KDD2025

Retrieval Augmented Cross-Domain Lifelong Behavior Modeling for Enhancing Click-through Rate Prediction

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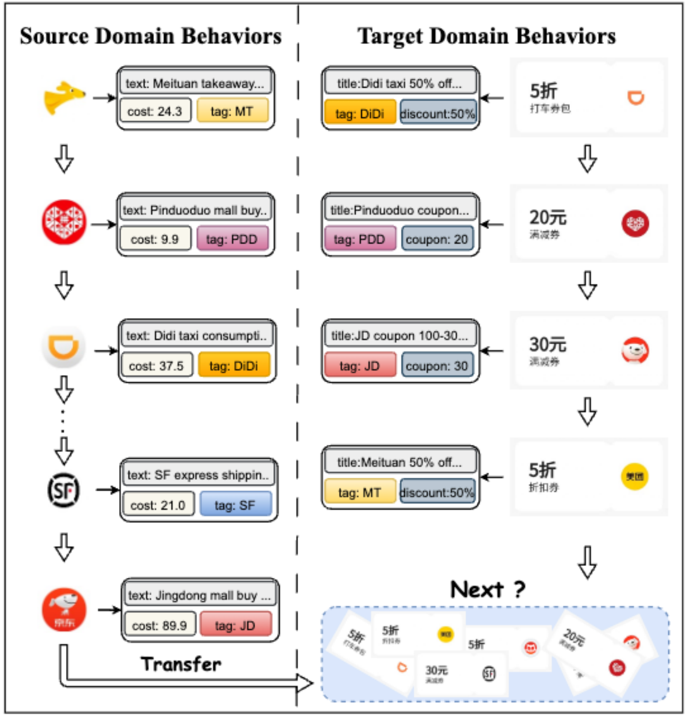
Lifelong Behavior Sequence



- Lifelong behavior modeling in single domain[1,2] proves effective.
- Target and rich user behavior sequence may not come from the same domain

[1] Qi Pi, and et al.. 2020. Search-based user interest modeling with lifelong sequential behavior data for click-through rate prediction. CIKM'20
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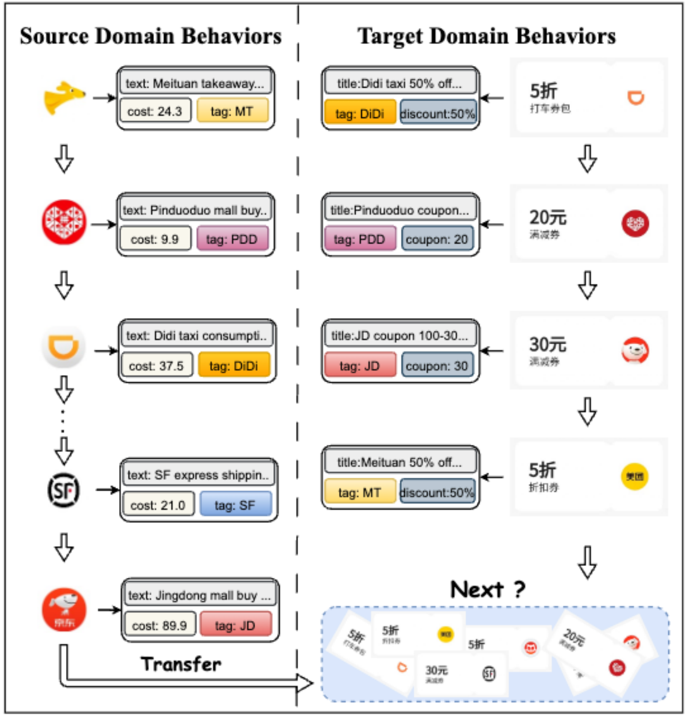

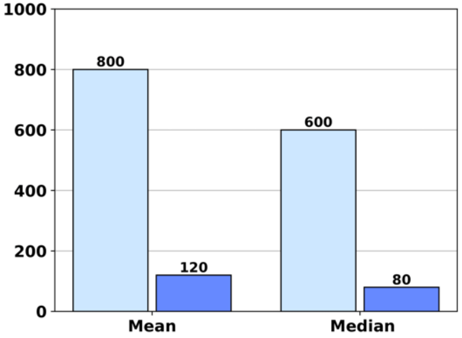

Source sequence being 8x longer than target sequence

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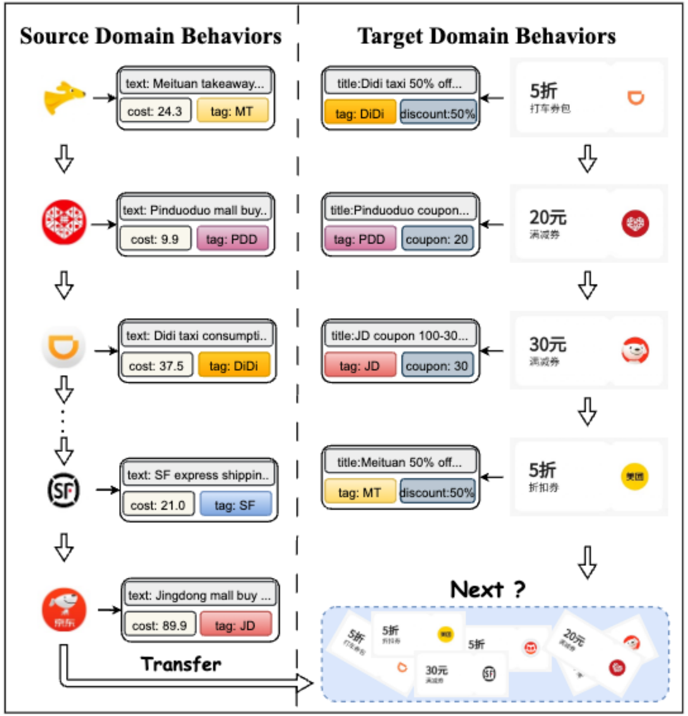

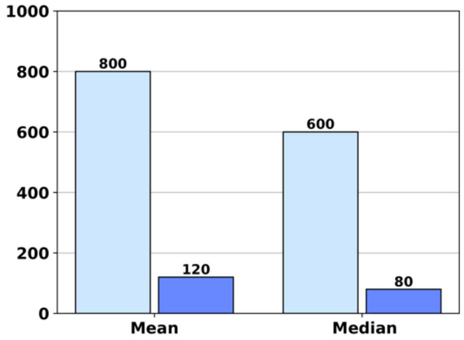

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How to utilize behavior seqs from other domain?

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Behavior sequences from other domain

Retrieve from Single Domain

- General Search Unit: seeks the most related K candidates

- Exact Search Unit: utilize MHA to capture user’s diverse interest

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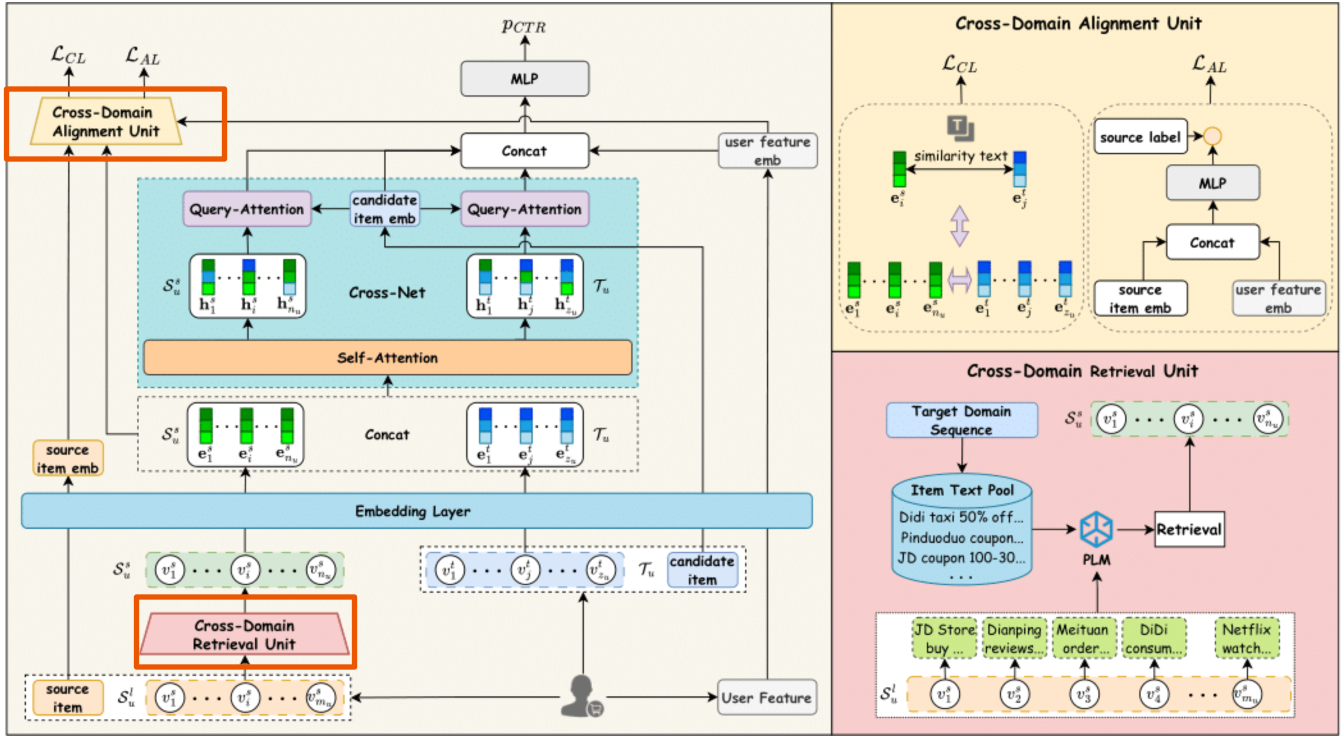
Intuition: Only find the informative instances from target domain

- Sparsity Issue: hard to get relevant behavior from another domain
- Alignment issue: Same behavior means different across domains

Overall Structure



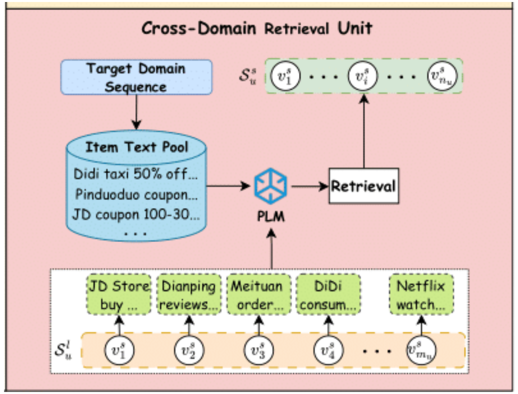
Cross Retrieval Unit

Intuition: Transform into textual space

$$m_i = 1 \iff \exists j \in \{1, \cdots, z_u\}, \cos(\mathbf{rep}_i^s, \mathbf{rep}_j^t) > \theta,$$

$$\text{where} \quad \cos(\mathbf{rep}_i^s, \mathbf{rep}^t) = \frac{\mathbf{rep}_i^s \cdot \mathbf{rep}_j^t}{\|\mathbf{rep}_i^s\|\|\mathbf{rep}_j^t\|}.$$

Use LMs to calculate the semantic representation of item



Cross Alignment Unit

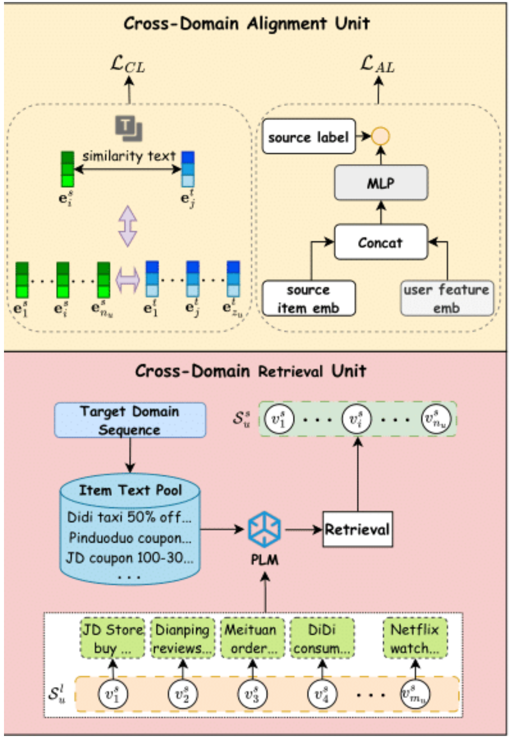
Contrastive Loss is used to align the embedding across the domains.

$$\mathcal{L}_{CL} = -\log \frac{\sum_i^{n_u} \sum_j^{z_u} m_{ij} \cdot \exp((\mathbf{e}_\mathrm{i}^\mathrm{s} \odot \mathbf{e}_\mathrm{j}^\mathrm{t})/\tau)}{\sum_i^{n_u} \sum_j^{z_u} (1 - m_{ij}) \cdot \exp((\mathbf{e}_\mathrm{i}^\mathrm{s} \odot \mathbf{e}_\mathrm{j}^\mathrm{t})/\tau)}$$

$$\text{s.t.} \quad m_{ij} = \mathbb{I}(\cos(\mathbf{rep}_i^s, \mathbf{rep}_j^t) > \theta),$$

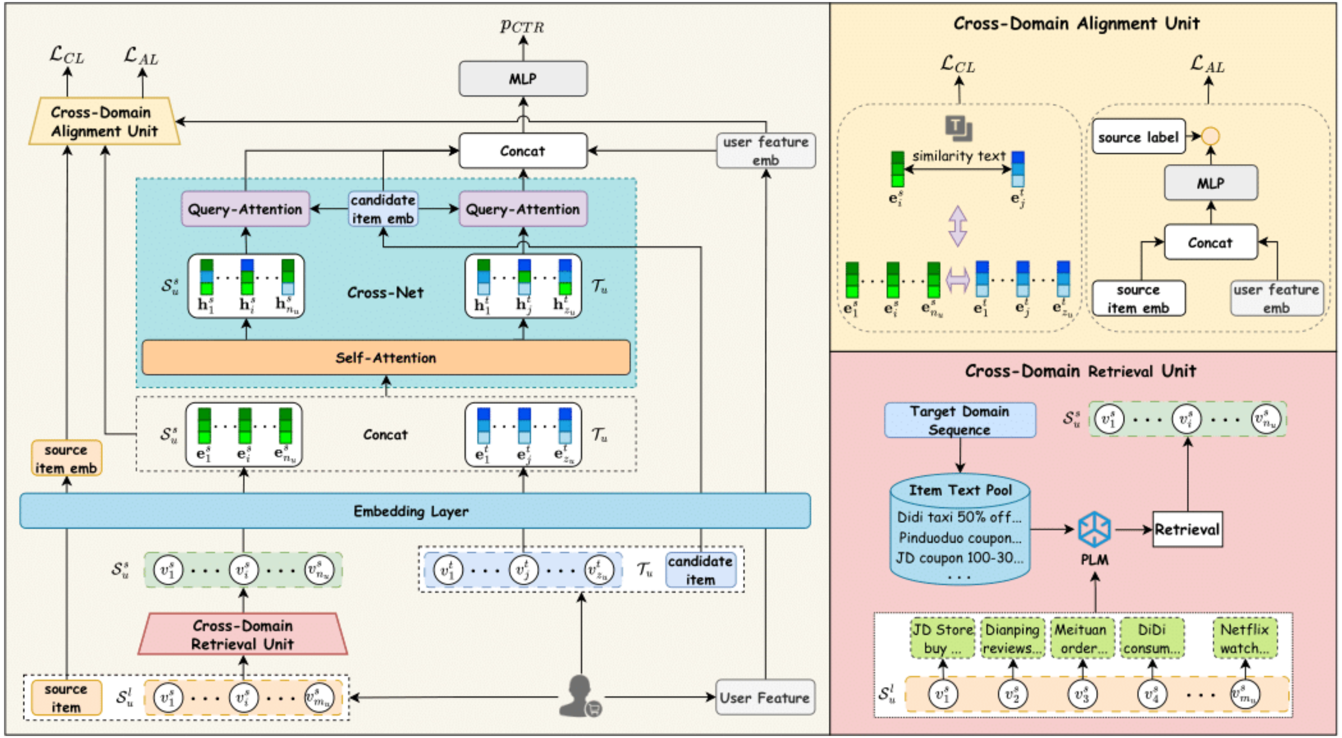
Auxiliary Loss is used to preserve the source information.

$$\mathcal{L}_{AL} = -[y_i \cdot \log(p_{click}) + (1 - y_i) \cdot \log(1 - p_{click})],$$



Cross-Net

$$\mathcal{L} = \mathcal{L}_{CTR} + \lambda_{CL}\mathcal{L}_{CL} + \lambda_{AL}\mathcal{L}_{AL},$$



Evaluation

Dataset	Amazon				Industrial	
	Source:Book	Target:Movie	Source:Book	Target:CD	Source	Target
#Shared users	133,103		54,835		272,415,397	
#Items	1,006,743	121,386	691,947	238,329	9,572	1,033
#Train instances	1,682,884		852,743		501,349,887	
#Valid instances	133,103		54,835		18,617,498	
#Test instances	133,103		54,835		18,617,498	
Max.Len/Avg.Len #clicked	9,463/24.12	1,919/11.58	9,463/28.16	2,938/15.18	499,284/887.68	86/15.18

Setup:

- Datasets: Amazon*2 + Industrial
- Baselines: DNN, DeepFM, DIN, SIM, TWIN, CoNet, CDANet, MiNet, LCN

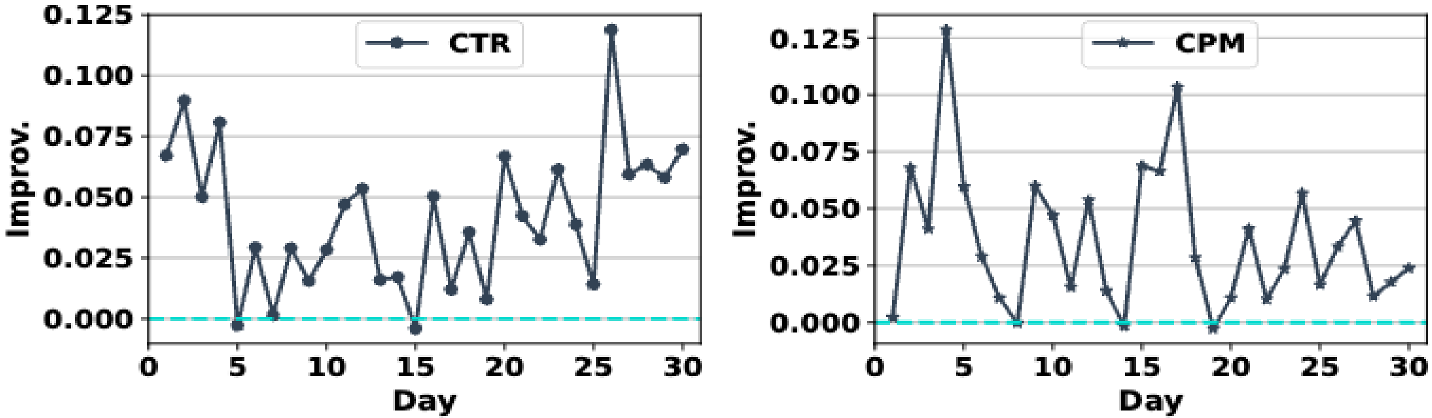
Offline Evaluation

Dataset	Amazon				Industrial	
Source → Target	Book → Movie		Book → CD		Payment → Ad	
	AUC↑	Logloss↓	AUC↑	Logloss↓	AUC↑	Logloss↓
DNN	0.7584	0.4413	0.7153	0.3255	0.8361	0.2100
DeepFM	0.7574	0.4421	0.7154	0.3306	0.8371	0.2096
DIN	0.7617	0.4672	0.7164	0.3293	0.8381	0.2091
SIM(Hard)	0.7612	0.5200	0.7158	0.3255	0.8380	0.2091
SIM(Soft)	0.7618	0.5128	0.7163	0.3253	0.8382	0.2091
TWIN	0.7624	0.4690	0.7176	0.3290	0.8379	0.2092
CoNet	0.7635	0.4270	0.7212	**0.3228**	0.8378	0.2093
CDAnet	0.7640	0.4267	0.7215	0.3229	0.8381	0.2094
MiNet	0.7662	0.4311	0.7269	0.3449	0.8384	0.2092
LCN	0.7643	0.4318	0.7221	0.3323	0.8387	0.2089
RAL-CDNet(Hard)	0.7708	0.4230	0.7301	0.3309	0.8405	0.2080
RAL-CDNet	**0.7717***	**0.4210***	**0.7310***	0.3291	**0.8407***	**0.2079**

Observations:

- Lifelong behaviors are useful. *Sequential > DNN/DeepFM*
- Cross-domain is useful *Cross-domain > Single domain*
- Cross-domain Sequential are better *MiNet&LCN > others*
- RAL-CDNet yields SOTA *RAL-CDNet > others*

Online Evaluation



Online tests on WeChat advertising platform for 4 weeks

CTR+5.34%, CPM+7.67%

Summary

- Cross-domain lifelong behaviors modeling is an effective way to improve the performance.

- RAL-CDNet:

  - CD-RU is responsible to retrieval cross-domain items

  - CD-AU introduces two task to explore the relation.

- Evaluation on both online and offline datasets.