# **KEPS**

Knowledge Enhanced Personalized Search



01 基本概念

02 具体内容

03 训练与实验

contents

## 基本概念



personalized search

external knowledge



entity-oriented search

difficulty of query entity linking



本文的工作

together these advantages

### 基本思路

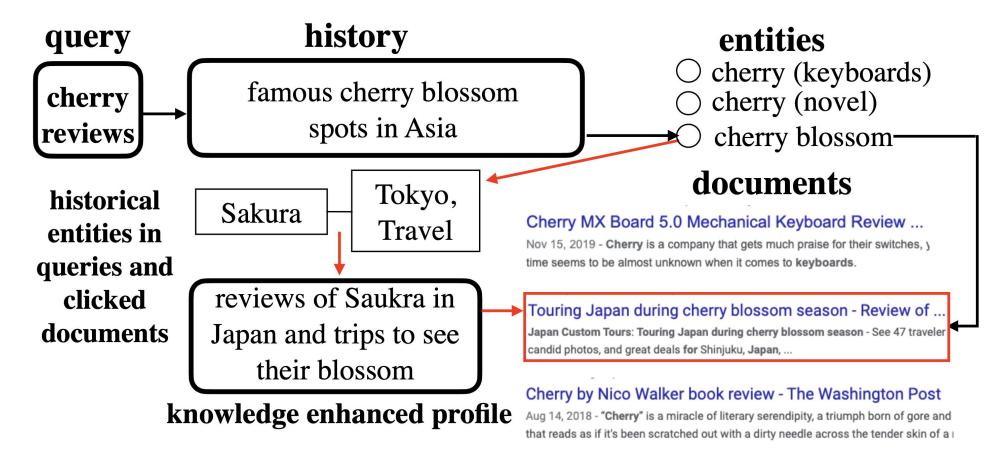


Figure 1: knowledge enhanced personalized search example

### 具体内容

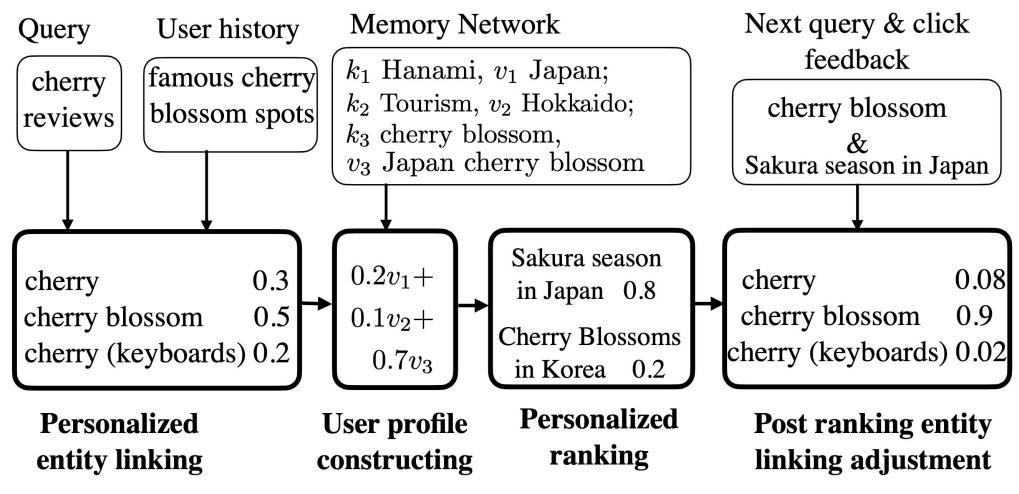
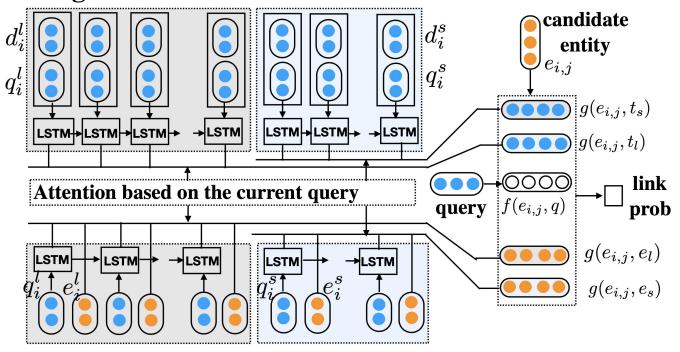


Figure 2: The KEPS framework.

### Personalized Entity Linking

#### long-term RNN short-term RNN



$$p_{i,j} = \mathcal{F}(e_{i,j}|q,\mathcal{H}) = \frac{\exp(\text{MLP}(f(e_{i,j},q) \oplus f(e_{i,j},\mathcal{H})))}{\sum_{k=1}^{n_i} \exp(\text{MLP}(f(e_{i,k},q) \oplus f(e_{i,k},\mathcal{H})))},$$

$$f(e_{i,j},q) = \tanh(\boldsymbol{e}_{i,j}^{\mathsf{T}} * \mathrm{MLP}(\boldsymbol{q})) \oplus \mathrm{MLP}(\boldsymbol{l}_{i,j}),$$

$$g(\mathbf{x}, \mathbf{y}) = \tanh(\mathbf{x}^T * \text{MLP}(\mathbf{y}))$$

long-term entity short-term entity

Figure 3: Structure of personalized entity linking.

$$f(\mathbf{e}_{i,j},\mathcal{H}) = g(\mathbf{e}_{i,j},\mathbf{t}_s) \oplus g(\mathbf{e}_{i,j},\mathbf{t}_l) \oplus g(\mathbf{e}_{i,j},\mathbf{e}_s) \oplus g(\mathbf{e}_{i,j},\mathbf{e}_l)$$

### **User Profile Constructing**

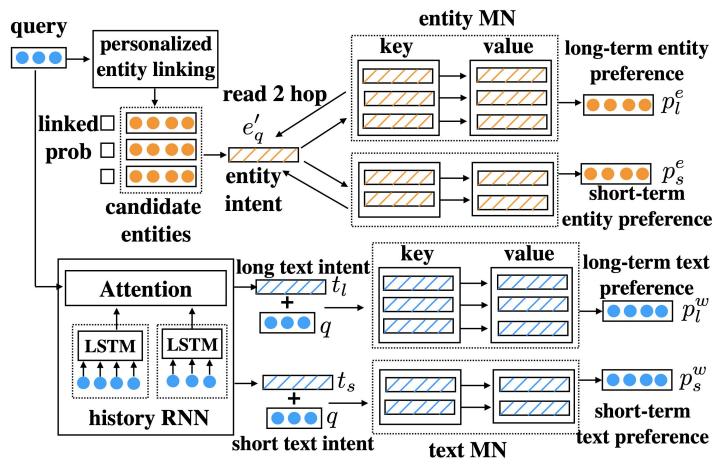


Figure 4: Structure of preference profile constructing.

$$\mathbf{K}_{s} = [\mathbf{k}_{1}^{s}, ..., \mathbf{k}_{|Q_{s}|}^{s}] = [\mathbf{e}_{1}^{s}, ..., \mathbf{e}_{|Q_{s}|}^{s}],$$
 $\mathbf{V}_{s} = [\mathbf{v}_{1}^{s}, ..., \mathbf{v}_{|Q_{s}|}^{s}],$ 

$$\mathbf{K}_{s} = [\mathbf{k}_{1}^{s}, ..., \mathbf{k}_{|Q_{s}|}^{s}] = [\mathbf{q}_{1}^{s}, ..., \mathbf{q}_{|Q_{s}|}^{s}]$$

$$\mathbf{V}_{s} = [\mathbf{v}_{1}^{s}, ..., \mathbf{v}_{|Q_{s}|}^{s}],$$

### Personalized Ranking

$$\mathcal{F}(d|q,\mathcal{H}) = \text{MLP}(f(d \oplus \mathcal{I}) \oplus f(d,\mathcal{P}) \oplus f(d,q)),$$

# Intention Relevance

$$f(d, I) = g(d, t_s) \oplus g(d, t_l) \oplus g(d^e, e_q) \oplus g(d, e_q)$$

#### **Preference Relevance**

$$f(d,\mathcal{P}) = g(\boldsymbol{d},\boldsymbol{p}_s^w) \oplus g(\boldsymbol{d},\boldsymbol{p}_l^w) \oplus g(\boldsymbol{d}^e,\boldsymbol{p}_s^e) \oplus g(\boldsymbol{d}^e,\boldsymbol{p}_l^e)$$

### Query relevance

$$f(d,q) = g(d,q) \oplus MLP(f_d) \oplus f_m$$

d,q is the text embedding of the query and document,  $f_d$  is click features,  $f_m$  is interactive word-entity duet matching features (EDRM [ACL18]).  $f_m f_d$ 

### Post-ranking Entity Linking Adjustment

$$\begin{aligned} p_{i,j}^t &= p_{i,j}^t + \boldsymbol{e}_{i,j}^t^\top * \boldsymbol{W} * \boldsymbol{d}_e^t, \\ p_{i,j}^t &= \frac{\exp(p_{i,j}^t)}{\sum_{k=1}^{n_i^t} \exp(p_{i,k}^t)}, \\ p_{i,j}^k &= p_{i,j}^k + \text{MLP}(\boldsymbol{e}_a^t^\top * \boldsymbol{W}_1 * \boldsymbol{e}_{i,j}^k \oplus \boldsymbol{q}^{t^\top} * \boldsymbol{W}_2 * \boldsymbol{q}^k), \quad 1 <= k <= t-1 \\ \boldsymbol{e}_a^t &= \sum_{j=1}^{n_a^t} p_{a,j}^t * \boldsymbol{e}_{a,j}^t \end{aligned}$$

When conduct post-ranking adjustment, our main idea is: firstly select the entity with the highest linking probability which reflects the user's intention; then use this entity to adjust the linking prob- abilities of entities associated with other mentions in the session.

### **Traaning**

$$l = \sum_{u} \sum_{S} \sum_{q \in S} \sum_{d^{-}, d^{+} \in \mathcal{D}} \max(0, 1 - f(q, d^{+}, \mathcal{H}) + f(q, d^{-}, \mathcal{H})),$$

where u denotes user, S denotes session, H is user's search history, q denotes query, and d + represents the positive documents while d - represents others in the document list D associated with q .

## 实验内容

Model	MAP		MRR		AR		Precision@1		Precision@3 P		Precision@5		
Ad-hoc Search models													
Model	MAP		MRR		AR		Precision						
Model							P@1		P@3		P@5		
PSGAN	.5480	-	.5600	-	10.2670	-	.4892	-	.5720	-	.6140	-	
KEPS-noEntity	.6618*	+20.77%	.6771*	+20.91%	5.6227*	+45.24%	.5868*	+19.95%	.7239*	+26.56%	.7805*	+27.12%	
KEPS-noPSLink	$.6700^*$	+22.27%	.6842*	+22.18%	5.4799*	+46.63%	.5929*	21.20%	.7320*	+27.97%	$.7889^*$	+28.48%	
KEPS-noMN	.6547*	+19.47%	.6691*	+19.48%	5.7821*	+43.68%	.5782*	+18.19%	.7129*	+24.63%	.7719*	+25.72%	
KEPS-noAdjust	.6811*	+24.29%	$.6942^{*}$	+23.96%	5.2180*	+49.18%	.6020*	+23.06%	.7456*	+30.35%	$.8017^*$	+30.57%	
KEPS-QR	.6481*	+18.27%	.6609*	+18.02%	5.6743*	+44.73%	.5637*	+15.23%	.7089*	+23.93%	.7748*	+26.19%	
KEPS	.6903*\$	+25.97%	.7044**	+25.79%	5.0645**	+50.67%	.6124**	+25.18%	.7578**	+32.48%	.8118**	+32.21	
Knowledge Enhanced Personalization models													
HRNN-Entity			.5565†‡	-0.63%	10.4791	RECEIVED AND AND AND AND AND AND AND AND AND AN				77% .607		<u> </u>	
KEPS	.6903	+25.97%	.7 <b>044</b> <sup>†‡</sup>	* +25.79%	5.0645 <sup>†‡</sup> *	+50.67%	.6124 <sup>†‡*</sup> +	-25.18% .7	7 <b>578</b> <sup>†‡*</sup> +32	2.48%   .81	18 <sup>†‡*</sup> +32.2	21%	

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# Thanks