

# One for All, All for One: Learning and Transferring User Embeddings for Cross-Domain Recommendation

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1. University of Alberta, AB, Canada

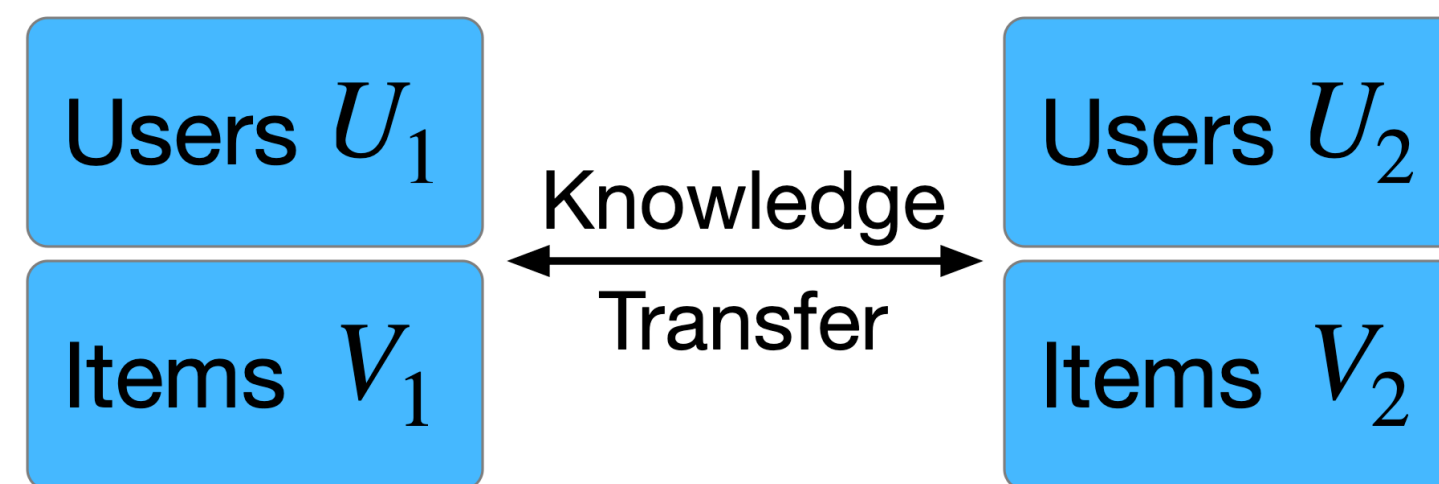
2. Platform and Content business group, Tencent, Shenzhen, China

3. Sun Yat-sen University, Shenzhen, China

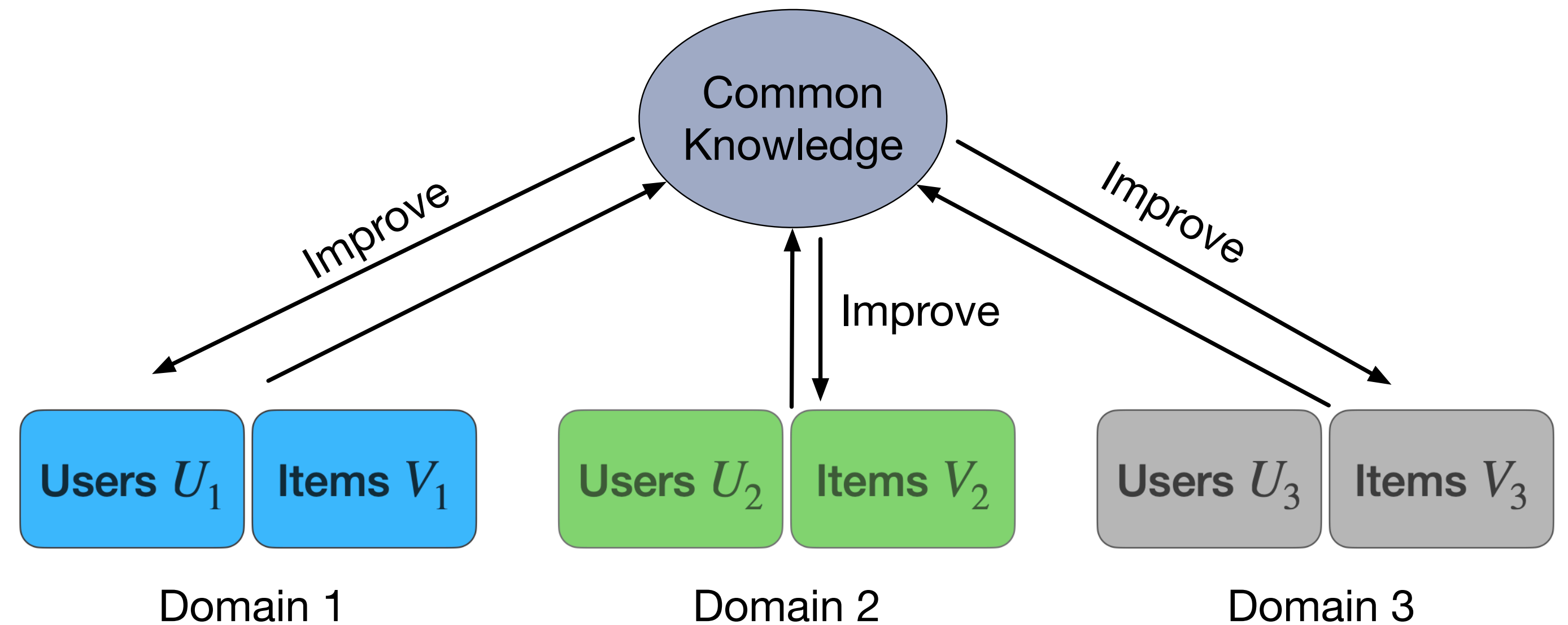
Presented by: Chenglin Li

# Multi-target CDR

- Multiple domains ( $\geq 3$ )
- Boost recommendations in all domains simultaneously



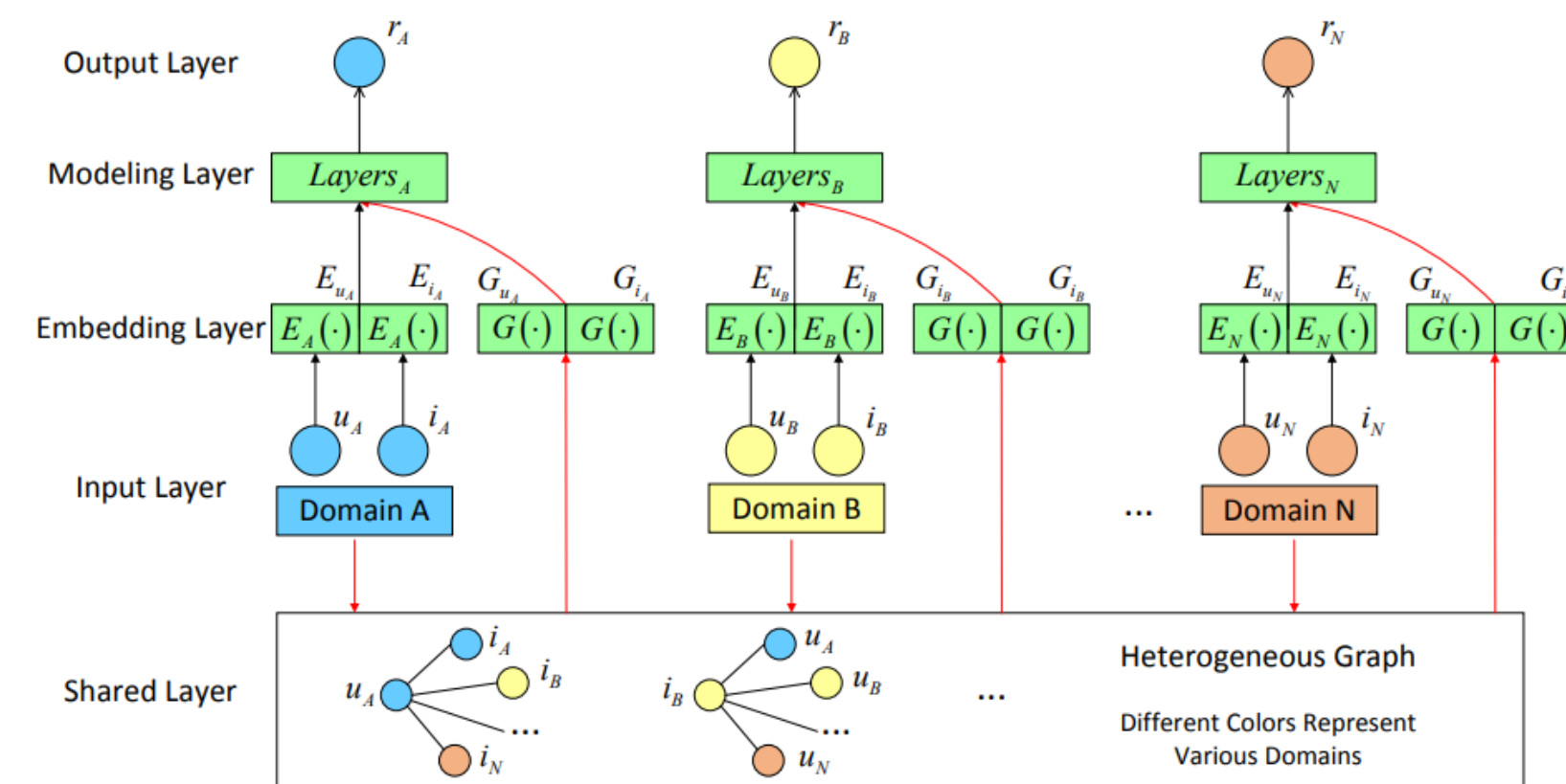
**CDR**



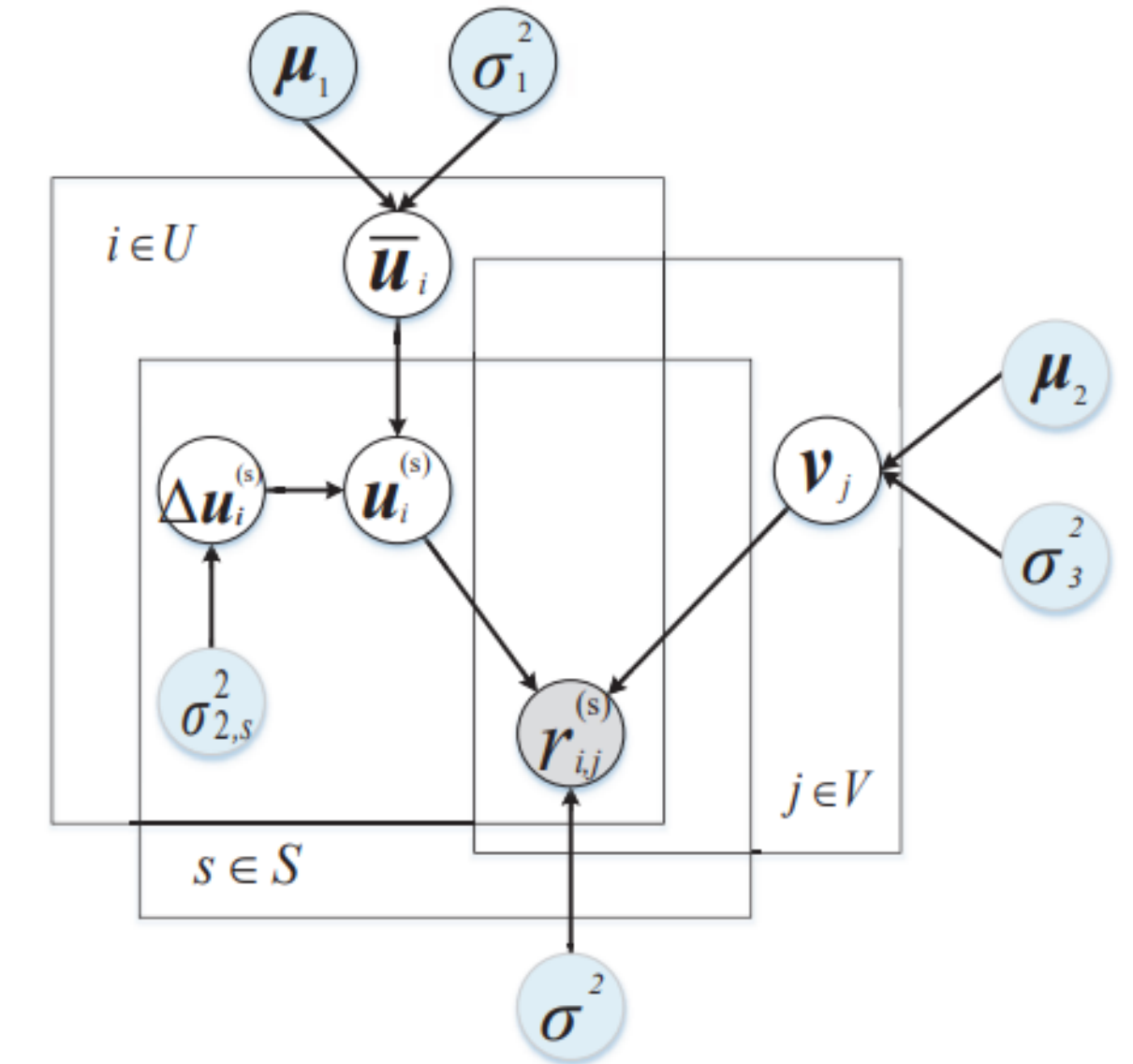
**MTCDR**

# Previous Methods

- Global representation
- Joint training
- Sharing of raw data



**HeroGraph<sup>1</sup>**

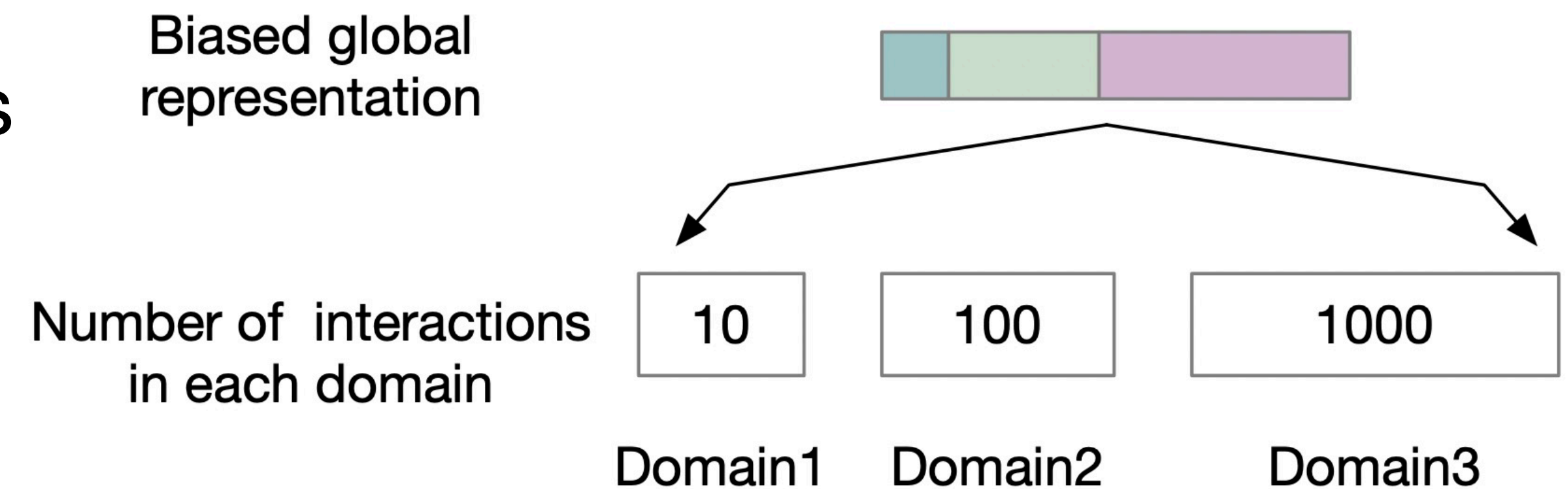
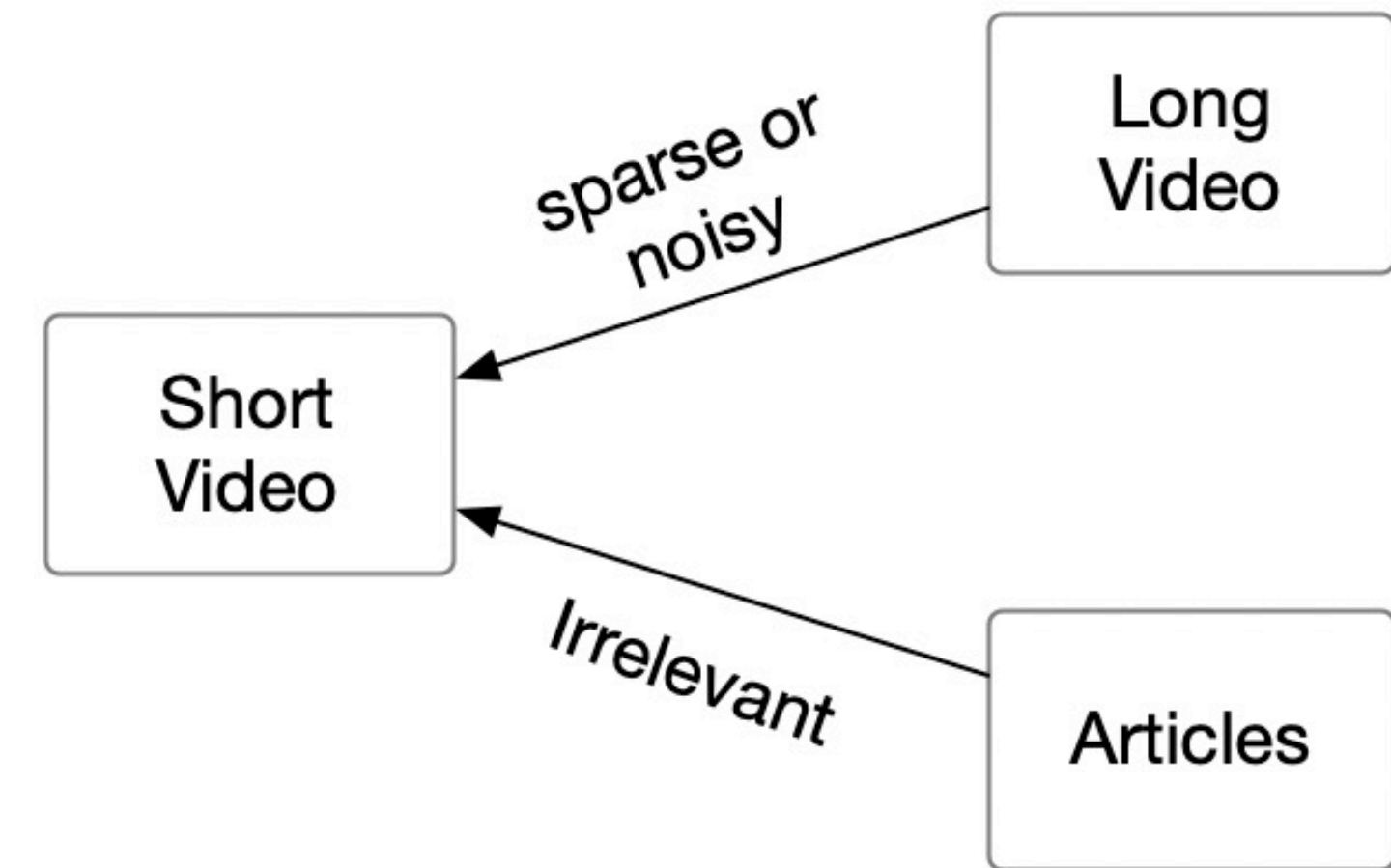


**MPF<sup>2</sup>**

[1]HeroGRAPH: A Heterogeneous Graph Framework for Multi-Target Cross-Domain Recommendation  
[2]Multi-site User Behavior Modeling and Its Application in Video Recommendation

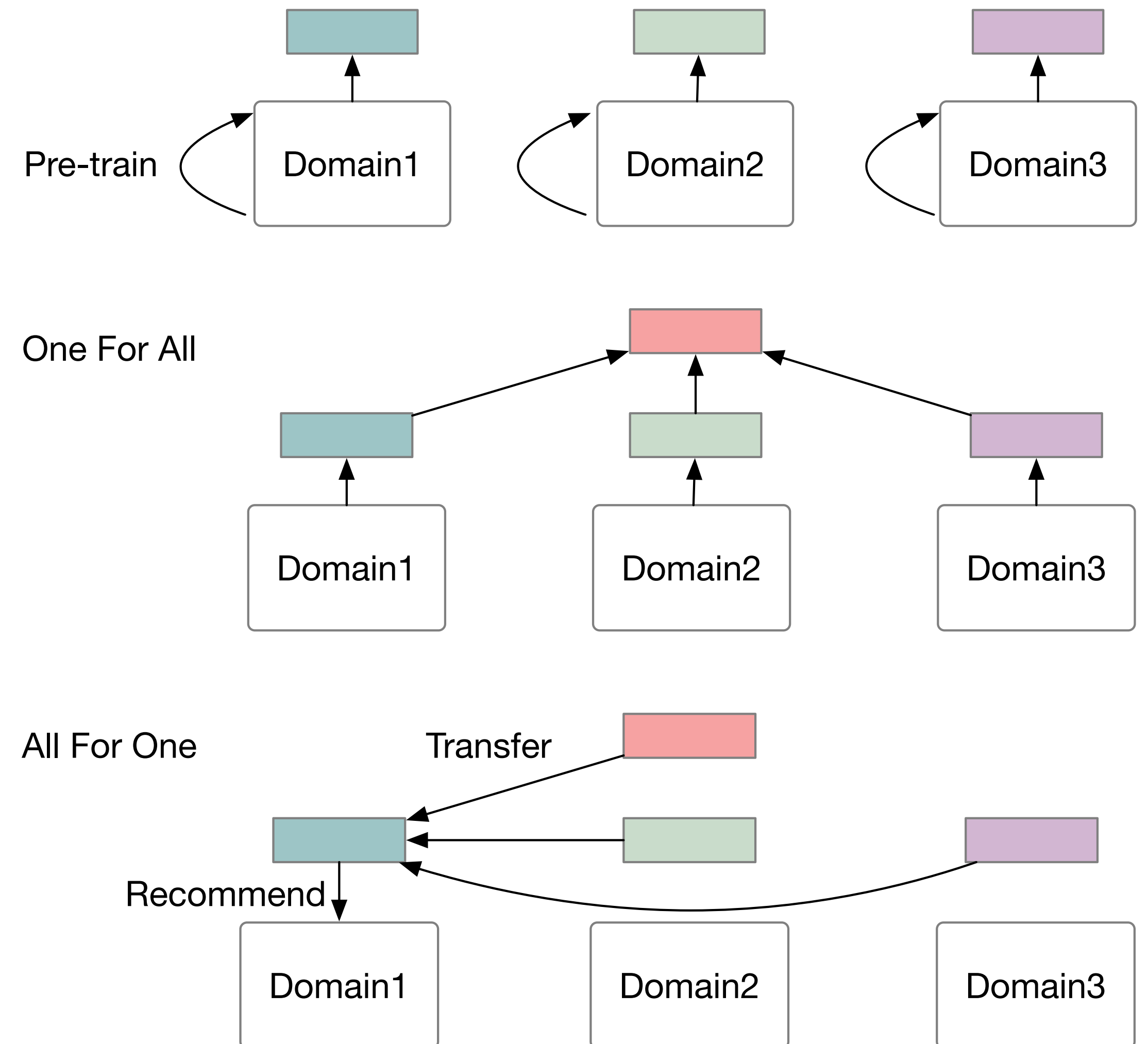
# MTCDR: Challenges

- Negative transfer
  - Irrelevant or noisy information
- Biased global representation
  - Data unbalance between domains
  - Biased towards dense domain
- Data privacy



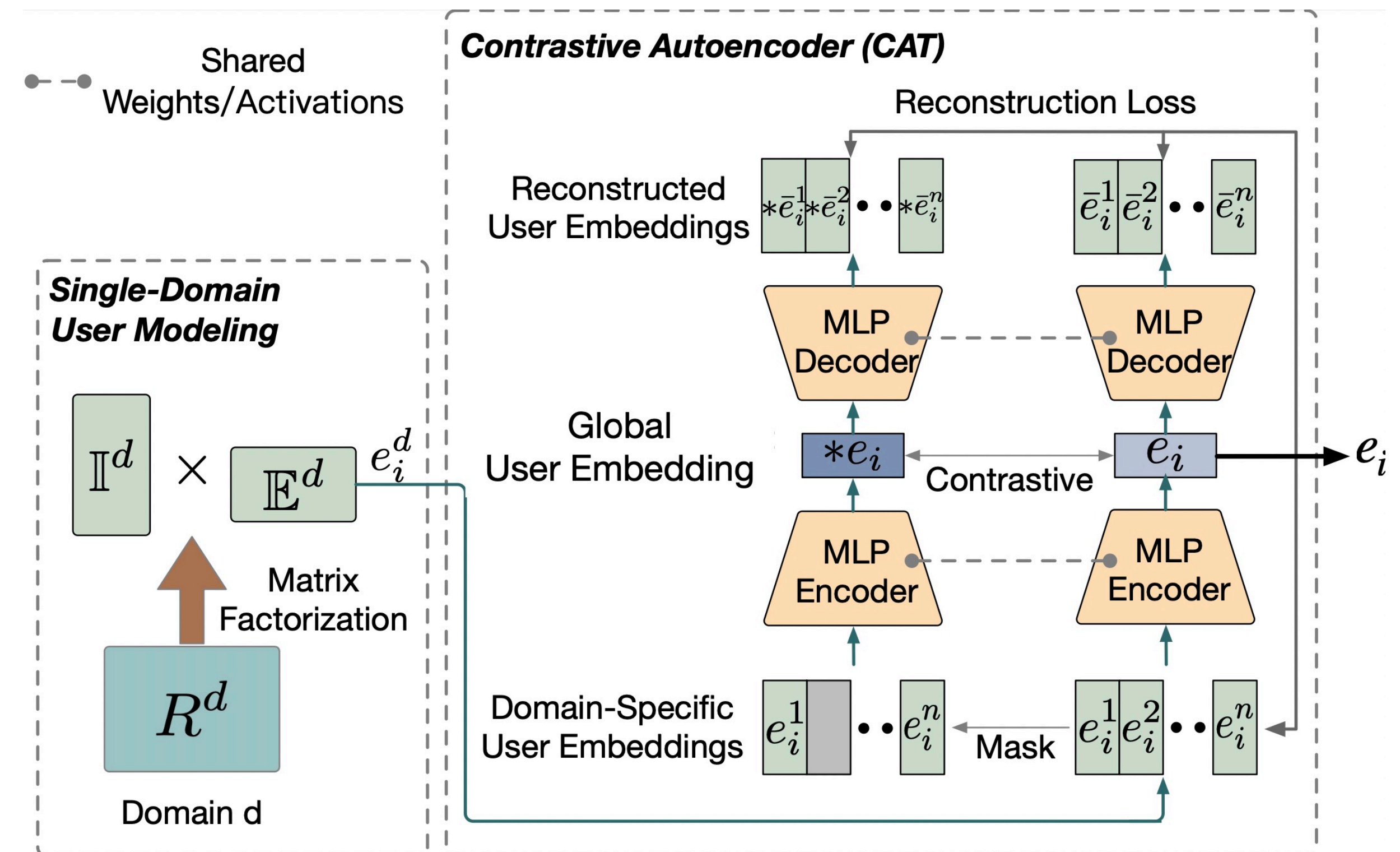
# Proposed Method

- Overview
  - Pre-train in a single domain
    - Share latent user embedding
- One For All
  - Extract unbiased global representation
- All For One
  - Transfer all useful features to help recommend in the target domain



# One For All

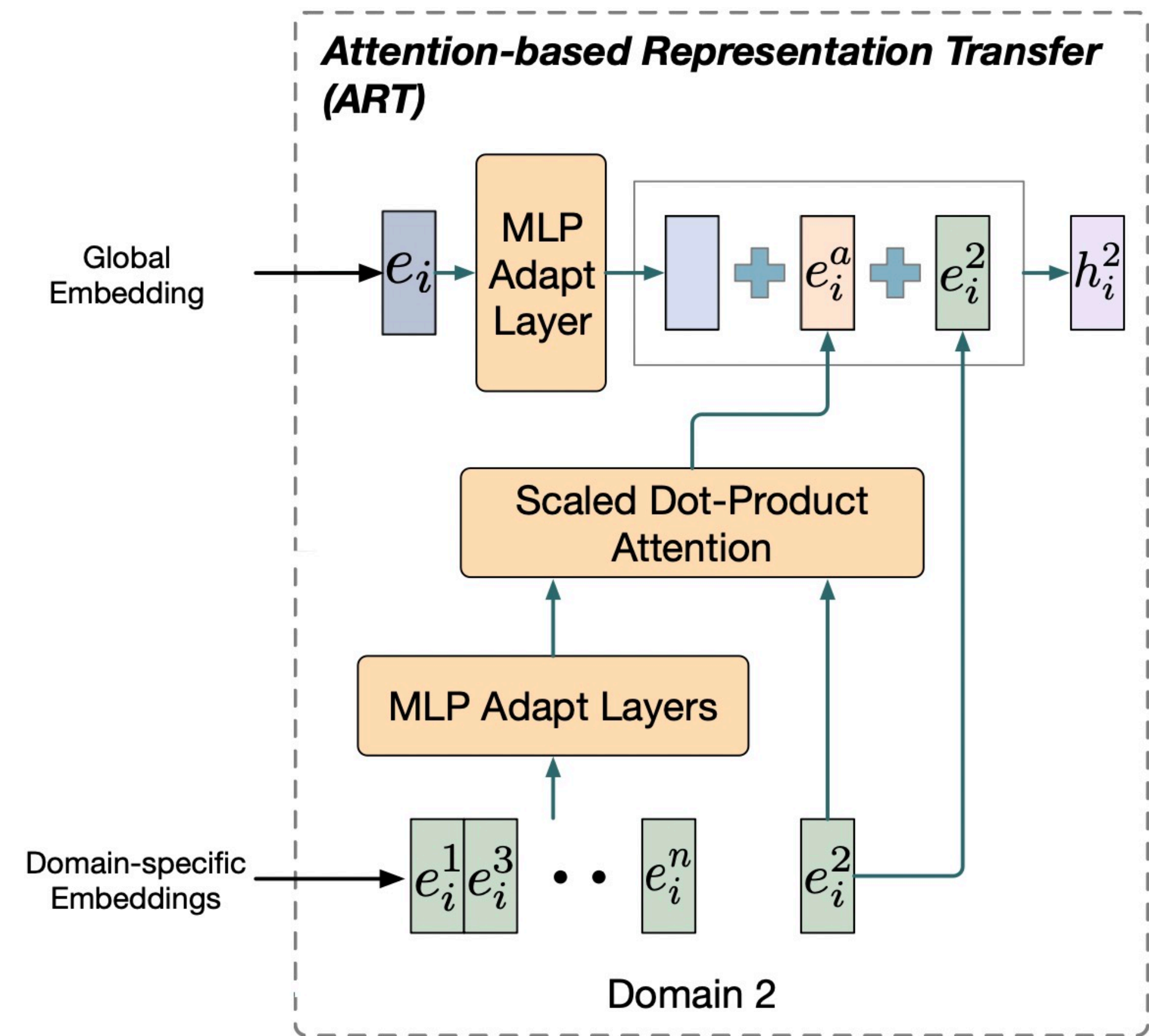
- Global user representation
  - AutoEncoder
- Unbiased global representation
  - Contrastive AutoEncoder (CAT)
    - Randomly mask out one domain





# All For One

- All available features are transferred
- Final user embedding
  - Target domain-specific features
  - Unbiased global embedding
  - Source domain-specific features
- Attention-based representation transfer (ART)



# Model Training

- Loss
  - BPR loss
  - Reconstruction (MSE)
  - Contrastive (Cross-entropy)
- Training scheme

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**Algorithm 1:** CAT-ART Algorithm

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**Input:** User set  $U$ , and item sets:  $\{V_1, \dots, V_n\}$ ,  $n \geq 3$ ;

User-Item interaction matrices:  $\{R^1, \dots, R^n\}$ ;

**Stage 1 (parallel):**

**for**  $\forall d \in [1, n]$  **do**

    Train domain-specific user and item embeddings:  $\mathbb{E}^d$   
    and  $\mathbb{I}^d$  according to BPR loss.

**Stage 2:**

Train the CAT module according to reconstruction and contrastive loss.

**Stage 3 (parallel):**

Fix the CAT module and domain-specific user embeddings in all domains.

**for**  $\forall d \in [1, n]$  **do**

    Train the ART unit according to the BPR loss and the enhanced user embedding.

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# Evaluation: Experiment Settings

- Datasets
  - 5 domains: App install, App usage, Articles, Long video, Short video
- Baselines
  - Single-domain MF
  - CMF, MPF, GA-MTCDR, HeroGraph
- Metrics
  - Precision, Recall, NDCG

**Table 1: Statistics of the Collected Dataset with 5 Domains.**

Domain	#Users	#Items	#Interactions	Density(‰)
App-Ins		100,000	101,981,793	0.874
APP-Use		100,000	18,156,535	0.155
Articles	1,166,552	50,000	102,832,656	1.763
Video-S		50,000	74,911,020	1.284
Video-L		50,000	11,412,988	0.196

# Evaluation: Main Results

- Negative transfer
- Avoiding NT in all domains
- Boosted performance in all domains

Model	Domain	Precision		Recall		NDCG	
		@10	@20	@10	@20	@10	@20
SMF	APP-Ins	33.82±0.70	25.46±0.88	21.51±0.39	31.91±1.22	32.56±0.43	32.53±0.89
	APP-Use	20.91±0.23	12.21±0.26	65.5±0.89	75±1.50	57.39±1.46	60.81±1.72
	Article	16.02±0.73	12.05±0.58	16.64±0.43	23.25±0.40	21.59±1.30	21.93±1.06
	Video-S	3.9±0.03	3.86±0.02	3.59±0.44	6.9±0.77	3.83±0.13	4.84±0.25
	Video-L	5.98±0.20	3.91±0.10	26.73±0.87	34.6±0.88	20.37±1.19	22.91±1.2
CMF	APP-Ins	33.57±0.37↓	25.19±0.37↓	21.8±0.19	32.05±0.43	32.39±0.29↓	32.45±0.27↓
	APP-Use	20.41±0.11↓	12.17±0.05↓	64.91±0.27↓	75.54±0.16	43.99±0.78↓	47.89±0.74↓
	Article	10.29±0.27↓	8.37±0.19↓	8.83±0.23↓	13.79±0.28↓	11.24±0.34↓	12.07±0.31↓
	Video-S	3.87±0.12	3.81±0.12↓	4.08±0.17	7.6±0.29	4.00±0.14	5.04±0.18
	Video-L	4.74±0.03↓	3.26±0.01↓	21.44±0.12↓	29.14±0.06↓	12.67±0.07↓	15.14±0.05↓
MPF	APP-Ins	36.08±1.53	27.11±0.41	23.28±0.99	34.29±0.44	36.95±5.56	36.53±4.02
	APP-Use	20.95±0.12	12.26±0.16	65.55±0.44	75.18±0.84	55.67±2.71↓	59.14±2.52↓
	Article	14.55±0.16↓	11.14±0.11↓	15.35±0.07↓	21.72±0.12↓	20.96±0.63↓	21.29±0.52↓
	Video-S	3.63±0.29↓	3.67±0.13↓	3.71±0.30	7.16±0.68	3.85±0.40	4.91±0.11
	Video-L	2.74±0.95↓	2.09±0.52↓	11.96±4.31↓	18.2±4.66↓	8.03±3.65↓	10.01±3.79↓
GA-MTCDR	APP-Ins	16.77±0.05↓	10.35±0.02↓	11.7±0.01↓	14.37±0.03↓	17.81±0.08↓	16.01±0.03↓
	APP-Use	13.88±0.05↓	10.46±0.01↓	45.44±0.13↓	67.2±0.16↓	32.35±0.13↓	40.16±0.1↓
	Article	4.62±0.13↓	3.73±0.03↓	4.12±0.14↓	6.37±0.11↓	6.22±0.18↓	6.36±0.13↓
	Video-S	3.44±0.03↓	3.1±0.02↓	3.48±0.08↓	6.03±0.06↓	4.22±0.05	4.69±0.04
	Video-L	3.18±0.15↓	2.22±0.07↓	14.21±0.74↓	19.76±0.54↓	10.46±0.63↓	12.23±0.49↓
HeroGRAPH-L	APP-Ins	34.05±2.01	24.47±1.16↓	22.34±1.14	31.61±1.35↓	40.5±1.91	38.12±1.51
	APP-Use	20.68±0.36↓	11.98±0.15↓	66.11±0.83	74.96±0.61↓	59.51±1.08	62.74±0.98
	Article	11.27±0.12↓	8.61±0.12↓	15.01±0.2↓	20.68±0.33↓	18.19±0.16↓	18.86±0.23↓
	Video-S	<b>3.99</b> ±0.14	3.7±0.15	<b>5.29</b> ±0.21	<b>8.97</b> ±0.34	<b>5.31</b> ±0.18	<b>6.2</b> ±0.23
	Video-L	5.42±0.29↓	3.65±0.15↓	24.62±1.22↓	32.84±1.29↓	18.71±1.21↓	21.35±1.24↓
<b>CAT-ART</b>	APP-Ins	<b>38.36</b> ±0.58	<b>27.96</b> ±0.31	<b>24.86</b> ±0.34	<b>35.46</b> ±0.39	<b>43.47</b> ±1.23	<b>41.55</b> ±0.94
	APP-Use	<b>21.23</b> ±0.18	<b>12.33</b> ±0.18	<b>66.53</b> ±0.65	<b>75.66</b> ±1.02	<b>59.98</b> ±0.86	<b>63.27</b> ±1.02
	Article	<b>16.82</b> ±0.21	<b>12.4</b> ±0.13	<b>18.76</b> ±0.56	<b>25.47</b> ±0.6	<b>25.97</b> ±0.61	<b>25.79</b> ±0.58
	Video-S	3.93±0.08	<b>3.93</b> ±0.06	3.83±0.50	7.35±0.82	3.93±0.14	5.05±0.24
	Video-L	<b>6.08</b> ±0.09	<b>3.96</b> ±0.08	<b>27.18</b> ±0.39	<b>35.01</b> ±0.67	<b>21.03</b> ±0.38	<b>23.54</b> ±0.86

# Evaluation: Ablation Study

- Base model (SMF)
- +Autoencoder
- +Contrastive
  - The full CAT module
- +ART
  - Features from all domains
- -Attention

Domain	Metric	SMF	+Autoencoder	+Contrastive	+ART	-Attention
App-Ins	Precision@10	33.82±0.70	37.64±1.17	37.95±0.45	<b>38.36±0.58</b>	36.24±0.26
	Recall@10	21.51±0.39	24.35±0.76	24.58±0.35	<b>24.86±0.34</b>	23.35±0.23
	NDCG@10	32.56±0.43	41.34±3.75	42.56±2.02	<b>43.47±1.23</b>	36.08±1.54
APP-Use	Precision@10	20.91±0.23	21.00±0.11	21.08±0.23	<b>21.23±0.18</b>	21.01±0.07
	Recall@10	65.50±0.89	65.77±0.33	66.01±0.88	<b>66.53±0.65</b>	65.92±0.41
	NDCG@10	57.39±1.46	59.09±0.37	58.61±0.40	<b>59.98±0.86</b>	59.28±0.24
Article	Precision@10	16.02±0.73	16.54±0.46	16.46±0.34	<b>16.82±0.21</b>	15.88 ± 0.15↓
	Recall@10	16.64±0.43	17.48±1.21	17.19±1.13	<b>18.76±0.56</b>	15.89±0.38↓
	NDCG@10	21.59±1.30	23.98±2.28	23.54±2.75	<b>25.97±0.61</b>	22.25±1.71
Video-S	Precision@10	3.89±0.025	3.91±0.08	<b>3.97±0.13</b>	3.93±0.08	3.82±0.28↓
	Recall@10	3.59±0.44	3.71±0.40	3.72±0.37	<b>3.83±0.50</b>	3.46±0.25↓
	NDCG@10	3.83±0.13	3.87±0.08	3.91±0.05	<b>3.93±0.14</b>	3.73±0.18↓
Video-L	Precision@10	5.98±0.20	6.04±0.01	6.07±0.04	<b>6.08±0.09</b>	5.86±0.03↓
	Recall@10	26.73±0.87	27.00±0.08	27.17±0.20	<b>27.18±0.39</b>	26.27±0.09↓
	NDCG@10	20.37±1.19	21.00±0.14	21.12±0.21	<b>21.03±0.38</b>	20.26±0.15↓

**Thank you!**  
**Q & A**