A Context-Aware Click Model for Web Search

先看看模型整体架构

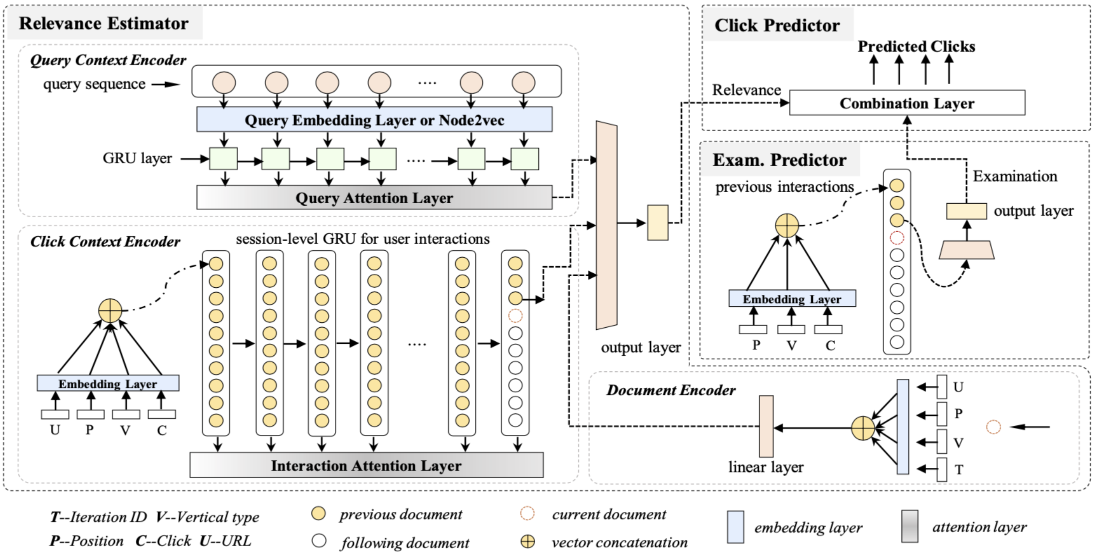


Figure 1: Framework of the proposed CACM. CACM consists of a relevance estimator and an examination predictor. The relevance estimator encodes both the inter-session contexts (i.e., the query context and the click context) and the current document to estimate the context-aware relevance $\mathcal{R}$. The examination predictor utilizes the intra-session context to predict the examination probability $\mathcal{E}$. Then through a combination layer, CACM integrates the $\mathcal{R}$ and $\mathcal{E}$ into the click prediction.

Definition

DEFINITION 1. *For the n-th document in the l-th query ($d_{l,n}$), given the user's query history $Q = \langle q_1, q_2, ..., q_l \rangle$ and the previous interactions $\mathcal{I} = \{\mathcal{I}_{i,j} | i \leq l, j < n\}$ within the session, we would like to estimate the context-aware relevance of $d_{l,n}$ as well as to predict whether it will be clicked by the user.*

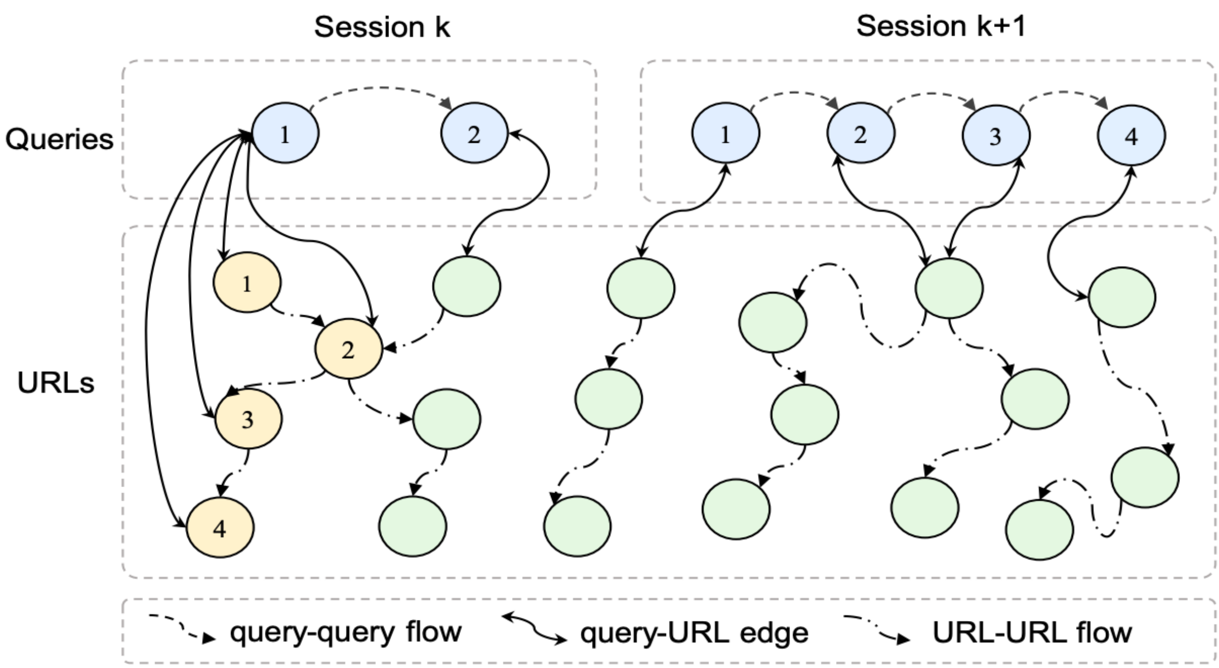
Framework

主要包括Relevance Estimator、Examination Probability Predictor以及Click Predictor

Relevance Estimator

Query context encoder

采用query-query、url-url、qury-url图模型，node2vec获得embedding，GRU+attention编码



其中，变得权重定义

- query-query，paper中给的固定值2.0
- query-url

$$\mathcal{W}_{q-u} = \begin{cases} 1, & C_{i,j} = 1, \\ -1, & C_{i,j} = 0, j < max(\mathcal{P}_{C_i}), \\ 0, & C_{i,j} = 0, j > max(\mathcal{P}_{C_i}); \end{cases}$$

  $C_{i,j}$表示$query_i$和url_j的状态（点击or不点击）。$max(P_{C_i})$表示$query_i$下点击的$query$中最大位置

- url-url

$$\mathcal{W}_{u-u} = \frac{1}{\log_2(j+1)};$$

Click context encoder

Session level GRU编码用户多个session的点击行为

$$\mathbf{v}_{\mathcal{I}_{i,j}} = [\mathbf{v}_u \oplus \mathbf{v}_p \oplus \mathbf{v}_v \oplus \mathbf{v}_c],$$
$$\mathcal{S}_c = GRU(\mathbf{v}_{\mathcal{I}_{1,1}}, \ldots \mathbf{v}_{\mathcal{I}_{t,n-1}}),$$

其中，V_u表示url的embedding，V_p表示文档的position（最大取10），V_v表示文档的垂直内容形式（类似百科、图集这种，总共19种），V_c表示是否点击。

最后，gru的输出向量过一遍attention layer

$$\mathcal{S}_{c,att} = \sum_{i=1,j=1}^{t,n-1} \alpha_c^{i,j} h_{i,j},\ \alpha_c^{i,j} = \frac{exp(h_{t,n-1}^T h_{i,j})}{\sum_{p=1,q=1}^{t,n-1} exp(h_{t,n-1}^T h_{p,q})},$$

Document encoder

对当前用户看到的doc编码，做法跟Click context encoder类似

$$\mathbf{v}'_{d_{t,n}} = [\mathbf{v}_u \oplus \mathbf{v}_p \oplus \mathbf{v}_v \oplus \mathbf{v}_t],$$
$$\mathbf{v}_{d_{t,n}} = Tanh(\mathcal{F}_d(\mathbf{v}'_{d_{t,n}})),$$

这里的T指的是query的query iteration_id

最后，结合query context encoder、click context encoder、document encoder的输出，经过MLP输出relevance score

$$\mathbf{v}_{\mathcal{R}_{t,n}} = [\mathcal{S}_{q,att} \oplus \mathcal{S}_{c,att} \oplus \mathbf{v}_{d_{t,n}}],$$
$$\mathcal{R}_{t,n} = MLP(\mathbf{v}_{\mathcal{R}_{t,n}}),$$

Examination Estimator

假设exam取决于用户行为，和文档内容无关，GRU编码当前session中之前的用户行为，其他的跟上述encoder没有区别

$$\mathbf{v}_{\mathcal{I}_{t,j}} = [\mathbf{v}_p \oplus \mathbf{v}_v \oplus \mathbf{v}_c], \quad j < n,$$
$$\mathcal{E}'_{t,n} = GRU(\mathbf{v}_{\mathcal{I}_{t,1}}, \ldots, \mathbf{v}_{\mathcal{I}_{t,n-1}}),$$

Click Prediction

基于一个假设，只有当用户exam到一个doc，并且对doc感兴趣，才会点击这个doc，因此将exam score和relevance score结合起来预估ctr。

Table 1: Five combination function for the relevance score and the examination probability (E.H is short for examination hypothesis, C–Click, $\mathcal{R}$–Relevance, $\mathcal{E}$–Examination, σ–sigmoid function, λ, μ, α, β are learnable hyperparameters).

function	Formula	Support E.H?
mul	$C = \mathcal{R} \cdot \mathcal{E}$	√
exp_mul	$C = \mathcal{R}^{\lambda} \cdot \mathcal{E}^{\mu}$	√
linear	$C = \alpha \cdot \mathcal{R} + \beta \cdot \mathcal{E}$	×
nonlinear	$C = MLP(\mathcal{R}, \mathcal{E})$	×
sigmoid_log	$C = 4\sigma(log(\mathcal{R})) \cdot \sigma(log(\mathcal{E})) = 4\mathcal{R}\mathcal{E}/((\mathcal{R}+1)(\mathcal{E}+1))$	√

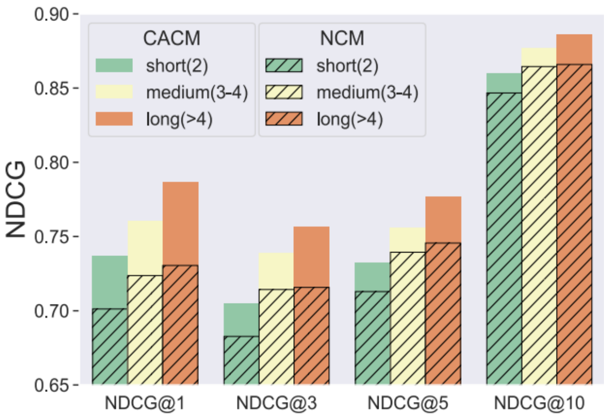
Experiment Results

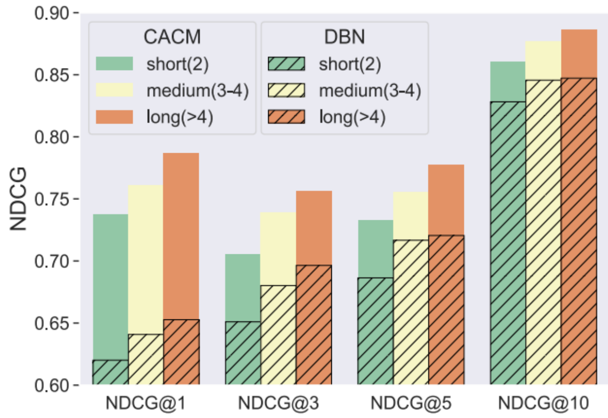
对比业界其他click model的效果，这里不做列举，一些基于结构和参数的分析，有参考意义，分享一下：

- 引入图模型embedding、attention机制以及query频次都有正向帮助

Model	NDCG@1	NDCG@3	NDCG@5	NDCG@10
0 CACM	**0.7542**	**0.7257**	**0.7484**	**0.8707**
I w/o IterID	0.7476	0.7240	0.7442	0.8681
II w/o Attn	0.7303	0.7201	0.7427	0.8675
III w/o Embed	0.7292	0.7135	0.7400	0.8648
NCM	0.7141	0.6993	0.7278	0.8562

- session长度越长，效果更明显





- 越接近当前query的用户行为，重要性越大；利用了context信息，比如d(1,3)没有点，在d(4,3)上就给了更低的相关性得分

Table 8: Case study of a session with four queries. $I_{i,j}$ denotes the j-th interaction round in the i-th query, √ represents a user click. Here we illustrate the query and interaction attention for $d_{4,3}$ in the left subtable. Relevance estimation by each model for documents in Q4 are given on the right.

CACM Attention				Relevance Estimation		
Q1	Q2	Q3	Q4	Label	CACM	NCM
√$I_{1,1}$	$I_{2,1}$	$I_{3,1}$	$I_{4,1}$	4	0.8541	0.4031
$I_{1,2}$	√$I_{2,2}$	√$I_{3,2}$	$I_{4,2}$	3	0.4844	0.3368
$I_{1,3}$	$I_{2,3}$	$I_{3,3}$	$I_{4,3}$*	0	0.0302	0.4519
$I_{1,4}$	$I_{2,4}$	$I_{3,4}$	$I_{4,4}$	0	0.0124	0.2048
$I_{1,5}$	$I_{2,5}$	$I_{3,5}$	$I_{4,5}$	2	0.0516	0.0421
$I_{1,6}$	$I_{2,6}$	$I_{3,6}$	$I_{4,6}$	2	0.1415	0.0483
$I_{1,7}$	$I_{2,7}$	$I_{3,7}$	$I_{4,7}$	1	0.0638	0.0166
$I_{1,8}$	$I_{2,8}$	$I_{3,8}$	$I_{4,8}$	0	0.0655	0.0173
$I_{1,9}$	$I_{2,9}$	$I_{3,9}$	$I_{4,9}$	2	0.0544	0.0130
$I_{1,10}$	$I_{2,10}$	$I_{3,10}$	$I_{4,10}$	2	0.0355	0.0160

* $\{d_{1,3}, d_{4,3}\}$, $\{d_{2,*}, d_{3,*}\}$, $\{d_{2,1}, d_{4,1}\}$ are the sets of same documents.
* On the left, the color depth of red and blue represent the weight of query and interaction attention, respectively. On the right, top 6 relevant documents estimated by each model for Q4 are highlighted in red.