can be accelerated using distributed processing frameworks for large-scale deployment.

Despite the encouraging results, several limitations remain. First, the current framework relies on handcrafted cognitive features derived from ratings, genres, and review keywords, which may not capture all aspects of user preferences. Second, the evaluation focuses on two Amazon domains (Books and Movies), and additional experiments on more heterogeneous domains would further validate generalizability. Third, cosine-based similarity assumes a linear relationship between user profiles and may not fully capture complex nonlinear preference patterns. Future work will investigate transformer-based user representations, graph-enhanced cognitive modeling, and broader multi-domain evaluations.

5 Conclusions

This study explored cross-domain collaborative filtering by leveraging user cognitive similarity to improve recommendation accuracy across domains. Using Amazon Product Reviews datasets from Books and Movies, the results show that cross-domain approaches outperform domain-specific methods, with the proposed Cognitive-CDR model achieving the best performance. By incorporating external knowledge and adversarial learning, the model improved recommendation relevance, achieving lower RMSE and higher Precision@10. In addition, MDS was used to visualize cognitive similarity between users. By projecting the

high-dimensional similarity matrix into a 2D space, MDS revealed clusters of users with similar preferences across domains. These visualizations provide intuitive insights into user relationships and demonstrate how cognitively similar users from different domains can be grouped together, facilitating more effective cross-domain knowledge transfer and improved personalization.

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