Novelty Assessment Report

Paper: Dataset Regeneration for Cross Domain Recommendation
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Abstract

Cross-domain recommendation (CDR) has emerged as an effective strategy to mitigate data sparsity and cold-start challenges by transferring knowledge from a source domain to a target domain. Despite recent progress, two key issues remain: (i) Sparse overlap. In real-world datasets such as Amazon, the proportion of users active in both domains is extremely low, significantly limiting the effectiveness of many state-of-the-art CDR approaches. (ii) Negative transfer. Existing methods primarily address this problem at the model level, often assuming that logged interactions are unbiased and noise-free. In practice, however, recommender data contain numerous spurious correlations, and this issue is exacerbated in CDR due to domain heterogeneity. To address these challenges, we propose a dataset regeneration framework. First, we leverage a prediction model to generate a pool of high-confidence candidate interactions to link non-overlapping target-domain users and source-domain items. Second, inspired by causal inference, we introduce a filtering process designed to prune spurious interactions. This process identifies and removes not only noisy edges created during generation but also those from the original dataset, retaining only the interactions that have a positive causal effect on the target-domain performance. Through these two processes, we can regenerate a source-domain dataset that exhibits a tighter coupling and a more explicit causal connection with the target domain. By integrating our method with three representative recommendation backbones—LightGCN, BiTGCF, and CUT—we show that it significantly boosts their predictive accuracy on the target domain, achieving substantial gains of up to 23.81\% in Recall@10 and 22.22\% in NDCG@10.

Core Task Landscape

This paper addresses: **Dataset Regeneration for Cross-Domain Recommendation**

A total of **26 papers** were analyzed and organized into a taxonomy with **24 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Knowledge Transfer Mechanisms**
- **User Representation Learning**
- **Data-Level Interventions**
- **Causal Inference and Debiasing**
- **Domain Bridging Strategies**
- **Privacy-Preserving Cross-Domain Methods**
- **Fairness and Non-Overlapping User Handling**
- **Cross-Domain Architectures and Benchmarking**
- **Cross-Domain Applications in Related Tasks**

Complete Taxonomy Tree

- Dataset Regeneration for Cross-Domain Recommendation Survey Taxonomy
- Knowledge Transfer Mechanisms
  - Bidirectional Transfer Architectures
  - Dual Learning and Reconstruction (2 papers)
    - [1] Ddtcdr: Deep dual transfer cross domain recommendation (Pan Li, 2020) View paper
    - [3] Cross-reconstructed Augmentation for Dual-target Cross-domain Recommendation (Qingyang Mao, 2024) View paper
  - Collaborative Cross-Networks (1 papers)
    - [6] Conet: Collaborative cross networks for cross-domain recommendation (G Hu, 2018) View paper
  - Unidirectional Transfer Architectures
  - Deep Domain Adaptation (1 papers)
    - [19] Cross-domain recommendation via deep domain adaptation (Heishiro Kanagawa, 2019) View paper
  - Tensor Factorization Methods (1 papers)
    - [17] Cross domain recommendation using multidimensional tensor factorization (Anu Taneja, 2018) View paper
  - Autoencoder-Based Transfer (1 papers)
    - [13] Dual autoencoder network with swap reconstruction for cold-start recommendation (Bei Wang, 2020) View paper
  - Multi-Target Transfer
  - Unified Multi-Domain Learning (1 papers)
    - [10] One for all, all for one: Learning and transferring user embeddings for cross-domain recommendation (Li Chenglin, 2023) View paper
  - Consistent Preference Mining (1 papers)
    - [9] Mining User Consistent and Robust Preference for Unified Cross Domain Recommendation (Xiaolin Zheng, 2024) View paper

- User Representation Learning
  - Adversarial User Representation Learning (1 papers)
  - [8] RecGURU: Adversarial learning of generalized user representations for cross-domain recommendation (Li Chenglin, 2022) View paper
  - Preference Transformation (1 papers)
  - [5] Toward equivalent transformation of user preferences in cross domain recommendation (Xu Chen, 2023) View paper
- Data-Level Interventions
  - Dataset Regeneration and Filtering ★ (1 papers)
  - [0] Dataset Regeneration for Cross Domain Recommendation (Anon et al., 2026) View paper
  - Contrastive Data Augmentation (1 papers)
  - [4] Automated Self-Supervised Learning for Recommendation (Xia, 2023) View paper
- Causal Inference and Debiasing
  - Causality-Based Enhancement (1 papers)
  - [2] Causality Enhancement for Cross-Domain Recommendation (Wu Zhibo, 2025) View paper
  - Behavioral Importance Perception (1 papers)
  - [12] Cross-domain Recommendation with Behavioral Importance Perception (Hong Chen, 2023) View paper
- Domain Bridging Strategies (1 papers)
  - [11] Domain-Oriented Knowledge Transfer for Cross-Domain Recommendation (Guoshuai Zhao, 2024) View paper
- Privacy-Preserving Cross-Domain Methods (1 papers)
  - [16] Cross-domain recommendation without sharing user-relevant data (Chen Gao, 2019) View paper
- Fairness and Non-Overlapping User Handling (1 papers)
  - [18] Leave No One Behind: Fairness-Aware Cross-Domain Recommender Systems for Non-Overlapping Users (Chen Wei-xin, 2025) View paper
- Cross-Domain Architectures and Benchmarking
  - Recommendation Libraries and Benchmarks (1 papers)
  - [21] RecBole 2.0: Towards a More Up-to-Date Recommendation Library (Zhao, 2022) View paper
  - Product-of-Experts Architectures (1 papers)
  - [24] Recommending Burgers based on Pizza Preferences: Addressing Data Sparsity with a Product of Experts (Milenkoski, 2021) View paper
  - Hashing-Based Methods (1 papers)
  - [23] Learning Similarity Preserving Binary Codes for Recommender Systems (Shi Yang, 2022) View paper
- Cross-Domain Applications in Related Tasks
  - Reinforcement Learning Transfer (2 papers)
  - [15] DmC: Nearest Neighbor Guidance Diffusion Model for Offline Cross-domain Reinforcement Learning (Nguyen Minh Hoang, 2025) View paper
  - [22] xTED: Cross-Domain Adaptation via Diffusion-Based Trajectory Editing (Niu Haoyi, 2024) View paper
  - Dialogue and QA Systems (2 papers)
  - [7] GenKI: Enhancing Open-Domain Question Answering with Knowledge Integration and Controllable Generation in Large Language Models (T Shen, 2025) View paper
  - [14] Does Collaborative Humanâ□□LM Dialogue Generation Help Information Extraction from Humanâ□□Human Dialogues? (BR Lu, 2024) View paper
  - Educational Resource Embedding (1 papers)
  - [25] Data-Driven Embedding of Educational Resources in a Vector Space with Interpretable Dimensions for Explainable Recommendation (Stenkamp, n.d.) View paper
  - Privacy and Security Analysis (1 papers)
  - [20] Privacy Risks of LLM-Empowered Recommender Systems: An Inversion Attack Perspective (Wang Yubo, 2025) View paper
  - Generative AI in Recommendation (1 papers)
  - [26] Analysis of Recommender System Using Generative Artificial Intelligence: A Systematic (KHAN, n.d.) View paper

Narrative

Core task: dataset regeneration for cross-domain recommendation. Cross-domain recommendation addresses the challenge of leveraging knowledge from multiple domains to improve recommendation quality, particularly when data in a target domain is sparse. The field's structure, as reflected in the taxonomy, spans several complementary directions. Knowledge Transfer Mechanisms and User Representation Learning focus on how to share and encode user preferences across domains, often through embedding alignment or shared latent spaces. Data-Level Interventions and Dataset Regeneration and Filtering emphasize direct manipulation of training data—augmenting, filtering, or synthesizing samples to bridge domain gaps. Causal Inference and Debiasing tackle selection bias and confounding, while Domain Bridging Strategies and Privacy-Preserving Cross-Domain Methods address the practical challenges of aligning heterogeneous data sources and protecting user information. Fairness and Non-Overlapping User Handling, along with Cross-Domain Architectures and Benchmarking, round out the landscape by ensuring equitable treatment of diverse user groups and providing standardized evaluation frameworks.

Within Data-Level Interventions, a handful of works explore how to regenerate or augment datasets to improve cross-domain transfer. Cross-reconstructed Augmentation[3] and Automated Self-Supervised[4] methods generate synthetic samples or augment existing data to enrich sparse domains, while Equivalent Transformation[5] reframes data to facilitate transfer. Dataset Regeneration[0] sits squarely in this cluster, emphasizing the creation of new training instances tailored to cross-domain scenarios. Compared to Cross-reconstructed Augmentation[3], which focuses on reconstruction-based augmentation, Dataset Regeneration[0] may adopt a more direct synthesis or filtering strategy. Meanwhile, Causality Enhancement[2] and Deep Dual Transfer[1] illustrate adjacent themes—causal reasoning and dual-network architectures—that complement data regeneration by addressing why and how to transfer knowledge. The interplay between data augmentation, causal modeling, and architectural design remains an active area, with open questions about the optimal balance between synthetic data quality and transfer effectiveness.

Related Works in Same Category

No sibling papers were found in the same taxonomy leaf. A taxonomy-subtopic-level comparison will be produced instead.

Taxonomy-Level Summary

Both subtopics address data quality and enhancement challenges in cross-domain recommendation systems, but through fundamentally different mechanisms. Dataset Regeneration and Filtering focuses on creating causally-valid training data by generating candidate interactions and removing spurious correlations, while Contrastive Data Augmentation employs self-supervised contrastive learning techniques to augment existing data. The two approaches are complementary: one emphasizes causal validity and filtering, the other emphasizes representation learning through augmentation.

Similarities: - Both aim to improve recommendation model performance by enhancing training data quality - Both address limitations in existing datasets for cross-domain recommendation scenarios - Both can be considered preprocessing or data preparation techniques that operate before model training

Differences: - Dataset Regeneration creates new candidate interactions and filters based on causal principles, while Contrastive Augmentation transforms existing data through self-supervised learning - Dataset Regeneration explicitly targets spurious correlations and causal connections, while Contrastive Augmentation focuses on learning robust representations through positive/negative sample pairs - Dataset Regeneration is a filtering/generation pipeline, while Contrastive Augmentation is a learning-based augmentation approach - The original leaf excludes contrastive methods by design, indicating a methodological boundary between causal filtering and representation-based augmentation

Suggested Search Directions: - Hybrid approaches combining causal filtering with contrastive learning for cross-domain recommendation - Evaluation frameworks comparing causal regeneration versus contrastive augmentation effectiveness - Sequential pipelines applying dataset regeneration followed by contrastive augmentation

Sibling Subtopics

- **Contrastive Data Augmentation** (leaves: 1, papers: 1)
- Scope: Automated self-supervised learning approaches using contrastive methods for data augmentation in recommendation.
- Exclude: Excludes causal filtering and dataset regeneration; see Dataset Regeneration and Filtering.

Contributions Analysis

Overall novelty summary. The paper proposes a dataset regeneration framework for cross-domain recommendation that addresses sparse overlap and negative transfer through a generate-and-filter approach. It sits in the 'Dataset Regeneration and Filtering' leaf under 'Data-Level Interventions', where it is currently the sole paper. This positioning reflects a relatively sparse research direction within the broader taxonomy, which contains 26 papers across multiple branches. The work's focus on data-level manipulation distinguishes it from the more populated 'Knowledge Transfer Mechanisms' branch, which emphasizes architectural designs for embedding alignment and latent space sharing.

The taxonomy reveals neighboring directions that contextualize this work. 'Contrastive Data Augmentation' (one paper) explores self-supervised augmentation methods, while 'Causal Inference and Debiasing' (two papers) addresses bias through causal modeling. The 'Knowledge Transfer Mechanisms' branch is more densely populated with bidirectional and unidirectional architectures (seven papers total), suggesting that model-level transfer has received more attention than data-level interventions. The paper's dual emphasis on generation and causal filtering bridges these areas, connecting data augmentation with causal reasoning in a way that appears less explored in the current taxonomy structure.

Among 22 candidates examined, the self-supervised generation module (Contribution 2) shows potential overlap with one prior work among four candidates reviewed. The generate-and-filter framework (Contribution 1) and counterfactual filtering process (Contribution 3) examined eight and ten candidates respectively, with no clear refutations found. These statistics suggest that while the generation component may have precedent in limited prior work, the overall framework combining generation with causal filtering appears less directly addressed in the examined literature. The modest search scope (22 papers) means these findings reflect top-K semantic matches rather than exhaustive coverage.

Based on the limited search scope, the work appears to occupy a relatively underexplored intersection of data augmentation and causal filtering for cross-domain recommendation. The taxonomy structure confirms that data-level interventions receive less attention than architectural approaches, and the paper's position as the sole occupant of its leaf suggests a distinct methodological angle. However, the single refutable candidate for the generation module indicates that components of the approach may connect to existing augmentation techniques, warranting careful positioning relative to prior data synthesis methods.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: Generate-and-filter dataset regeneration framework for CDR

Description: The authors introduce a data-level framework that addresses sparse overlap and negative transfer in cross-domain recommendation by regenerating the source dataset. This framework operates through two processes: generating high-confidence candidate interactions and filtering spurious interactions using causal inference principles.

This contribution was assessed against **8 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Identifiability of cross-domain recommendation via causal subspace disentanglement

URL: View paper

Brief Assessment

Causal Subspace[30] addresses negative transfer through model-level causal subspace disentanglement of user representations, not through dataset regeneration. The original paper operates at the data level by regenerating source datasets, while this candidate focuses on representation learning and feature hierarchy.

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2. Exploring false hard negative sample in cross-domain recommendation

URL: View paper

Brief Assessment

False Hard Negative[28] focuses on negative sampling strategies to filter false hard negatives during training, not on regenerating source datasets to address sparse overlap and negative transfer through causal inference-based edge filtering.

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3. Cross-reconstructed Augmentation for Dual-target Cross-domain Recommendation

URL: View paper

Brief Assessment

Cross-reconstructed Augmentation[3] focuses on data augmentation through cross-reconstructed representations and domain alignment techniques, not on dataset regeneration via generation-and-filtering of interactions using causal inference principles.

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4. Joint Identifiability of Cross-Domain Recommendation via Hierarchical Subspace Disentanglement

URL: View paper

Brief Assessment

Hierarchical Subspace[32] focuses on hierarchical subspace disentanglement for joint identifiability in cross-domain recommendation, not on dataset regeneration frameworks that generate and filter interactions to address sparse overlap and negative transfer.

5. Counterfactual Learning-Driven Representation Disentanglement for Search-Enhanced Recommendation

URL: View paper

Brief Assessment

Counterfactual Representation[31] focuses on search-enhanced recommendation by disentangling query-independent item features from search behaviors to address negative transfer between search and recommendation domains. The original paper addresses cross-domain recommendation (CDR) with sparse overlap and negative transfer through dataset regeneration. These are fundamentally different problem settings and methodological approaches.

6. A Unified Framework for Cross-Domain and Cross-System Recommendations

URL: View paper

Brief Assessment

Unified Framework[29] focuses on cross-domain recommendation through graph embedding and attention mechanisms for combining user/item embeddings across domains, not on dataset regeneration or causal filtering of interactions as in the original paper.

7. Leave No One Behind: Fairness-Aware Cross-Domain Recommender Systems for Non-Overlapping Users

URL: View paper

Brief Assessment

Fairness-Aware[18] focuses on generating virtual users to address fairness bias for non-overlapping users, not on dataset regeneration with causal filtering to mitigate negative transfer and sparse overlap.

8. A Collaborative Transfer Learning Framework for Cross-domain Recommendation

URL: View paper

Brief Assessment

Collaborative Transfer[27] addresses cross-domain recommendation through transfer learning at the model level (evaluating information gain, adjusting transfer weights), not through dataset regeneration. The original paper's data-level framework that generates candidate interactions and filters spurious edges using causal inference is fundamentally different from Collaborative Transfer[27]'s model-centric approach.

Contribution 2: Self-supervised generation module for synthetic interactions

Description: A self-supervised prediction model is pretrained to generate synthetic interactions in the source domain for users who only appear in the target domain. This augments cross-domain connections by creating a pool of high-confidence candidate interactions that bridge the domain gap.

This contribution was assessed against **4 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Cross-domain transfer of valence preferences via a meta-optimization approach

URL: View paper

Brief Assessment

Valence Meta-Optimization[34] focuses on sampling pseudo-interaction items using pre-trained models and item popularity to ensure distribution integrity, rather than generating synthetic interactions specifically for non-overlapping users to bridge domain gaps as in the original paper's self-supervised prediction model approach.

2. An empirical investigation of commonsense self-supervision with knowledge graphs

URL: View paper

Brief Assessment

Commonsense Self-Supervision[35] focuses on generating synthetic question-answer pairs from knowledge graphs for language model adaptation in commonsense reasoning tasks, not on generating synthetic user-item interactions for cross-domain recommendation systems. The domains, tasks, and technical approaches are fundamentally different.

3. Self-Supervised Cross Domain Social Recommendation

URL: View paper

Brief Assessment

Self-Supervised Social[33] focuses on cold-start social recommendation using heterogeneous graphs combining social and information domains, not on generating synthetic interactions for non-overlapping users in cross-domain recommendation systems.

4. Leave No One Behind: Fairness-Aware Cross-Domain Recommender Systems for Non-Overlapping Users

URL: View paper

Prior Art Analysis

Fairness-Aware[18] demonstrates prior work on generating synthetic interactions for non-overlapping users in cross-domain recommendation. The candidate paper explicitly proposes 'a novel solution that generates virtual source-domain users for non-overlapping target-domain users' using a dual attention mechanism to synthesize realistic virtual user embeddings. This directly addresses the same problem space as the original paper's self-supervised generation module, which creates synthetic interactions for users who only appear in the target domain. Both approaches aim to augment cross-domain connections by creating representations that bridge the domain gap for non-overlapping users.

Evidence

Evidence 1 - **Rationale**: Both approaches learn from overlapping users to generate representations for non-overlapping users, showing the candidate paper proposed this technique for the same purpose. - **Original**: to address this issue, we let the model learn from the behavior patterns of existing overlapping users of both domains and then predict the potential behaviors of users who have no interactions in one of the domains. - **Candidate**: our method utilizes a dual attention mechanism to discern similarities between overlapping and non-overlapping users, thereby synthesizing realistic virtual user embeddings.

Contribution 3: Counterfactual filtering process for causal interaction identification

Description: The authors develop a filtering mechanism inspired by causal inference that uses counterfactual evaluation to identify which source-domain interactions have genuine causal effects on target-domain performance. This process removes both noisy generated edges and spurious correlations from the original dataset.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. A Counterfactual Neural Causal Model for Interactive Recommendation

URL: View paper

Brief Assessment

Interactive Causal Model[45] focuses on counterfactual evaluation for preference transitions in interactive recommendation systems, not on filtering source-domain interactions for cross-domain recommendation tasks.

2. Learning from counterfactual links for link prediction

URL: View paper

Brief Assessment

Counterfactual Links[36] focuses on link prediction in graphs by creating counterfactual links to answer 'what-if' questions about edge existence under different graph structures. The original paper addresses cross-domain recommendation by filtering source-domain interactions based on their causal impact on target-domain performance. These are fundamentally different applications and methodologies.

3. Integrating Deep Learning and Counterfactual Methods for Causal Inference in Genomics

URL: View paper

Brief Assessment

Genomics Causal[43] applies counterfactual reasoning to genomic disease prediction tasks, focusing on identifying causal links between genomic features and disease outcomes. The original paper's counterfactual filtering targets cross-domain recommendation interactions to improve target-domain performance, which is a fundamentally different application domain and technical problem.

4. Causal inference and counterfactual prediction in machine learning for actionable healthcare

URL: View paper

Brief Assessment

Actionable Healthcare[39] discusses general counterfactual inference in healthcare machine learning contexts, not a filtering mechanism for identifying causal interactions in cross-domain recommendation datasets. The candidate focuses on healthcare prediction rather than dataset regeneration for recommendation systems.

5. Domain Counterfactual Data Augmentation for Explainable Recommendation

URL: View paper

Brief Assessment

Domain Counterfactual[38] focuses on counterfactual data augmentation for explainable recommendation to address text degeneration issues, not on filtering source-domain interactions to identify causal effects on target-domain performance in cross-domain recommendation systems.

6. SCGAN: Sparse CounterGAN for counterfactual explanations in breast cancer prediction

URL: View paper

Brief Assessment

SCGAN[40] focuses on generating counterfactual explanations for breast cancer prediction using GANs, not on filtering source-domain interactions for cross-domain recommendation. The candidate addresses counterfactual generation for medical diagnosis, while the original paper addresses dataset regeneration for recommendation systems.

7. Selecting among counterfactual methods to evaluate conservation interventions

URL: View paper

Brief Assessment

Conservation Interventions[37] focuses on evaluating conservation policies using counterfactual methods to compare observed outcomes with hypothetical scenarios. The original paper develops a filtering mechanism for cross-domain recommendation that removes noisy interactions in datasets. These are fundamentally different application domains (conservation vs. recommendation systems) with distinct technical approaches and objectives.

8. When AI meets counterfactuals: the ethical implications of counterfactual world simulation models

URL: View paper

Brief Assessment

AI Counterfactual Ethics[41] focuses on ethical frameworks for counterfactual world simulation models in legal/forensic contexts (e.g., traffic accidents), not on filtering mechanisms for cross-domain recommendation systems or identifying causal interactions in datasets.

9. Variational counterfactual prediction under runtime domain corruption

URL: View paper

Brief Assessment

Runtime Domain Corruption[42] focuses on counterfactual evaluation for handling domain shift and missing variables during runtime inference in causal effect estimation, not on filtering source-domain interactions to improve cross-domain recommendation performance.

10. Counterfactual invariance to spurious correlations in text classification

URL: View paper

Brief Assessment

Counterfactual Invariance[44] focuses on text classification with counterfactual invariance to spurious correlations in features (e.g., sentiment, genre), not on filtering interactions in cross-domain recommendation systems. The candidate addresses a fundamentally different problem domain (NLP classification vs. recommendation systems) and does not demonstrate prior work on filtering source-domain interactions for target-domain performance improvement.

Appendix: Text Similarity Detection

No high-similarity text segments were detected across any compared papers.

References

- [0] Dataset Regeneration for Cross Domain Recommendation View paper
- [1] Ddtcdr: Deep dual transfer cross domain recommendation View paper
- [2] Causality Enhancement for Cross-Domain Recommendation View paper
- [3] Cross-reconstructed Augmentation for Dual-target Cross-domain Recommendation View paper
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- [42] Variational counterfactual prediction under runtime domain corruption View paper
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