Dual Autoencoder Network with Swap Reconstruction for Cold-Start Recommendation

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Outline

- Background
- Our Approach
- Experiments

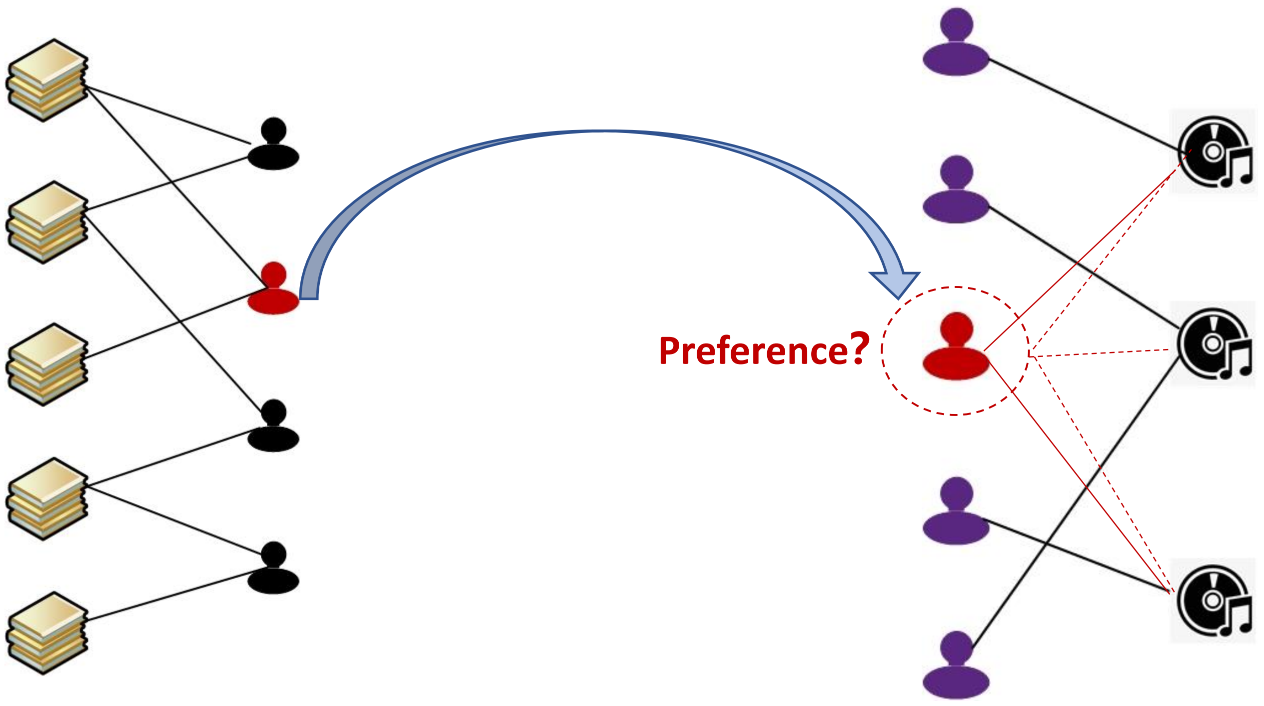
Background

Cross-domain Recommendation

- Challenge

  Cold-start issue in recommendation

Transfer and share user preference among different domains



Background

➢ Motivation

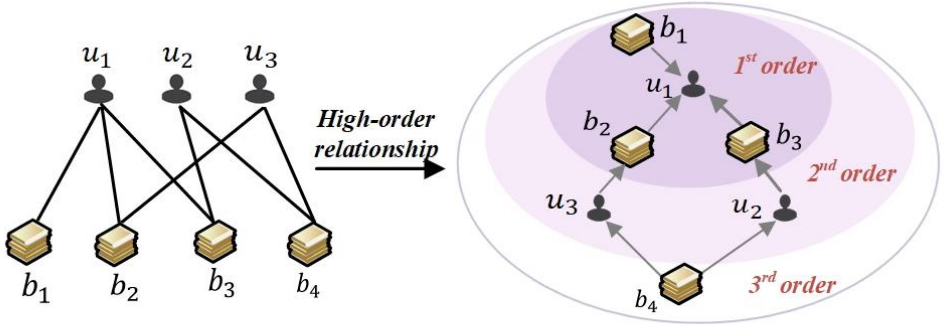
Limitations of existing methods

- Two-stage embedding-and-mapping framework, not in an end-to-end manner

⟶ not optimized for the cross-domain recommendation objective, leading to suboptimal representation

⟶ time-consuming

- Insufficiently model the high-order structural information
- Only leverage the data of source domain to learn a mapping function



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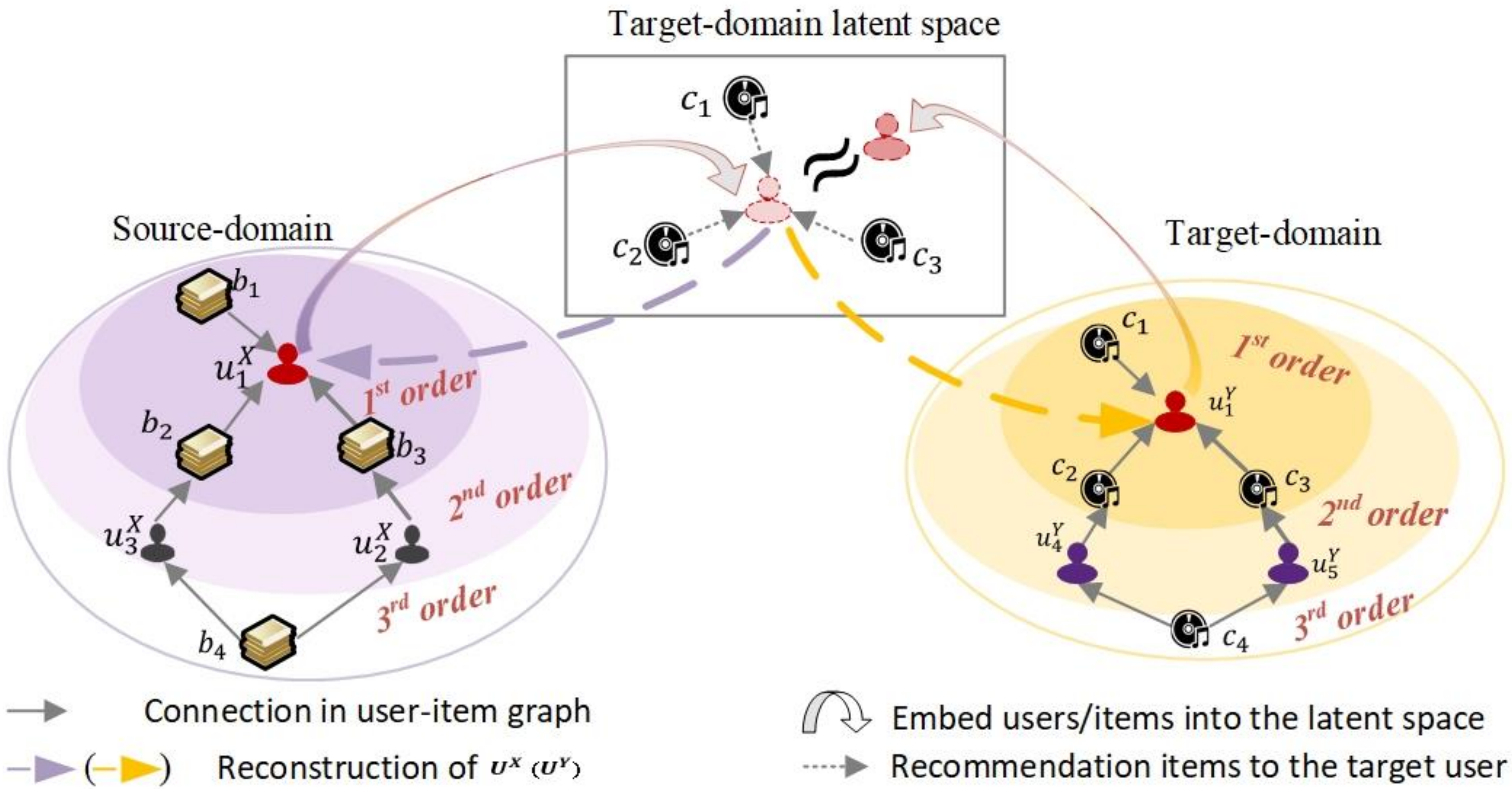
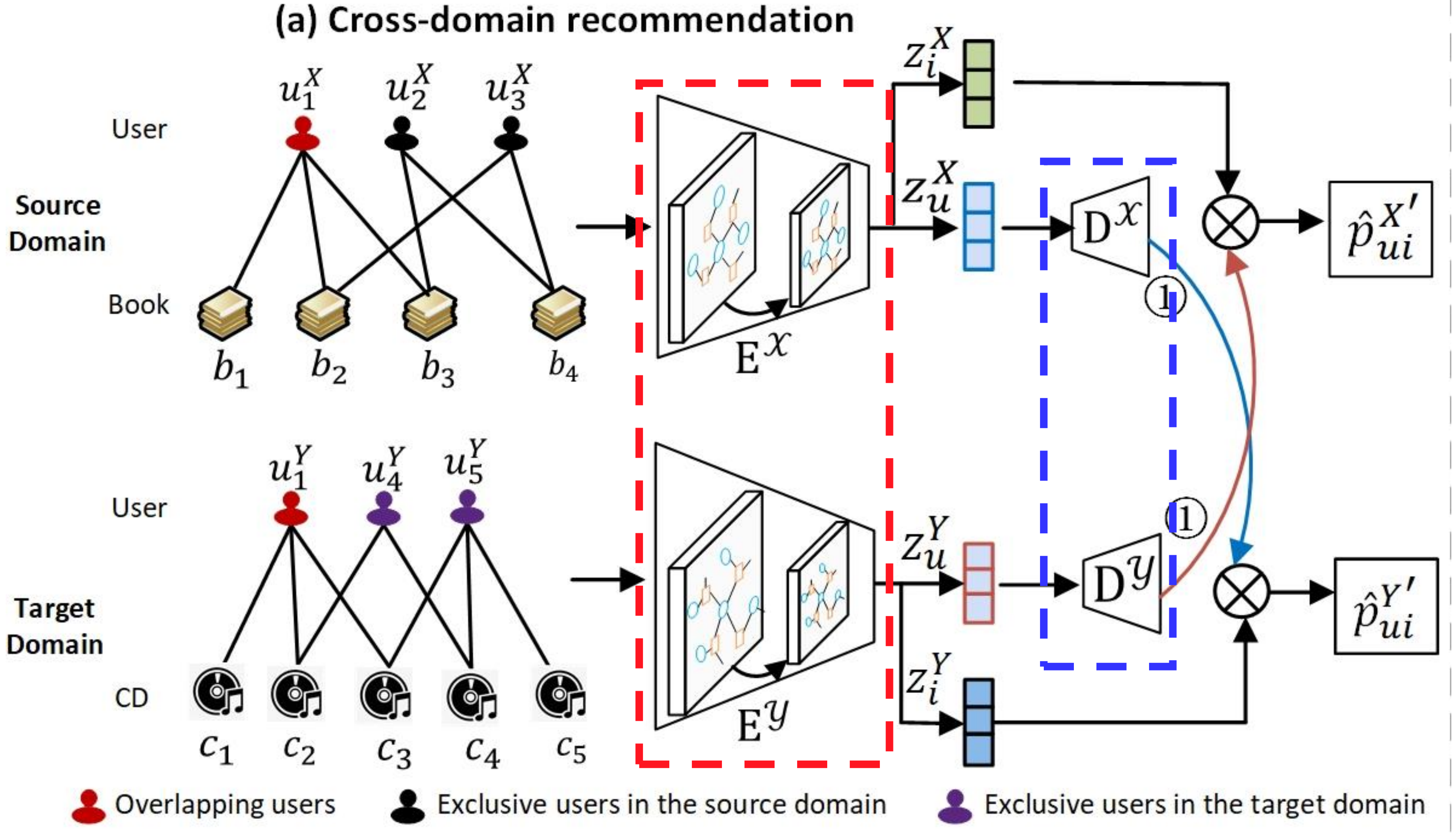
Overview

- Capture the high-order collaborative information for user preference learning
- Transfer the representations close to the ground-truth in the target latent space



Dual Autoencoder Network (DAN)

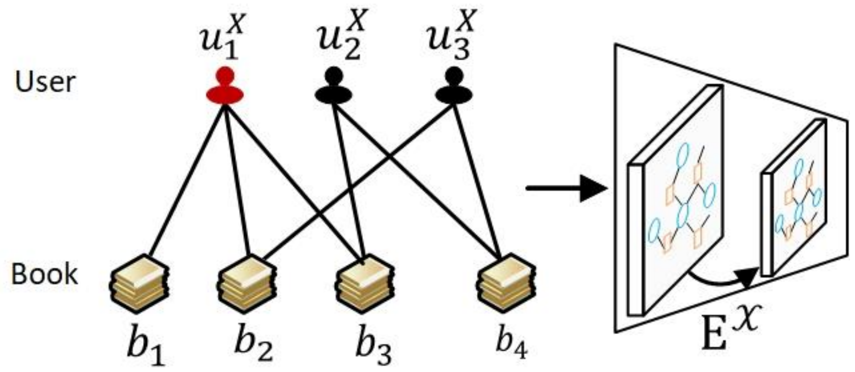
- Encoder
  - Learns the latent representation of users/items in each domain
- Decoder
  - Two-branched
  - Transfers users under a domain swapping strategy



GCN-based Encoder

Updated representation

$$Z^{(l)} = LeakyReLU\left(\widetilde{D}^{-1}\tilde{A}Z^{(l-1)}W_g\right) \tag{1}$$



Optimizing representation of each domain

$$\mathcal{L}^X = \sum_{(u,i,i')\in\mathcal{R}^{\mathcal{X}}} -ln\sigma(z_u^T z_i - z_u^T z_{i'}) + \lambda\|\Theta\|_2^2 \tag{2}$$

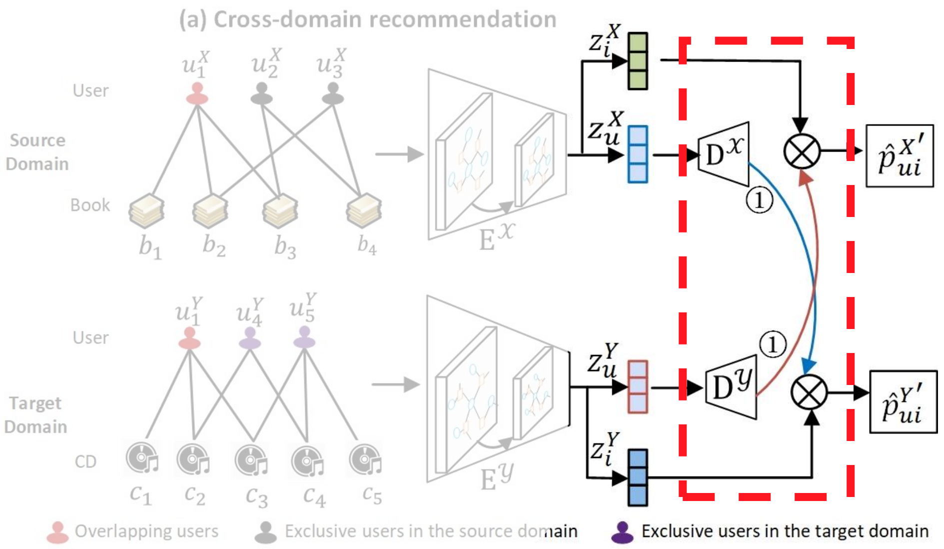
Two-Branched Decoder

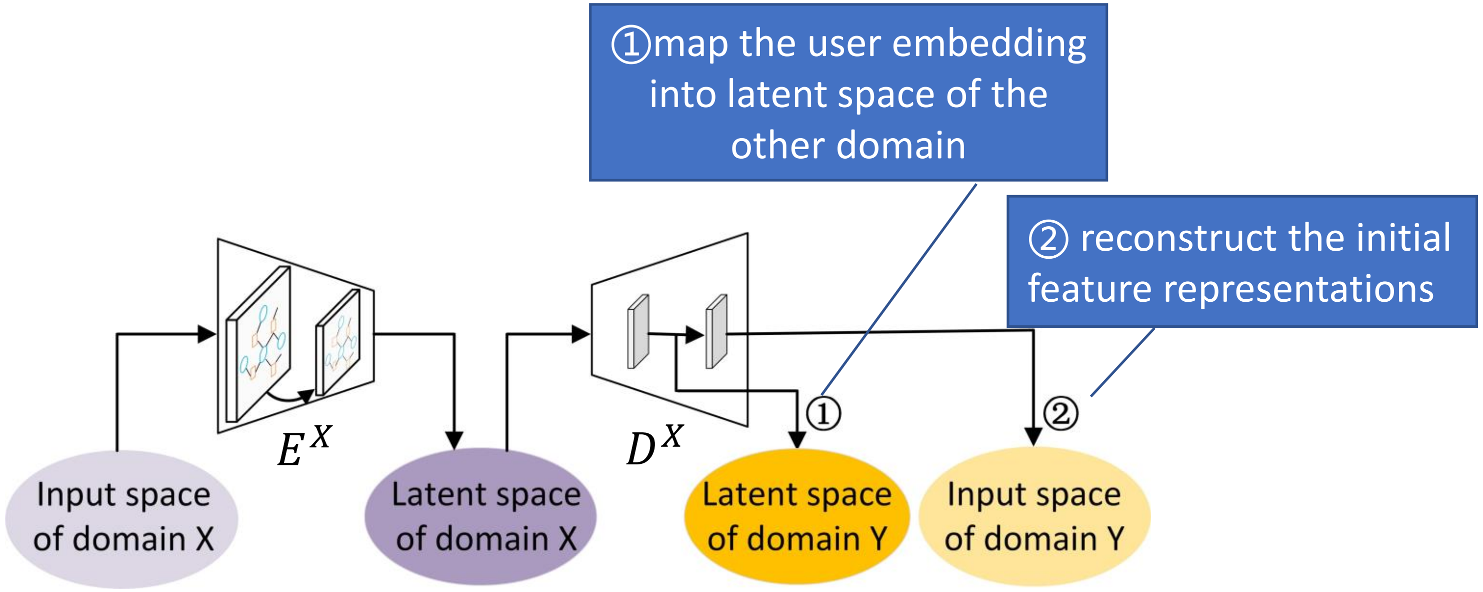
The output of the first branch

$$z_u^{Y'} = W_{d1}^T\left(Tanh\left(W_{d2}^T z_u^X + b_{d2}\right)\right) + b_{d1} \qquad (3)$$

The output of the second branch

$$\tilde{u}^Y = D^X(z_u^X) = W_{d3}Tanh\left(z_u^{Y'}\right) + b_{d3} \qquad (4)$$





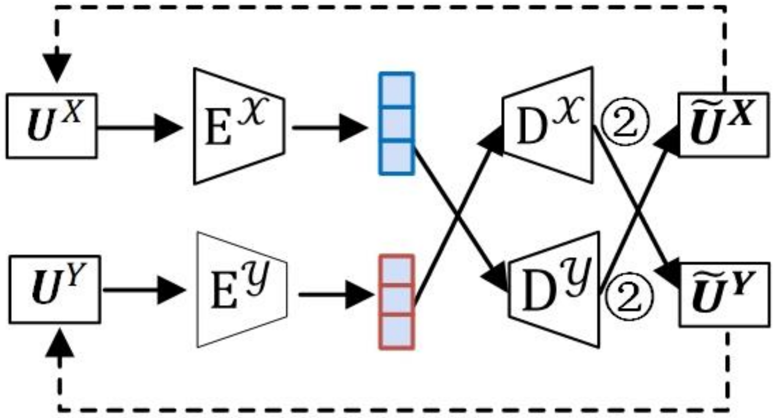
Reconstruction Constrains

Paired reconstruction loss

$$\mathcal{L}_p^X = \sum_{u \in \mathcal{U}^O} \| D^X(z_u^X) - \mathrm{u}^Y \|_2^2 \qquad (5)$$

Swap loss of the cross-domain reconstruction

$$\mathcal{L}_s^X = \sum_{u \in \mathcal{U}^O} \| D^Y(z_u^X) - \mathrm{u}^X \|_2^2 \qquad (6)$$



Note: $D^X(\cdot)$ or $D^Y(\cdot)$ is the output of the branch ②.

Cold-Start Recommendation

Prediction score

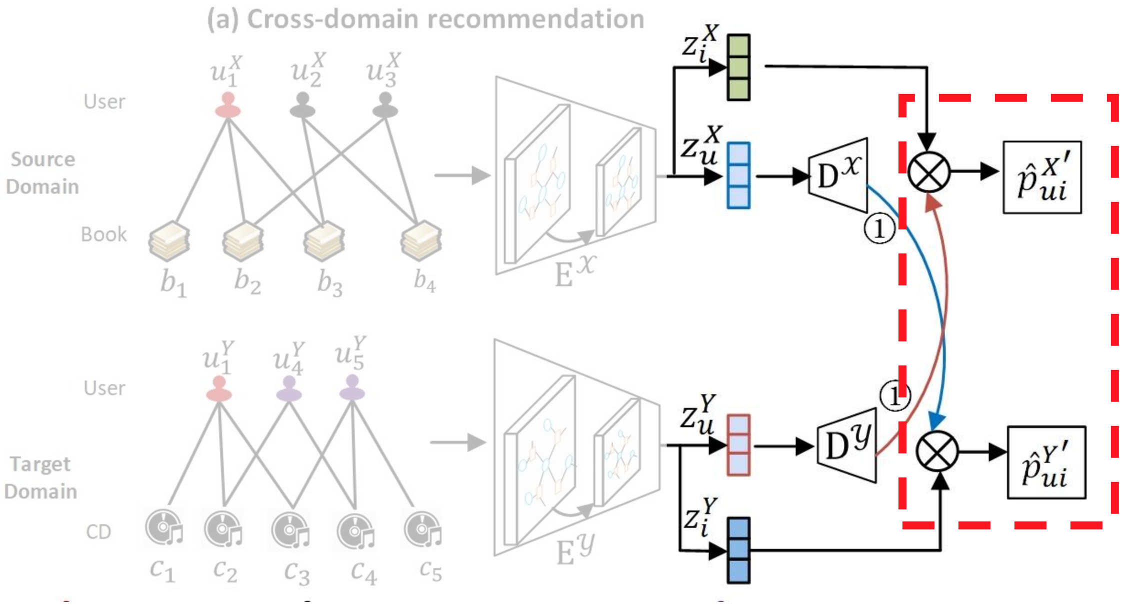
$$\hat{p}_{ui}^{Y'} = z_u^{Y'} \cdot z_i^{Y} \tag{7}$$

Cross-domain recommendation objective

$$\mathcal{L}^{X2Y} = \sum_{u \in \mathcal{U}^O} -ln\sigma\left(\hat{p}_{ui}^{Y'} - \hat{p}_{ui'}^{Y'}\right) + \lambda \|\Theta\|_2^2 \tag{8}$$

Objective of the whole bi-directional model

$$\mathcal{L} = (\mathcal{L}^X + \mathcal{L}^Y) + (\mathcal{L}^{X2Y} + \mathcal{L}^{Y2X}) + \left(\mathcal{L}_p^X + \mathcal{L}_p^Y\right) + (\mathcal{L}_s^X + \mathcal{L}_s^Y) \tag{9}$$



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Experiments

- Datasets

Table 1: Statistics of two cross-domain scenarios (Inter. denotes interactions and Overlap. denotes overlapping users)

Datasets	#Users	#Items	#Inter	density	#Overlap
Books	10,040	22,044	672,664	0.30%	5,739
CDs and Vinly	6,557	7,433	178,905	0.37%	
CDs and Vinly	10,992	14,680	185,041	0.11%	2,397
Movies and TV	10,514	8,184	149,480	0.17%	

Experiments

- Results

Table2: Cold-start recommendation performances of two cross-domain scenarios.

Dataset	Metrics	EMCDR-BPR	SSCDR	**DAN**
Books CDs and Vinly	HR@10	0.0959	0.1143	**0.1459**
	HR@20	0.1184	0.1353	**0.1728**
	NDCG@10	0.0921	0.1137	**0.1417**
	NDCG@20	0.1006	0.1206	**0.1508**
CDs and Vinly Movie	HR@10	0.2249	0.2565	**0.2864**
	HR@20	0.2713	0.3019	**0.3353**
	NDCG@10	0.2314	0.2632	**0.2941**
	NDCG@20	0.2507	0.2814	**0.3134**

✓ Model high-order collaborative information

✓ Directly leverage cross-domain recommendation objective

✓ Mutually enhances the domain data with designed reconstruction constraints

Thanks!

Q&A