Multi-Scale User Behavior Network for Entire Space Multi-Task Learning

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Slides: https://jinjiarui.github.io/files/cikm22_oral.pdf

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Multi-Scale User History

- Users are likely to follow behaviour path "observation → click → conversion", where CTR prediction covers "observation → click" and CVR prediction covers "click → conversion".

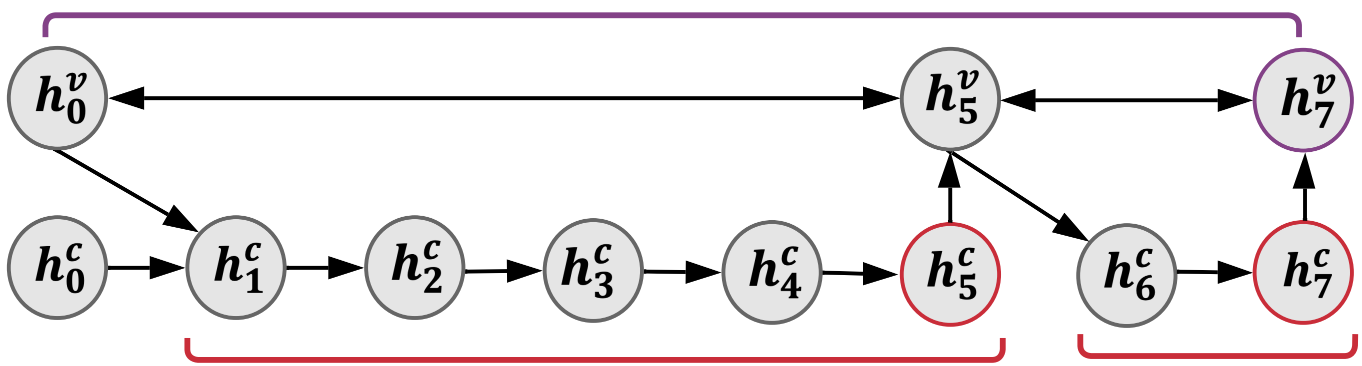

Figure: An illustrated example of users' multi-scale behavior pattern: the lower layer (i.e., CTR layer) models the engagement objective through "observation → click"; while the upper layer (i.e., CVR layer) models the satisfaction objective through "click → conversion".

Sequential Neural Networks in IR

- Classical sequential recommender systems mainly focus on capturing relative orders of items, where recurrent neural networks (e.g., LSTM) are widely adopted for user history modelling (e.g., Click-Through Rate prediction).
- We argue that this paradigm would be limited by ignoring (i) multiple behaviors: a user's behaviors vary and have strong correlations; (ii) multiple scales: a user's behavior paths occur with different frequency.

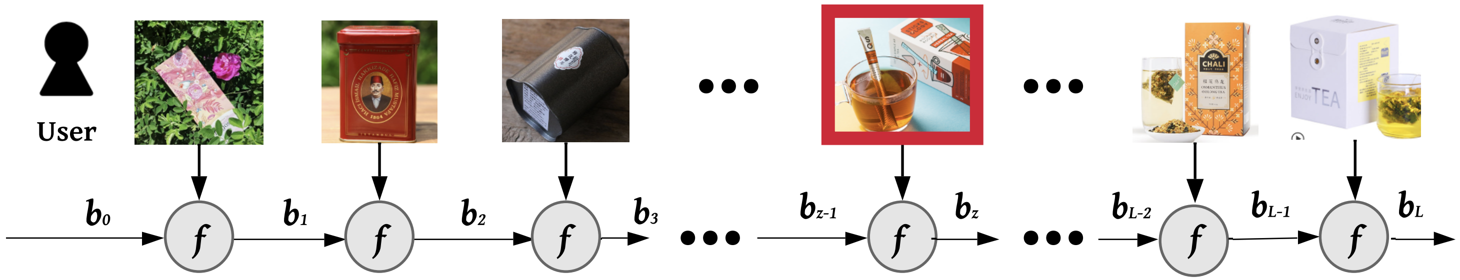

Figure: An illustrated example of modelling sequential user history via a plain recurrent neural network.

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HEROES: Intra-Layer Mechanism

- In order to model the mutual influence among multiple behaviors, we begin by introducing the definition of the **inherent relevance**. For each item d_i, we define $\widetilde{r_i}$ as inherent relevance (i.e., $\widetilde{r_i^v}$ to motivate purchase and $\widetilde{r_i^c}$ to motivate click) that are solely determinated by the item features and are free of the effect from all the external factors such as the contextual items and the user's past behaviors.

- In the contrast, we call r_i **behavioral relevance** which are affected by the external factors. To estimate $\widetilde{r_i}$ and r_i for each item d_i, we further introduce $\widetilde{h_i}$ and h_i which are defined as

$$\widetilde{h_i^c} \coloneqq P\left(\widetilde{r_i^c} = 1\right), \widetilde{h_i^v} \coloneqq P\left(\widetilde{r_i^v} = 1\right)$$
$$h_i^c \coloneqq P(r_i^c = 1), h_i^v \coloneqq P(r_i^v = 1)$$

HEROES: Intra-Layer Mechanism

- In each layer, a user's behavior on each item can be either excited or discouraged by the user's past behaviors.

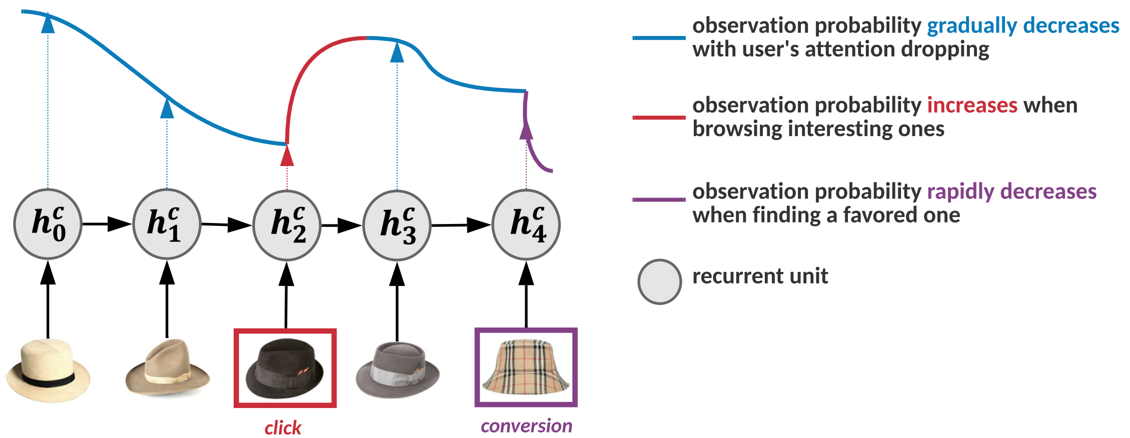

Figure: An illustrated example of contextual dependence: click occurs when browsing interesting items.

$$h_i := \widetilde{h}_i + \sum_{j \le i} \lambda_i \exp(-\delta_j (t_i - t_j)),$$

where $\lambda_i \in \mathbb{R}$ is the learnable degree to which the user's behaviors on d_j initially excite (when $\lambda_i > 0$) or discourage (when $\lambda_i < 0$), and $\delta_j > 0$ is the learnable decay rate of the excitation or discouragement.

HEROES: Inter-Layer Mechanism

- We explicitly model the correlations across two layers as

$$h_i^v = \mathrm{MLP}\left(\widetilde{h_i^v};\ \varphi\right), h_i^c = \mathrm{MLP}\left(\widetilde{h_i^c};\ \phi\right)$$

- Overall, the hierarchical architecture can be expressed as

$$h_i^c, \widetilde{h_i^c} = f_\theta^c\left(h_{i-1}^c, \widetilde{h_{i-1}^c}, {\color{red}h_{i-1}^v}, {\color{red}\widetilde{h_{i-1}^v}}; \boldsymbol{x}_q\right)$$
$$h_i^v, \widetilde{h_i^v} = f_\theta^v(h_{i-1}^v, \widetilde{h_{i-1}^v}, {\color{green}h_i^c}, {\color{green}\widetilde{h_i^c}}; \boldsymbol{x}_q)$$

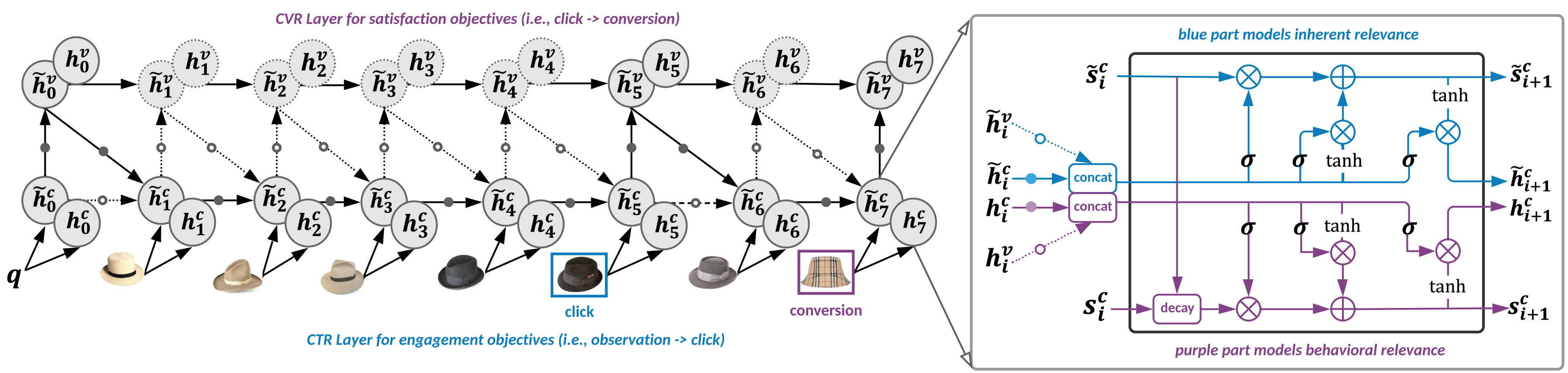

Figure: An illustrated example of HEROES architecture.

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HEROES: Gate Mechanism

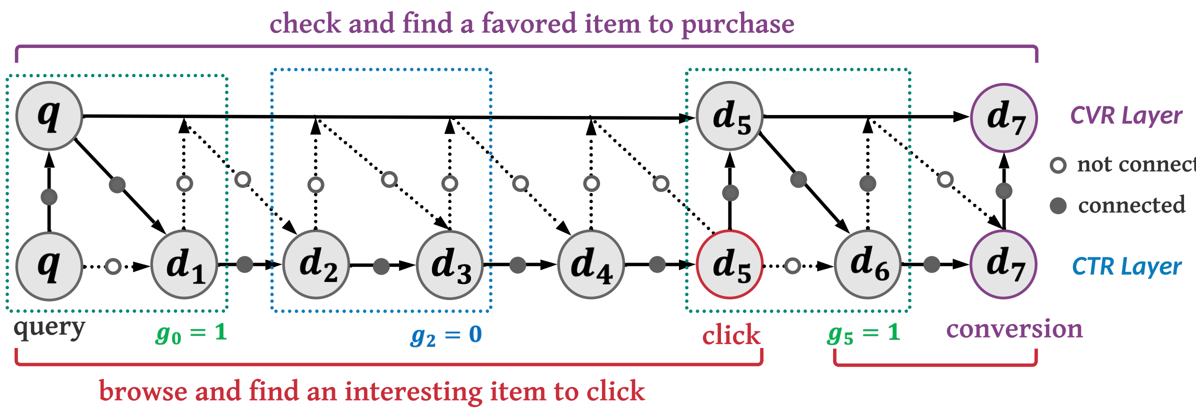


Figure: An illustrated example of motivations of gate mechanism.

- To explicitly learn the gate status, we define g_i as a boundary detector:

$$g_i = \begin{cases} 1 & \text{if } P(c_i = 1) > 0.5 \\ 0 & \text{otherwise} \end{cases}$$

HEROES: Intra-Layer Mechanism

- Let $\widetilde{s_i}$ and s_i denote the unit states in each cell which correspond to $\widetilde{h_i}$ and h_i. To achieve intra-layer mechanism, these states are recursively updated as

$$\widetilde{s_i^c} = \begin{cases} \widetilde{\mathrm{f}_i^c} \odot \widetilde{s_{i-1}^c} + \widetilde{\mathrm{i}_i^c} \odot \widetilde{\mathrm{g}_i^c}, & \text{UPDATE} \\ \widetilde{\mathrm{i}_i^c} \odot \widetilde{\mathrm{g}_i^c}, & \text{SUMMARIZE} \end{cases}, \quad s_i^c = \begin{cases} \mathrm{f}_i^c \odot s^c(t_{i-1}) + \mathrm{i}_i^c \odot \mathrm{g}_i^c & \text{UPDATE} \\ \mathrm{i}_i^c \odot \mathrm{g}_i^c, & \text{SUMMARIZE} \end{cases}$$

  where $\odot$ denotes element-wise product operation, UPDATE is $g_{i-1} = 0$ and SUMMARIZE is $g_{i-1} = 1$. Here, f_i, i_i, o_i are forget, input, output gates and g_i is a cell proposal vector which will be determinated by inter-layer mechanism. $s^c(t_{i-1})$ formulates the Hawkes process as

$$s^c(t) = \widetilde{s_{i+1}^c} + \left(s_{i+1}^c - \widetilde{s_{i+1}^c}\right) \exp\left(-\delta_{i+1}(t - t_i)\right), \text{ for } t \in (t_i, t_{i+1}]$$

  where $\delta_{i+1} = f_\gamma\left(\mathrm{MLP}(h_{i+1}^c)\right)$ and $f_\gamma(x) \coloneqq \gamma \log(1 + \exp(x/\gamma))$, γ is set as 5.

- Then the hidden states $\widetilde{h_i^c}$ and h_i^c can be calculated as

$$\widetilde{h_i^c} = \widetilde{\mathrm{o}_i^c} \odot \tanh\left(\widetilde{s_i^c}\right), \qquad h_i^c = \mathrm{o}_i^c \odot \tanh(s_i^c)$$

HEROES: Intra-Layer Mechanism

- Similarly, the states in the CVR layer are recursively updated following

$$\widetilde{s_i^v} = \begin{cases} \widetilde{f_i^c} \odot \widetilde{s_{i-1}^v} + \widetilde{i_i^v} \odot \widetilde{g_i^v}, & \text{UPDATE} \\ s_{i-1}^v, & \text{COPY} \end{cases}, \quad s_i^v = \begin{cases} f_i^v \odot s_{i-1}^v + i_i^v \odot g_i^v, & \text{UPDATE} \\ s_{i-1}^v, & \text{COPY} \end{cases}$$

where $\odot$ denotes element-wise product operation, UPDATE is $g_i = 1$ and COPY is $g_i = 0$. The hidden states $\widetilde{h_i^v}$ and h_i^v can be computed via

$$\widetilde{h_i^v} = \begin{cases} \widetilde{o_i^c} \odot \tanh(\widetilde{s_i^v}), & \text{UPDATE} \\ \widetilde{h_{i-1}^v}, & \text{COPY} \end{cases}, \quad h_i^v = \begin{cases} o_i^v \odot \tanh(s_i^v), & \text{UPDATE} \\ h_{i-1}^v, & \text{COPY} \end{cases}$$

HEROES: Inter-Layer Mechanism

- $\mathrm{i}_i, \mathrm{o}_i, \mathrm{g}_i$ are designed to encode the top-down contextual information as

$$\mathrm{f}_i = \mathrm{sigmoid}\big(\mathrm{MLP}(s_i)\big), \mathrm{i}_i = \mathrm{sigmoid}\big(\mathrm{MLP}(s_i)\big),$$
$$\mathrm{o}_i = \mathrm{sigmoid}\big(\mathrm{MLP}(s_i)\big), \mathrm{g}_i = \mathrm{sigmoid}\big(\mathrm{MLP}(s_i)\big),$$

  where s_i is the top-down state, computed as

$$s_i^c = [(1 - g_{i-1}) \cdot U_{i-1}^c \cdot h_{i-1}^c + g_{i-1} \cdot U_{i-1}^r \cdot h_{i-1}^v]$$
$$s_i^v = [U_{i-1}^v \cdot h_{i-1}^v + g_i \cdot W_i^r \cdot h_i^c]$$

  Here, HEROES forces the CVR layer to absorb the summary information from the CTR layer according to the top-down contexts.

(Biased) Loss Function

- Considering that both click and conversion signals are binary, we adopt binary cross entropy (BCE) loss as

$$L = L_c + \alpha \cdot L_v \text{ where}$$

$$L_b = - \sum_{(b, \boldsymbol{x}_q) \in \mathcal{D}_q} \left(b \cdot \log P\left(b \middle| \boldsymbol{x}_{\boldsymbol{q}}\right)\right) + (1-b) \cdot \log\left(1 - P\left(b \middle| \boldsymbol{x}_q\right)\right)),$$

where b can denote either click c or conversion v.

Modeling on Entire Space

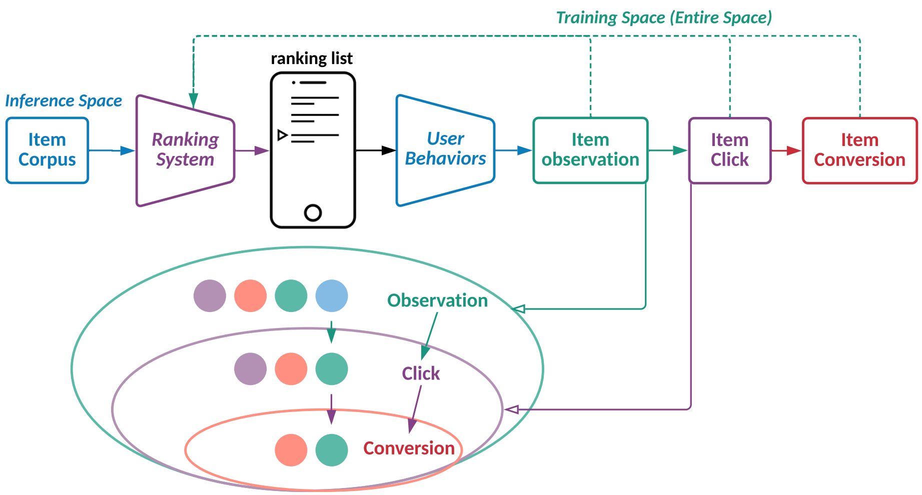


Figure: Top diagram shows the pipeline of information systems. Bottom figure illustrates the entire space behavior path "observation → click → conversion".

- Note that the observation factor does not explicitly modelled in the previous parts. In order to debias (recover the relevance from the click by considering "observation → click"), we have

$$h_i^c := P(r_i^c = 1) = \frac{P(c_i = 1)}{P(o_i = 1)},$$

$$h_i^v := P(r_i^v = 1) = \frac{P(v_i = 1)}{P(c_i = 1)}$$

HEROES: Unbiased Version

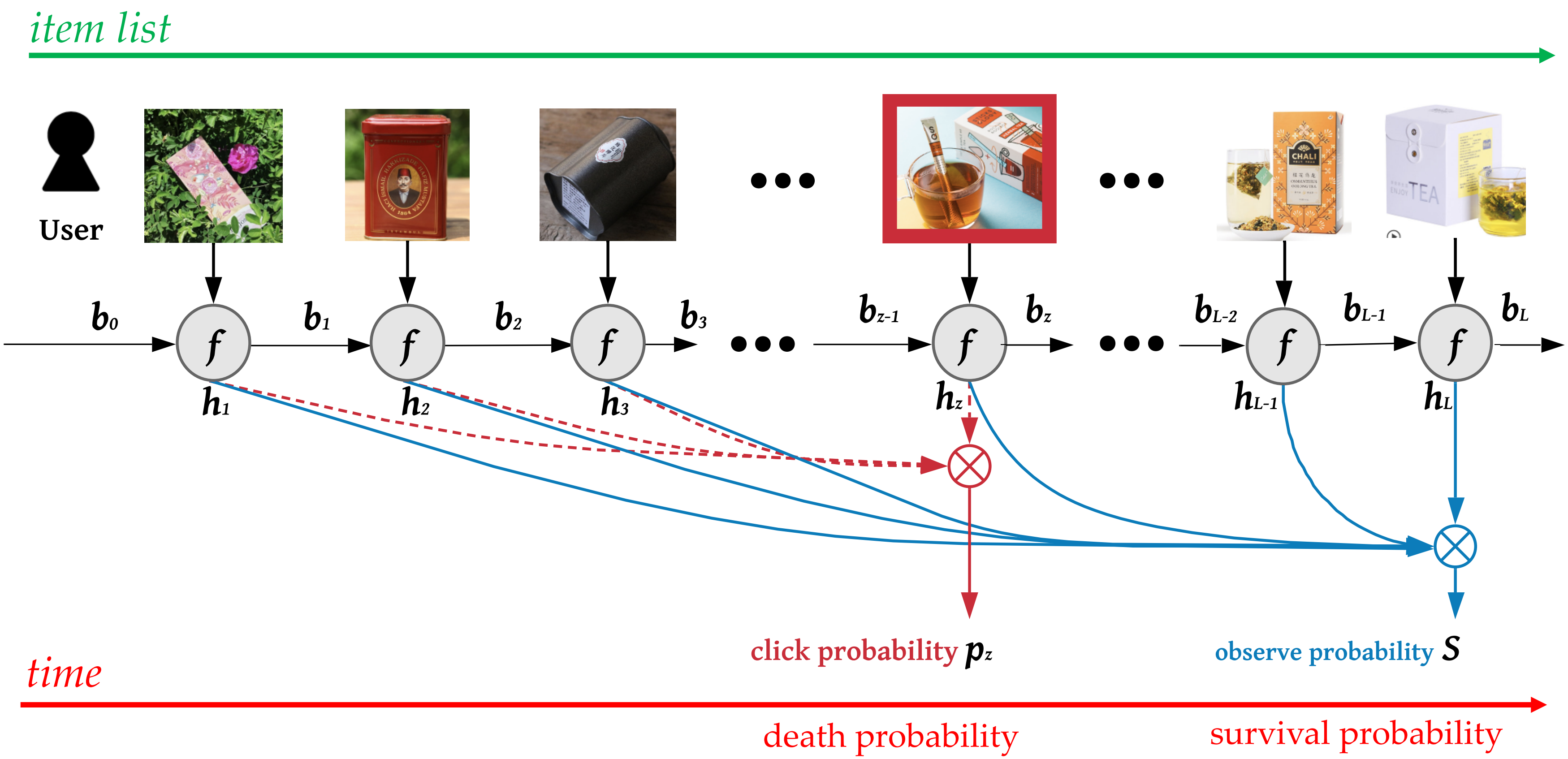


Figure: Illustration of Deep Recurrent Survival Ranking Model. Note that we mine click patterns in click case and observe patterns in both click and non-click cases.

HEROES: Unbiased Version

click event z

- click probability (death probability), the probability density function (P.D.F.) of click occurring at i-th item

$$p_i = P(c_i = 1) = P(z = i)$$

- observe probability (survival probability), the cumulative distribution function (C.D.F.), since user will keep browsing until she finds and clicks a favored one

$$S(i) = P(o_i = 1) = \sum_{\tau \geq i} P(z = \tau)$$

- relevance probability, the conditional click probability, the click probability at item given that the item is observed

$$h_i = P(r_i = 1) = \frac{P(c_i = 1)}{P(o_i = 1)} = \frac{P(z = i)}{P(z \geq i)} = \frac{p_i}{S_i}$$

HEROES: Unbiased Version

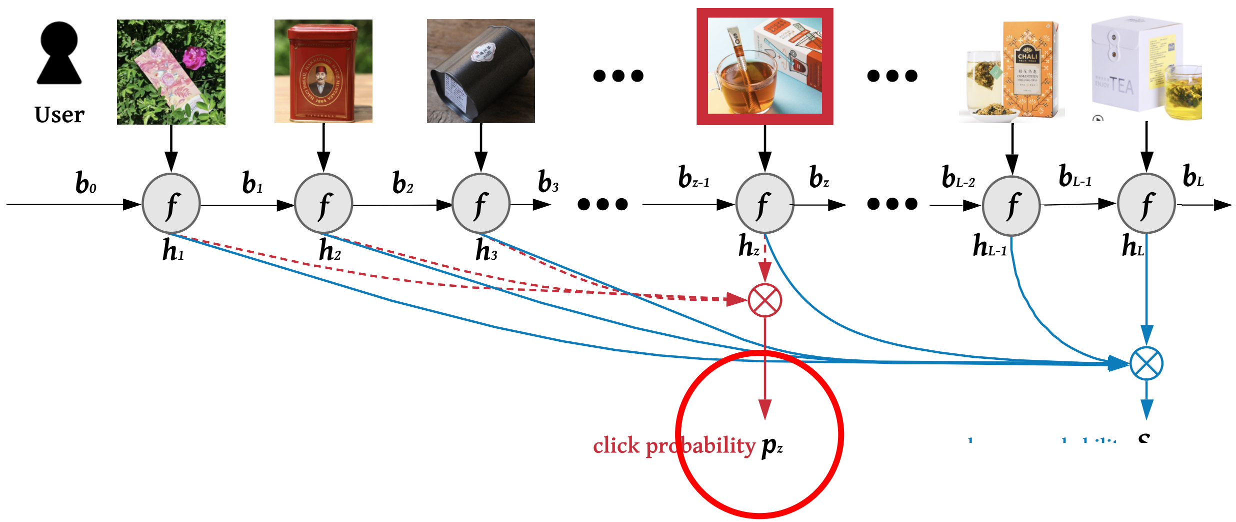
- relevance probability

$$h_i = P(z = i | z \geq i, x; \theta) = f_\theta\,(x_i\,|b_{i-1})$$

- click probability (death probability)

$$p_i = [1 - S(i+1)] - [1 - S(i)] = S(i) - S(i+1)$$

$$p_i = P(z = i | x; \theta) = h_i \prod_{\tau:\tau<i} (1 - h_\tau)$$



Unbiased Loss Functions

- click probability (P.D.F.)
  - aims to minimize negative log-likelihood of the click item d_j over the clicked logs as

$$L_{\text{point}(z)} = -\log \prod_{(x,z)\in\mathcal{D}_{\text{click}}} P(z = j|x;\theta) = -\log \prod_{(x,z)\in\mathcal{D}_{\text{click}}} p_j$$

$$= -\log \prod_{(x,z)\in\mathcal{D}_{\text{click}}} \left[h_j \prod_{\tau:\tau<i} (1 - h_\tau) \right]$$

$$= - \sum_{(x,z)\in\mathcal{D}_{\text{click}}} [\log h_j + \sum_{\tau:\tau<i} \log(1 - h_\tau)]$$

Unbiased Loss Functions

- observe probability (C.D.F.)
  - over the click cases

$$L_{\text{click}} = -\log \prod_{(x,l)\in\mathcal{D}_{\text{click}}} P(l \geq z|x;\theta) \approx -\log \sum_{(x,l)\in\mathcal{D}_{\text{click}}} [1 - S(l|x;\theta)]$$

$$= - \sum_{(x,l)\in\mathcal{D}_{\text{click}}} \log\,[1 - \prod_{\tau:\tau<l} (1 - h_\tau)]$$

  - over the non-click cases

$$L_{\text{non-click}} = -\log \prod_{(x,l)\in\mathcal{D}_{\text{non-click}}} P(z > l|x;\theta) \approx -\log \sum_{(x,l)\in\mathcal{D}_{\text{non-click}}} S(l|x;\theta)$$

$$= - \sum_{(x,l)\in\mathcal{D}_{\text{non-click}}} \sum_{\tau:\tau<l} \log(1 - h_\tau)$$

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Experiment

Table 2: Comparison of different multi-task models and sequential models on three industrial datasets. Results of both Click-Through Rate (CTR) and Conversion Rate (CVR) are reported. Bold values are the best in each column, while the second best values are underlined. * indicates $p < 0.001$ in significance tests compared to the best baseline.

Ranker	Task	Criteo			Taobao E-Commerce			Diantao Live Broadcast		
		AUC	LogLoss	NDCG	AUC	LogLoss	NDCG	AUC	LogLoss	NDCG
DUPN	CVR	0.9505	0.1137	0.7348	0.6747	0.5194	0.6843	0.8232	0.2345	0.7522
	CTR	0.7410	0.5863	0.7526	0.5777	0.7215	0.4576	0.7156	0.6032	0.7009
ESMM	CVR	0.8750	0.4466	0.7194	0.6443	0.6330	0.6490	0.7046	0.2743	0.6697
	CTR	0.6476	0.6511	0.7460	0.5410	0.7591	0.4166	0.6664	0.6577	0.6601
ESM^2	CVR	0.8798	0.4360	0.7235	0.6453	0.6376	0.6471	0.7039	0.2756	0.6688
	CTR	0.6740	0.6370	0.7496	0.5437	0.7573	0.4170	0.6742	0.6512	0.6608
MMoE	CVR	0.8817	0.4420	0.7182	0.6537	0.6267	0.6452	0.7283	0.2731	0.6653
	CTR	0.6779	0.6343	0.7540	0.5410	0.7463	0.4093	0.6770	0.6513	0.6618
DRSR	CVR	0.9468	0.1366	0.7644	0.6723	0.5156	0.6892	0.8140	0.2546	0.7697
	CTR	0.7452	0.5837	0.7687	0.5759	0.7171	0.4578	0.6985	0.6103	0.7053
RRN	CVR	0.9564	0.1169	0.7739	0.6732	0.5061	0.6890	0.8156	0.2698	0.7421
	CTR	0.7496	0.5797	0.7706	0.5766	0.7075	0.4575	0.6926	0.6019	0.6928
NARM	CVR	0.9524	0.1172	0.7644	0.6733	0.5160	0.6893	0.8234	0.2595	0.7612
	CTR	0.7511	0.5810	0.7724	0.5764	0.7186	0.4576	0.7082	0.5958	0.7012
STAMP	CVR	0.9406	0.1209	0.8014	0.6668	0.5210	0.6892	0.8467	0.2465	0.7689
	CTR	0.7391	0.5929	0.7702	0.5748	0.7235	0.4575	0.7123	0.5940	0.7070
Time-LSTM	CVR	0.9622	0.1132	0.7979	0.6745	0.5169	0.6889	0.8540	0.2412	0.7787
	CTR	0.7602	0.5703	0.7738	0.5776	0.7192	0.4576	0.7195	0.6040	0.7124
LSTM	CVR	0.8429	0.4841	0.6629	0.6721	0.4783	0.6885	0.7124	0.2736	0.7475
	CTR	0.6032	0.6042	0.7503	0.5749	0.7222	0.4493	0.6633	0.6542	0.6792
NHP	CVR	0.9533	0.1127	0.7682	0.6743	0.4914	0.6893	0.8267	0.2535	0.7622
	CTR	0.7428	0.5816	0.7656	0.5773	0.7214	0.4576	0.7033	0.6042	0.7068
HEROES$^{-}_{\mathtt{intra}}$	CVR	0.8801	0.4270	0.7327	0.6917	0.5209	0.6998	0.8045	0.2675	0.7712
	CTR	0.6764	0.6612	0.7521	0.5483	0.7174	0.4682	0.7091	0.5976	0.7135
HEROES$^{-}_{\mathtt{inter}}$	CVR	0.9682	0.1152	0.7832	0.6932	0.4918	0.7082	0.8346	0.2225	0.7883
	CTR	0.7632	0.5721	0.7882	0.5927	0.7032	0.4721	0.7138	0.6021	0.7123
HEROES$^{-}_{\mathtt{unit}}$	CVR	0.9705	0.1016	0.8348	0.7402	0.4366	0.7106	0.8601	0.2350	0.7810
	CTR	0.7787	0.5483	0.7832	0.5920	0.7084	0.4701	0.7412	0.5942	0.7111
HEROES	CVR	**0.9759***	**0.0975***	**0.8551***	**0.7503***	**0.3519***	**0.7137***	**0.8649***	**0.2203***	**0.7893***
	CTR	**0.7870***	**0.5400***	**0.7913***	**0.5953***	**0.7024***	**0.4727***	**0.7492***	**0.5893***	**0.7166***

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Experiment

Table 3: Comparison of unbiased LTR and biased LTR version of HEROES under click generation model PBM.

Ranker	Task	Taobao E-Commerce (PBM)		
		AUC	LogLoss	NDCG
Relevance Data (HEROES)	CVR	0.7503	0.3519	0.7137
	CTR	0.5953	0.7024	0.4727
HEROES$^+$	CVR	0.7442	0.3674	0.7064
	CTR	0.5735	0.7206	0.4567
HEROES$^+_{comb}$	CVR	0.7463	0.3638	0.7110
	CTR	0.5738	0.7202	0.4521
Click Data (HEROES)	CVR	0.7412	0.3746	0.7024
	CTR	0.5643	0.7563	0.4284

To evaluate the performance of HEROES under unbiased setting, we introduce a position-based simulation, where clicks are generated according to

$$P(c_i) = P(o_i) \cdot P(r_i)$$

where $P(o_i) = \rho_i^\tau$ and ρ_i is obtaining from an eye-tracking experiment and τ is set as 1.

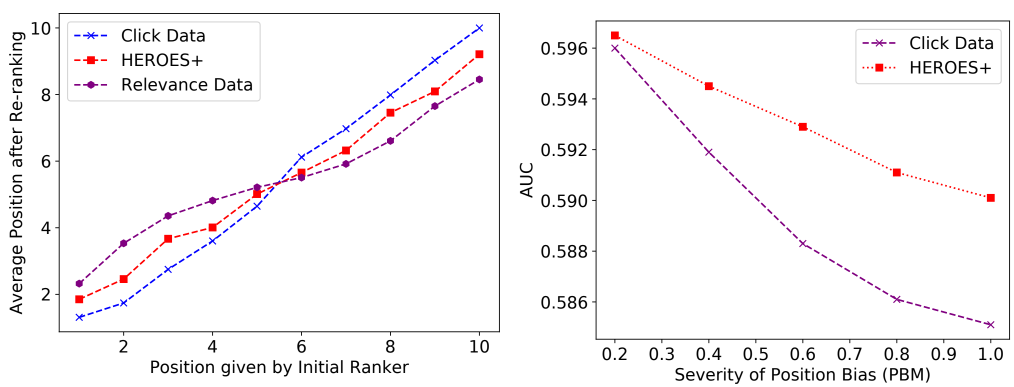

Figure 6: (a) Average position after re-ranking of the item at each original position. (b) Performance change of HEROES$^+$ against click data with different degrees of position bias.

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Conclusion

- Our main insight is to model the multiple user behaviors on the entire space (i.e., "observation → click → conversion") in a multi-scale manner.
- To achieve this, we design a novel recurrent unit to take both the contextual items and the user's previous behaviors into consideration.
- We show that our approach can be seamlessly used for unbiased ranking by incorporating with survival analysis technique.

Thanks for Your Listening