

CUIS at the NTCIR-12 MobileClick2 Task

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Introduction

- ▶ Problems of IR in mobile platform
 - ▶ small screen size
 - ▶ slow network speed and computing power
- ▶ MobileClick Solution
 - ▶ iUnit ranking
 - ▶ iUnit summarization

iUnit Ranking

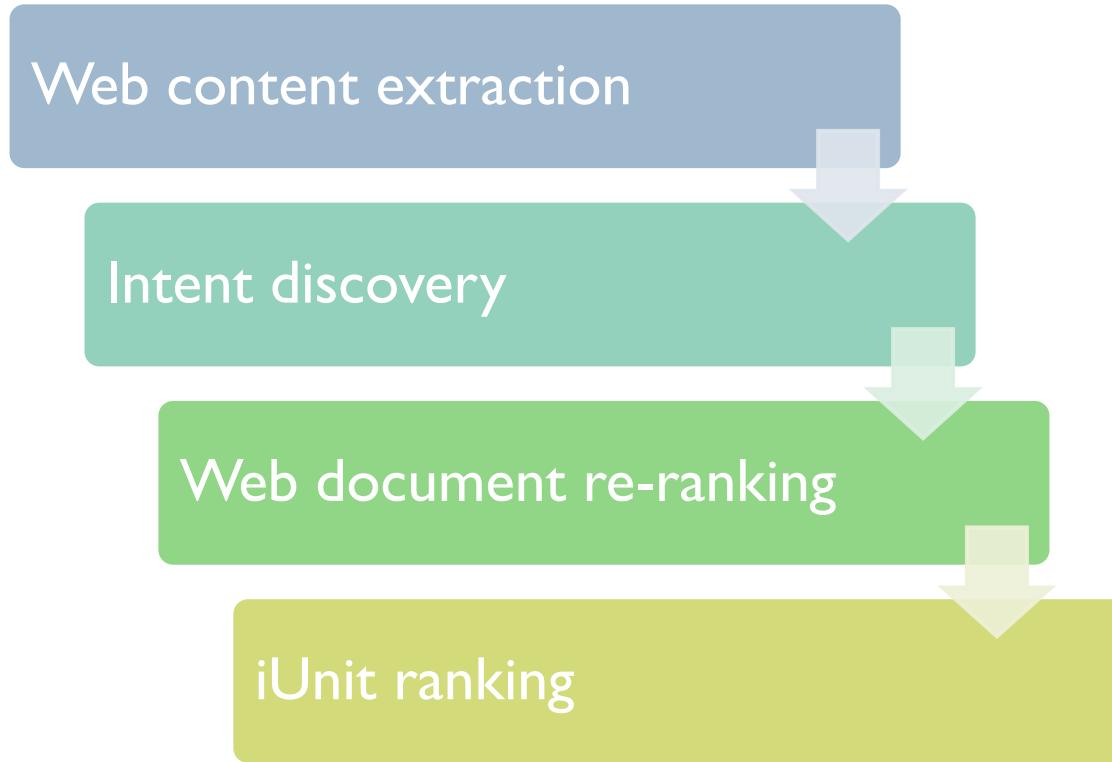
- ▶ **Input**

- ▶ a query
- ▶ a list of iUnits
- ▶ a collection of retrieved HTML documents

- ▶ **Output**

- ▶ a list of iUnits with ranking

iUnit Ranking Model



Web content extraction

- ▶ Aims at removing unimportant parts such as menu, navigation bar, scripts, etc.

- ▶ Tag-based

- ▶ paragraph (p tag)
- ▶ title (h tag)
- ▶ cell in table (td tag)
- ▶ list (li tag)

- ▶ Text feature-based

- ▶ Boilerpipe

Christian Kohlschütter, Peter Fankhauser, and Wolfgang Nejdl. "Boilerplate detection using shallow text features." Proceedings of the third ACM international conference on Web search and data mining. ACM, 2010.



Intent discovery

- ▶ Use Latent Dirichlet Allocation(LDA) to discover hidden intent
 - ▶ Train a LDA model using the Web content documents
 - ▶ Rank the intents based on $P(i|q)$
 - ▶ q : query
 - ▶ i : intent
 - ▶ Query folding-in
 - ▶ $q = \{q_1, q_2, \dots, q_k\}$, where $k = |q|$

$$P(i|q_j) = \frac{P(q_j|i)P(i)}{P(q_j)}$$

- ▶ $P(q_j|i)$ is inferred by the LDA model
- ▶ Set a uniform prior



Intent discovery

- ▶ Random sampling of the latent topic n times for each q_i

$$P(i|q) = \frac{c_i}{nr}$$

- ▶ c_i : total number of latent topics of the intent i being sampled
 - ▶ n : number of sampling of the query
 - ▶ r : total number of terms of the query
-
- ▶ Inspired by the work of He et al. (2011)

Jiyin He, Edgar Meij, and Maarten de Rijke. "Result diversification based on query-specific cluster ranking." *Journal of the American Society for Information Science and Technology* 62.3 (2011): 550-571.



Web document re-ranking

- ▶ Associate one intent to each Web document

$$i^* = \arg \max_{i \in I} P(i|d)$$

- ▶ d: document
- ▶ i: intent
- ▶ the Web document with same intent form an intent document group G_i



- ▶ Web document re-ranking using Round-Robin
 - ▶ document weighting
 - $w_d = |D| + 1 - ranking(d)$
 - ▶ $|D|$: the total number of documents
 - ▶ $ranking(.)$: the new ranking score of the document

Web document re-ranking

Algorithm 1 Web document re-ranking

```
1: function RR-RANK( $|D|, G, R_I$ )
2: input: The total number of Web document  $|D|$ ; intent
   document group  $G$ ; intent ranking  $R_I$ 
3: output: New intent-based ranking of all Web docu-
   ment
4:    $ranking = \emptyset$ 
5:   while  $|ranking| \neq |D|$  do
6:     for each  $i \in R_I$  do
7:       if  $G_i \neq \emptyset$  then
8:          $ranking.add(G_i.poll())$ 
9:       end if
10:      end for
11:    end while
12:    return  $ranking$ 
13: end function
```



iUnit Ranking

- ▶ Importance measure $I(u,d)$

- ▶ The importance of iUnit u in each document d

$$I(u, d) = \frac{\sum_{w \in u} \text{exist}(w, d)}{|u|}$$

- ▶ $\text{exist}(w,d)$: indicator function denoting the existence of the word w in the document d

$$\text{exist}(w, d) = \begin{cases} 1 & w \in d \\ 0 & w \notin d \end{cases}$$

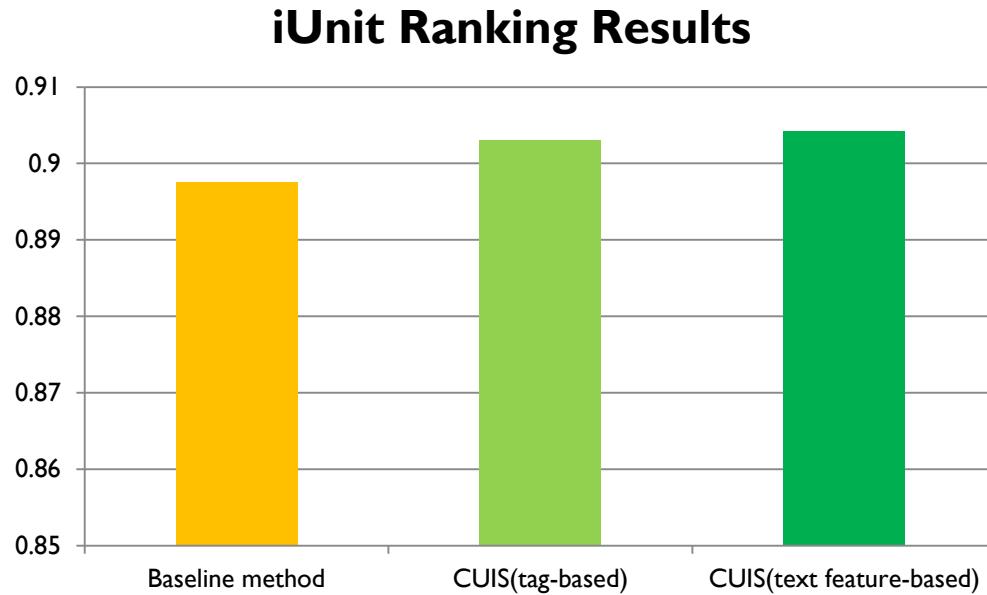


- ▶ Overall score

$$\text{score}(u) = \sum_{d \in D_q} w_d I(u, d)$$

- ▶ u : iUnit, w_d : document weighting of the document d

Result of iUnit Ranking Model



iUnit Summarization

- ▶ **Input**

- ▶ a query
- ▶ a list of iUnits
- ▶ a collection of retrieved HTML documents
- ▶ a list of intent labels

- ▶ **Output**

- ▶ a two-layered structure

iUnit Summarization Model

Constructing 1st layer

Associate web document
and iUnit to intent label

Constructing 2nd layers

Constructing 1st layer

- ▶ Concatenate the iUnits in the order obtained in iUnit ranking result until reaching character limit(420 characters)
- ▶ Append all intent labels at the tail



Associate Web document and iUnit to intent label

Web document containing words of intent label

- ▶ Probability of the intent given the Web document

$$P(i|d) = \frac{f(i, d)}{\sum_{i' \in I_q} f(i', d)}$$

- ▶ The intent importance in the Web document

$$f(i, d) = \min_{w \in i} tf(w, d)$$

Constructing 1st layer

Associate web document and iUnit to intent label

Constructing 2nd layers

Web document not containing words of intent label

$$P(i|d') = \frac{\sum_{d'' \in D_i} sim(\mathbf{v}_{d'}, \mathbf{v}_{d''})}{|D_i|}$$

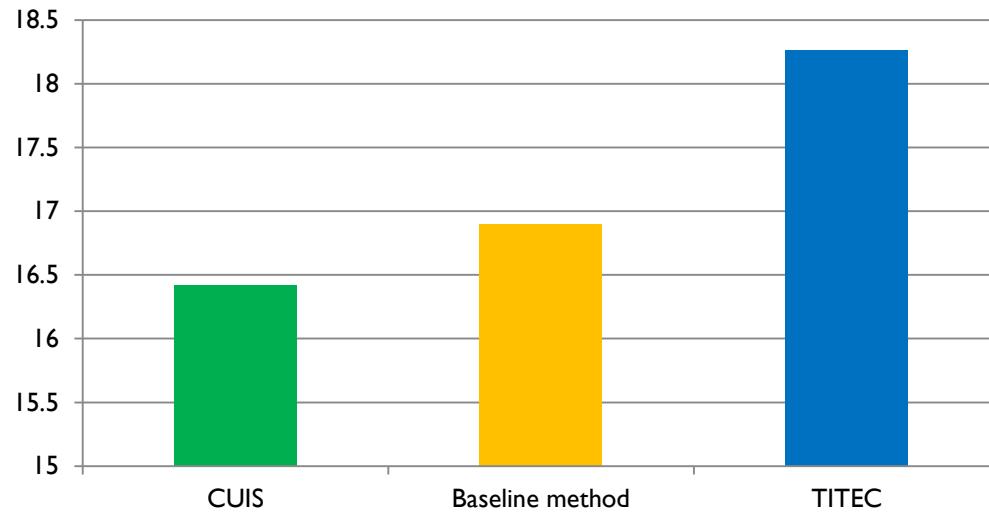
Constructing 2nd layers

- ▶ Construct a layer for each intent
- ▶ Concatenate the iUnits corresponding to the intent in the order obtained in iUnit ranking result



Result of iUnit Summarization Model

iUnit Summarization Results



► THANK YOU!