Decision-Making Context Interaction Network for Click-Through Rate Prediction

Xiang Li[1*], Shuwei Chen[1*], Jian Dong[1], Jin Zhang[1], Yongkang Wang[1], Xingxing Wang[1], Dong Wang[1]

[1]Meituan, Beijing, China
{lixiang172,chenshuwei04,dongjian03,zhangjin11}@meituan.com
{wangyongkang03,wangxingxing04,wangdong07}@meituan.com

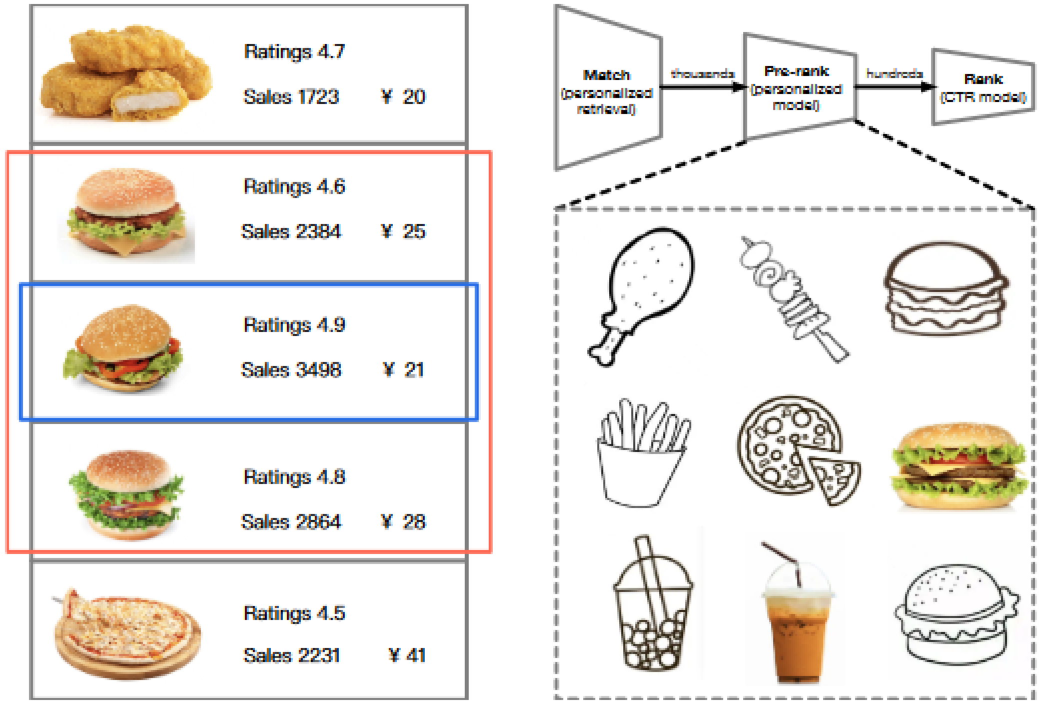
AAAI 2023
Code: None

Reported by liang li

Motivation

Details:

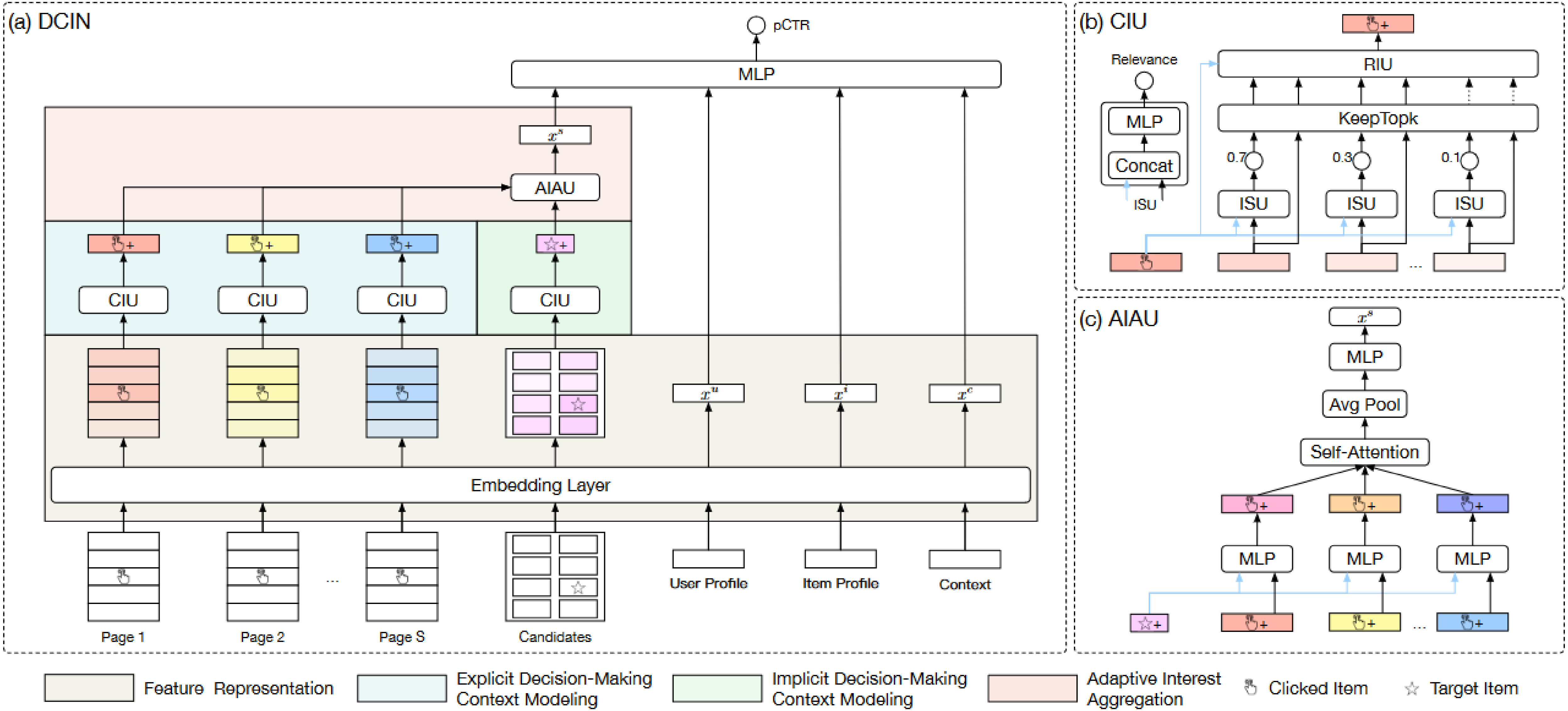
- Existing methods usually model user behaviors, while ignoring the informative context which influences the user to make a click decision.



(a) explicit context (b) implicit context

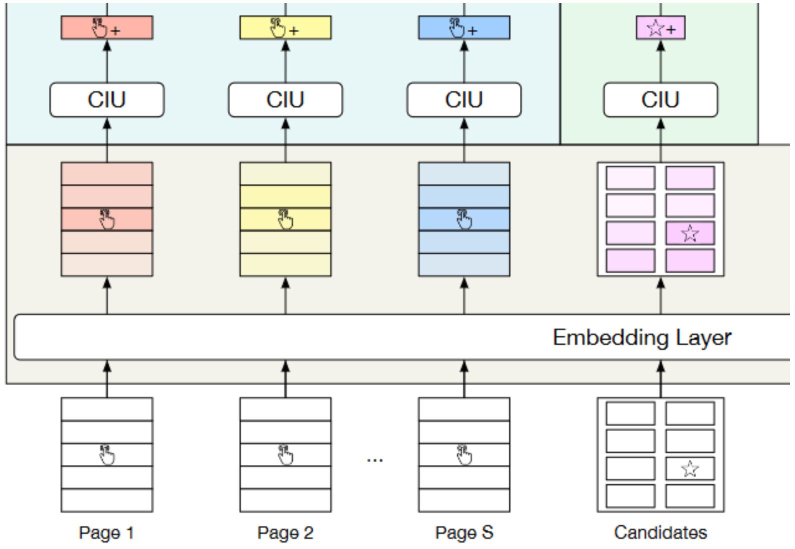
Figure 1: Illustration of explicit and implicit decision-making contexts. (a) The user proactively compares the attributes of the highly-related items in a local scope colored in red before making a click decision colored in blue. (b) We can deduce that the user likes fast food so much that the pre-ranking stage generates these candidates for him.

Problem Statement



$$xc = \{xc_1, xc_2, \ldots, xc_S\} \qquad p_i = \{p_{i,1}, p_{i,2}, \ldots, p_{i,P}\} \qquad xs = \{xs_1, xs_2, \ldots, xs_C\}$$

Method



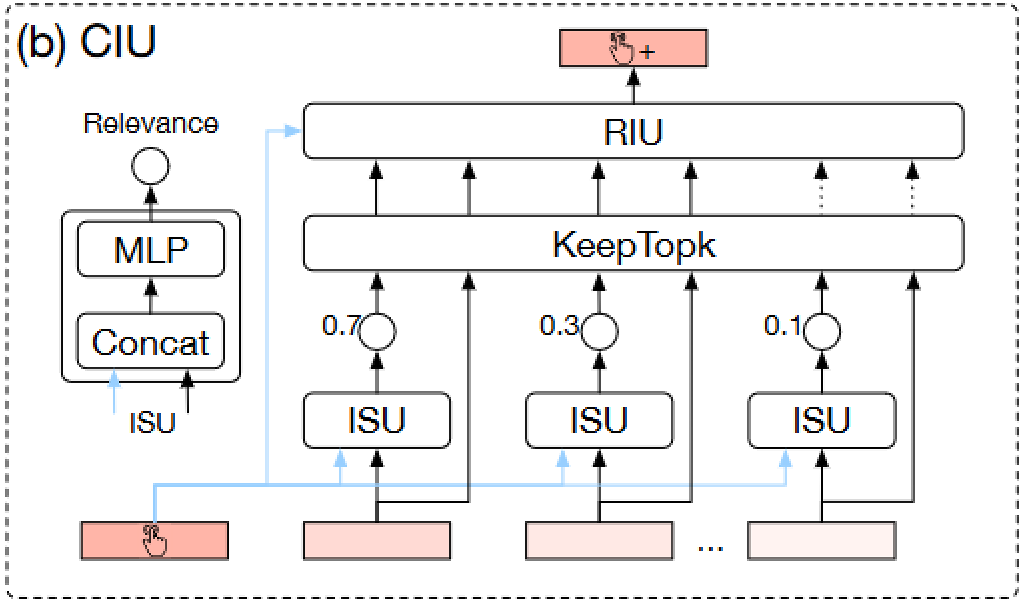
$$f_{i,j} = \mathrm{MLP}([xc_i, p_{i,j}, xc_i - p_{i,j}, xc_i \odot p_{i,j}]) \qquad (1)$$

$$f_{i,j} = \begin{cases} f_{i,j}, & \text{if } f_{i,j} \text{ is in the top-}k_1 \text{ elements of } f_i \\ -\infty, & \text{otherwise} \end{cases} \qquad (2)$$

$$Q_i = xc_i W^Q, \quad K_i = p_i W^K, \quad V_{i,j} = p_i W^V \qquad (3)$$

$$xc_i^{aug} = (\mathrm{softmax}(\frac{Q_i K_i^{\mathsf{T}}}{\sqrt{D_s}} + f_i) V_i) W^O + xc_i \qquad (4)$$

$$f_i = \{f_{i,1}, f_{i,2}, \ldots, f_{i,P}\}$$

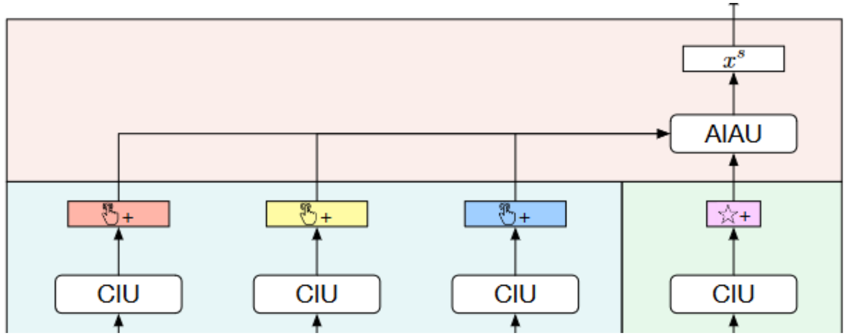


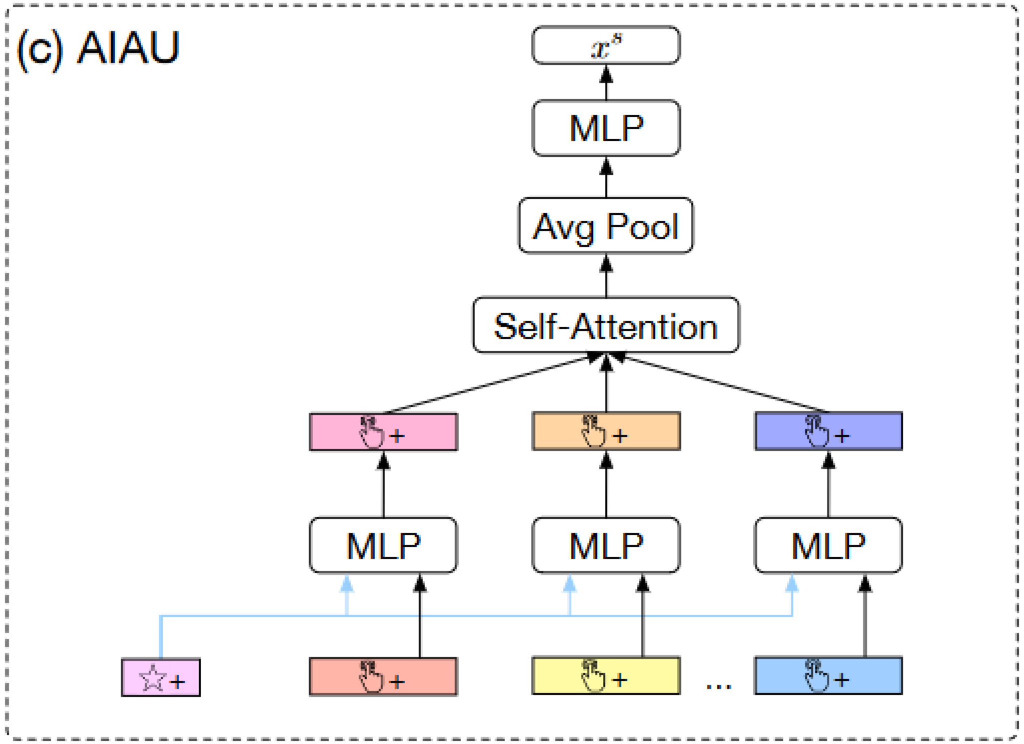
$$s_j = \mathrm{MLP}([xt, xs_j, xt - xs_j, xt \odot xs_j]) \qquad (5)$$

$$s_j = \begin{cases} s_j, & \text{if } s_j \text{ is in the top-}k_2 \text{ elements of } s \\ -\infty, & \text{otherwise} \end{cases} \qquad (6)$$

$$Q = xtW^Q, \quad K = xsW^K, \quad V = xsW^V$$
$$xt^{re} = (\mathrm{softmax}(\frac{QK^{\mathsf{T}}}{\sqrt{D_t}} + s)V)W^O + xt \qquad (7)$$

Method





$$xc_i^a = \mathrm{MLP}([xt^{re}, xc_i^{aug}]) \tag{8}$$

$$xc^m = \mathrm{softmax}(\frac{QK^\top}{\sqrt{D_a}})V \tag{9}$$

$$Q = xc^a W^Q, \quad K = xc^a W^K, \quad V = xc^a W^V \tag{10}$$

$$x^s = \mathrm{MLP}(\mathrm{Avg\,Pool}(xc^m)) \tag{11}$$

$$\hat{y} = \mathrm{sigmoid}(\mathrm{MLP}([x^s, x^u, x^i, x^c])) \tag{12}$$

$$\ell = -\frac{1}{N}\sum_{k=1}^{N}(y_k\, log\, \hat{y}_k + (1 - y_k)\, log\, (1 - \hat{y}_k)) \tag{13}$$

Experiments

Dataset	Avito†	MeituanAds
# Users	0.54 million	0.2 billion
# Samples	0.88 million	5.3 billion
Avg # Behavior-Pages	1.9	7.3
# Candidates	20	60

Table 1: Statistics of datasets used in our experiments. Avito† denotes the constructed Avito dataset.

Model	Avito†		MeituanAds	
	LogLoss	AUC	LogLoss	AUC
DNN	0.5587	0.7756	0.1842	0.6891
DIN (Zhou et al. 2018)	0.5496	0.7834	0.1837	0.6936
DIEN (Zhou et al. 2019)	0.5490	0.7830	0.1833	0.6949
DFN (Xie et al. 2021)	0.5473	0.7841	0.1833	0.6961
DSIN (Feng et al. 2019)	0.5475	0.7847	0.1832	0.6963
CIM (Zheng et al. 2022)	0.5459	0.7852	0.1839	0.6960
RACP (Fan et al. 2022)	0.5452	0.7863	0.1830	0.6972
DCIN (ours)	**0.5445**	**0.7904**	**0.1825**	**0.7014**

Table 2: Performance of different models on datasets. Avito† denotes the constructed Avito dataset.

Experiments

Models	AUC
DCIN w/o explicit CIU	0.6986
DCIN w/o implicit CIU	0.6991
DCIN w/o AIAU	0.6993
DCIN	**0.7014**

Table 3: Ablation studies of the components. Each component brings significant improvement in AUC, verifying their effectiveness.

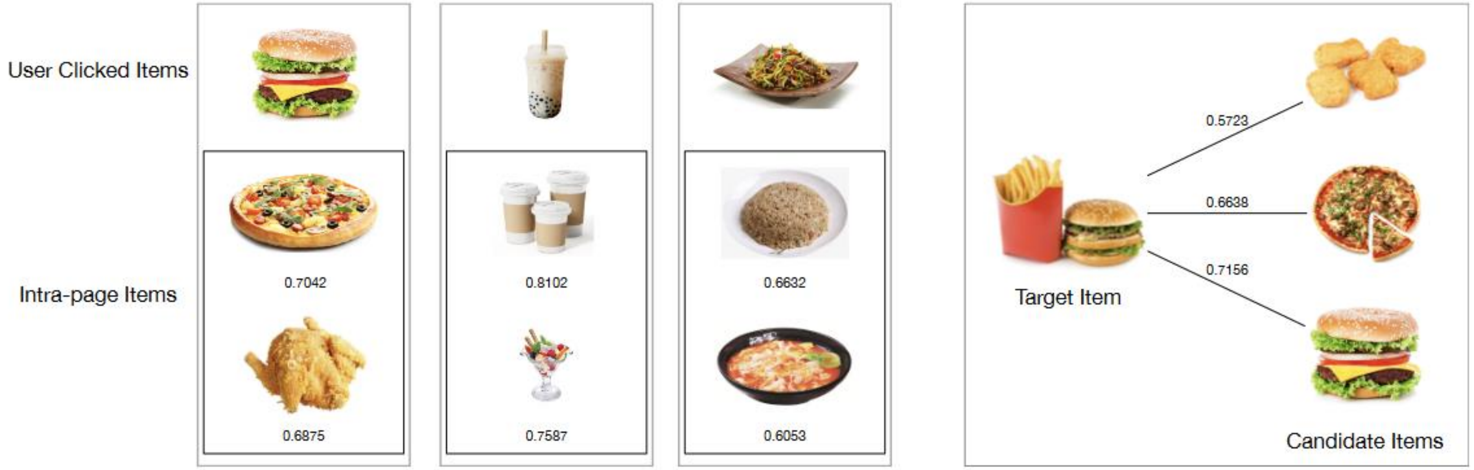


Figure 3: Case study on MeituanAds dataset. We show the relevance score calculated in CIUs in one CTR prediction. The left part corresponds to explicit context modeling, and the right part corresponds to implicit context modeling.

Experiments

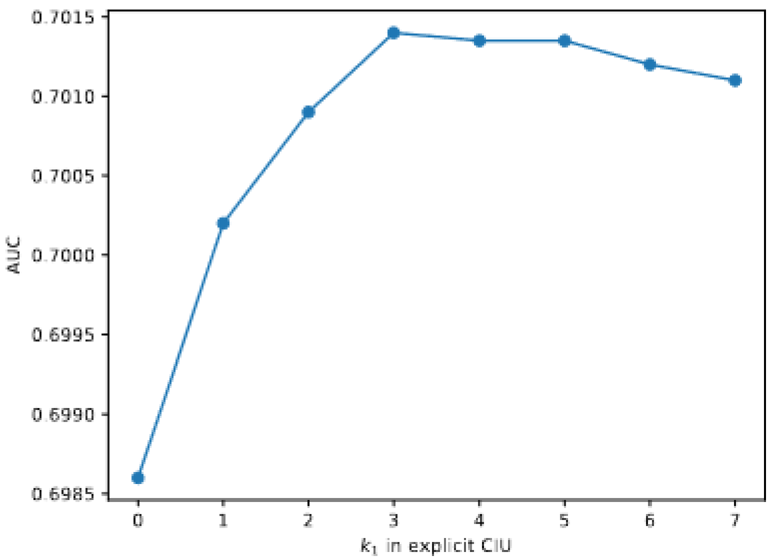


Figure 4: Ablation studies of k_1 in explicit CIU.

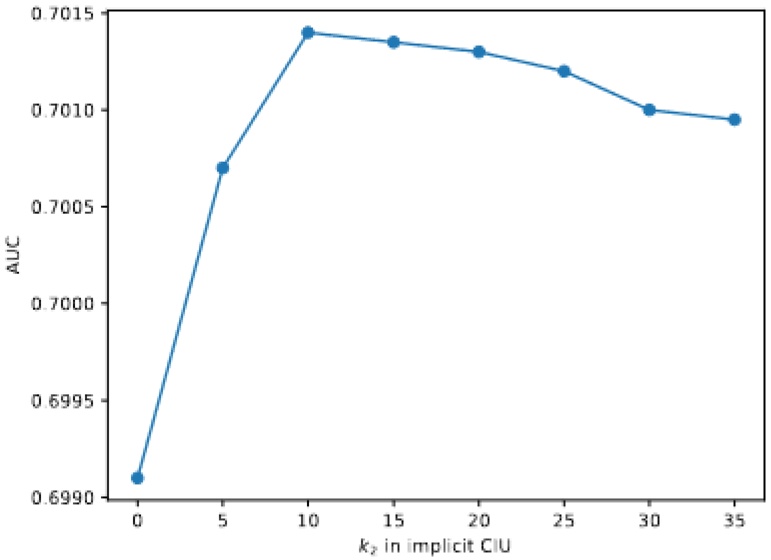


Figure 5: Ablation studies of k_2 in implicit CIU.

Model	CTR	CPM	GMV
DCIN	+2.9%	+2.1%	+1.5%

Table 4: The performance in real online advertising system.

Thanks