User Behavior Retrieval for Click-Through Rate Prediction

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- Background & Motivation
- Our Methodology
 - Overall Framework
 - User Behavior Retrieval Module
 - Prediction Module
- Training Algorithm
- Experimental Results



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Background & Motivation

• Users accumulate a large number of behavioral records on the online shopping platforms



- Typical Industrial Solution
 - truncate the sequences and just feed recent behaviors to the prediction model
 - 50 or 100 recent behaviors





Background & Motivation

- Limitations of current sequential CTR framework
 - Uses the most **recent** N behaviors, if N is large
 - Heavy burden on system overhead (latency + storage), DIEN etc
 - Longer sequences have a lot of noise
 - Each prediction pair uses exactly the same recent N behaviors, the pattern may be not embedded in the recent N behaviors
- Instead of designing more complex model, we turn to the data perspective
 - For each prediction, retrieve the most **useful** N behaviors (N is not large) from all the user's log
 - Use search engine technique





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Overall Framework

• Differences from original framework:





Overall Framework

- Framework:
 - User Behavior Retrieval Module
 - Prediction Module





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User Behavior Retrieval Module

- User behavior retrieval module:
 - Feature selection model using self-attention:





User Behavior Retrieval Module

- User behavior retrieval module:
 - Feature selection model using self-attention:

$$Q = K = V = \begin{pmatrix} f_1 \\ \vdots \\ f_{K_q} \end{pmatrix}$$
$$SA(Q, K, V) = softmax \left(\frac{QK^T}{\sqrt{d}}\right) V$$

E =Multihead(Q, K, V) =Concat $(head_1, ..., head_h)W^O$,

$$P = \begin{pmatrix} p_1 \\ \vdots \\ p_{K_q} \end{pmatrix} = \sigma(\hat{E}),$$



User Behavior Retrieval Module

- User behavior retrieval module:
 - Behavior searching:
 - Behavior storage: feature based inverted index



• The query is formulated as

```
f_1^u AND (f_1 OR f_2 OR...OR f_n),
```



User Behavior Retrieval for CTR Prediction

- User behavior retrieval module:
 - Behavior searching:
 - Use BM25 to score every behavior document

$$s = \sum_{i=1}^{n} \text{IDF}(f_i) \cdot \frac{tf(f_i, D) \cdot (k_1 + 1)}{tf(f_i, D) + k_1 \cdot \left(1 - b + b \cdot \frac{|D|}{\text{avgdl}}\right)},$$
$$\text{IDF}(f_i) = \log \frac{N - N(f_i) + 0.5}{N(f_i) + 0.5},$$



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Prediction Module

- Prediction module:
 - Attention-based Prediction Network







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Training Algorithm

- Model training:
 - Objective function:

$$J^{\pi_{\theta}, f_{\phi}} = \max_{\theta} \max_{\phi} \sum_{u} \sum_{v} E_{B^{u} \sim \pi_{\theta}(B^{u}|q)} [LL(y_{uv}, f_{\phi}(B^{u}, u, v, c))],$$

$$LL(y_{uv}, f_{\phi}(B^{u}, u, v, c)) = y_{uv} \cdot \log(f_{\phi}(B^{u}, u, v, c))$$

$$+ (1 - y_{uv}) \cdot \log(1 - f_{\phi}(B^{u}, u, v, c)).$$

• Optimize the prediction model:

$$\begin{split} \phi^* &= \arg\min_{\phi} (L_{ce} + \lambda L_r) \\ &= \arg\min_{\phi} \sum_{u} \sum_{v} E_{B^u \sim \pi_{\theta}(B^u | q)} [-LL(y_{uv}, f_{\phi}(B^u, u, v, c))] \\ &+ \frac{1}{2} \lambda \left(||\Phi||_2^2 \right) \,, \end{split}$$



Training Algorithm

- Model training:
 - As the retrieval operation is discrete so we use policy gradient to estimate the gradient of that operation
 - Optimize the retrieval module:

θ

$${}^{*} = \arg \max_{\theta} \sum_{u} \sum_{v} E_{B^{u} \sim \pi_{\theta}(B^{u}|q)} [LL(y_{uv}, f_{\phi}(B^{u}, u, v, c))]$$

$$J^{q} = E_{B^{u} \sim \pi_{\theta}(B^{u}|q)} [LL(\cdot)]$$

$$\nabla_{\theta}(J^{q}) = \nabla_{\theta} E_{B^{u} \sim \pi_{\theta}(B^{u}|q)} [LL(\cdot)]$$

$$= \sum_{B_{i}^{u} \in \mathcal{B}} \nabla_{\theta} \pi_{\theta}(B_{i}^{u}|q) [LL(\cdot)]$$

$$= \sum_{B_{i}^{u} \in \mathcal{B}} \pi_{\theta}(B_{i}^{u}|q) \nabla_{\theta} \log(\pi_{\theta}(B_{i}^{u}|q)) [LL(\cdot)]$$

$$= E_{B^{u} \sim \pi_{\theta}(B^{u}|q)} \nabla_{\theta} \log(\pi_{\theta}(B^{u}|q)) [LL(\cdot)]$$

$$\simeq \frac{1}{L} \sum_{l=1}^{L} \nabla_{\theta} \log(\pi_{\theta}(B_{l}^{u}|q)) [LL(\cdot)],$$



Training Algorithm

• Model training:

Algorithm 1 Training the UBR4CTR framework

Require: Dataset $\mathcal{D} = (\mathcal{U}_{target}, \mathcal{V}_{target}, C_{target})$ containing all the target user-item-context triples; User history archive H_u . **Ensure:** final CTR prediction \hat{Y} between all the target user u and target item v.

- 1: Initialize all parameters.
- 2: Select the features and form the queries Q = {q,...} for each prediction target [u, v, c] ∈ D using the initialized feature selection model.
- 3: Obtain the retrieved behaviors $\mathcal{B} = \{B^u, ...\}$ of the queries Q using the search engine as described in Section 3.2.2.
- 4: Train the attention-based prediction network using Eq. 17 for one epoch.
- 5: repeat
- 6: Train retrieval model using Eq. 18 for one epoch.
- 7: Select the features and form the queries $Q = \{q, ...\}$ for each prediction target $[u, v, c] \in \mathcal{D}$ using the feature selection model.
- 8: Obtain the retrieved behaviors $\mathcal{B} = \{B^u, ...\}$ of the queries Q using the search engine as described in Section 3.2.2.
- 9: Train attention-based prediction network using Eq. 17 for one epoch.
- 10: until convergence



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- Experimental results:
 - Group1: Same length of user sequences

Model	Tmall		Taobao		Alipay	
	AUC	LL	AUC	LL	AUC	LL
GRU4Rec	0.762	0.585	0.677	0.661	0.6131	0.699
Caser	0.762	0.579	0.673	0.657	0.655	0.676
SASRec	0.755	0.586	0.670	0.658	0.648	0.679
HPMN	0.763	0.579	0.668	0.660	0.615	0.703
MIMN	0.753	0.591	0.662	0.686	0.664	0.675
DIN	0.766	0.576	<u>0.678</u>	<u>0.649</u>	<u>0.732</u>	<u>0.616</u>
DIEN	<u>0.775</u>	<u>0.567</u>	0.677	0.659	0.730	<u>0.616</u>
UBR4CTR	0.807	0.516	0.752	0.571	0.895	0.417
Imprv.	4.1%	9.0%	10.9%	12.0%	22.3%	32.3%



- Experimental results:
 - Group2: Longer sequences for baselines

Model	Tmall		Taobao		Alipay	
	AUC	LL	AUC	LL	AUC	LL
GRU4Rec	0.781	0.560	0.677	0.660	0.639	0.684
Caser	0.774	0.566	0.645	0.659	0.705	0.631
SASRec	0.769	0.578	0.669	<u>0.654</u>	0.711	0.637
HPMN	0.767	0.579	0.655	0.664	0.703	0.643
MIMN	0.759	0.590	0.659	0.659	0.719	0.634
DIN	0.791	0.546	0.605	0.679	0.856	0.506
DIEN	0.805	0.538	0.704	0.656	0.843	0.491
UBR4CTR	0.807	0.516	0.752	0.571	0.895	0.417
Imprv.	0.2%	4.1%	6.8%	12.7%	4.6%	15.1%



- Experimental results:
 - Robustness study:





- Experimental results:
 - Ablation study:





- Experimental results:
 - Learning process:



- Experimental results:
 - Deployment feasibility:

Paper & Code

- Paper:
 - URL: <u>https://arxiv.org/pdf/2005.14171.pdf</u>
 - QR code:
- Code Repository:
 - URL: <u>https://github.com/qinjr/UBR4CTR</u>
 - QR code:

