

# Personalized click prediction in sponsored search

Cheng, H., & Cantú-Paz, E. (2010)

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2018.04.25

# 1. Introduction

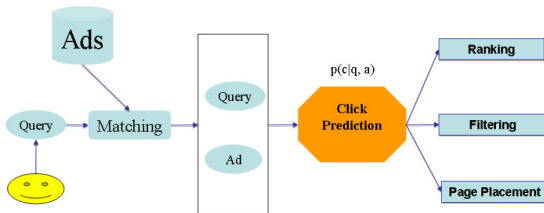


Figure 1 : Overview of sponsored search system

- Sponsored search: an Internet advertising system that generates most of the revenue of search engines by presenting targeted ads along with the search results.

# 1. Introduction

- ▶ Conventional approach
  - ▶ Use a machine learned model based on user-independent features to predict the click probability of ads.
  - ▶ Features for a machine learned model:
    1. the similarity of the query to the text of the ads;
    2. the historical performance of ads;
    3. contextual information (ex. time of day or day of the week).
  - ✓ This model will predict the same probability of click for every user.
- ▶ The objective of this paper is to design of pernalized click prediction models by developing new user-related features.

## 2. Click prediction

- ▶ Settings

- ▶  $\mathcal{D} = \{(f(q_j, a_j), c_j)\}_{j=1}^n$ :  $n$  training samples
- ▶  $f(q_j, a_j) \in \mathbb{R}^d$ : the  $d$ -dimensional feature space for query-ad pair  $j$ ,  
 $c_j \in \{-1, +1\}$ : corresponding class label (+1: click or -1: non-click)

- ▶ Given a query  $q$  and ad  $a$ , the maximum entropy model (ME) formulates the click probability as follows:

$$p(c|q, a) = \frac{1}{1 + \exp(\sum_{i=1}^d w_i f_i(q, a))},$$

where  $\mathbf{w} \in \mathbb{R}^d$  are weight parameters. Given the training set  $\mathcal{D}$ ,  $\mathbf{w}$  estimated as

$$\hat{\mathbf{w}} = \operatorname{argmax} \left[ \sum_{j=1}^n \log(p(c_j|q_j, a_j)) + \log(p(\mathbf{w})) \right].$$

## 2. Click prediction

### 2.1 Features

- Features derived from the historical performance of ads:

- Click-through rate (CTR) at position  $r$  :

$$CTR_r(q, a) = \frac{c_r(q, a)}{i_r(q, a)},$$

where  $i_r(q, a)$  is the number of times that query  $q$  and ad  $a$  were shown together at position  $r$ , and  $c_r(q, a)$  is the number of times those impression were clicked.

- Clicks over expected clicks (COEC):

$$COEC(q, a) = \frac{\sum_{r=1}^R c_r(q, a)}{\sum_{r=1}^R i_r(q, a) \times CTR_r},$$

where  $CTR_r$  is the average  $CTR$  for each position  $r$  computed over all queries and ads and the denominator can be viewed as the expected clicks (ECs).

- NV: total number of ad views
  - NCLI: total number of ad clicks

## 2. Click prediction

### 2.2 Feature quantization, conjunctions, and selection

- ▶ Feature quantization:
  - ▶ In this work, the features are transformed into the log form and then quantized using simple  $K$ -means clustering.
  - ▶ We introduce binary indicator features for each cluster, and use these binary features as inputs to the ME model.
  - ▶ For new ads or new queris, we also use a binary indicator feature to indicate that a certain value is missing.
- ▶ Feature conjunctions:
  - ▶ To model relationships among features, create feature conjunctions by taking the cross product of the binary indicators for pairs of features.
  - ▶ We select the features to be conjoined using domain knowledge.

### 3. User click analysis

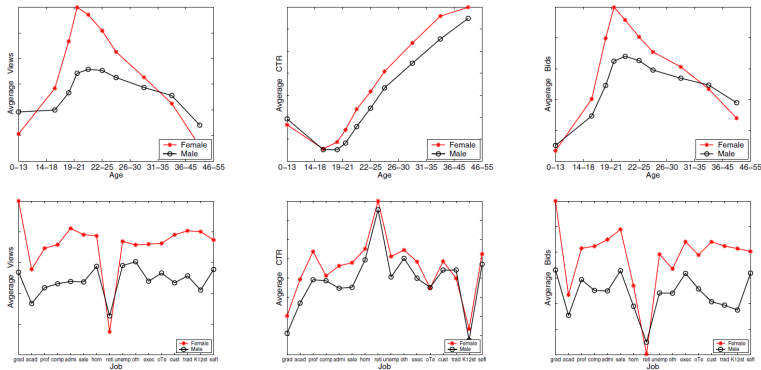


Figure 2 : User click, view and bid distributions with regard to demographic background

## 4. Personalized click prediction

- ▶ Let  $\mathcal{D} = \{(f(q_j, a_j, u_j), c_j)\}_{j=1}^n$  represent the new training set, where each sample  $j$  represents a click or non-click event when ad  $a_j$  is presented to user  $u_j$  for query  $q_j$ .
- ▶ We develop a new click prediction function as:

$$p(c|q, a, u) = \frac{1}{1 + \exp(\sum_{i=1}^d w_i f_i(q, a, u))},$$

where  $\mathbf{w} \in \mathbb{R}^d$  are weight parameters. Given the training set  $\mathcal{D}$ ,  $\mathbf{w}$  is estimated as

$$\hat{\mathbf{w}} = \operatorname{argmax} \left[ \sum_{j=1}^n \log(p(c_j|q_j, a_j, u_j)) + \log(p(\mathbf{w})) \right].$$



## 5. User features

### 1. Demographic group features

- ▶ We partition users into demographic segments based on age, gender, marriage status, interests, job status, and occupation.

### 2. User-specific features

- ▶ User-specific features capture individual user's interaction with the ads shown in the search result page.
- ▶  $UCOEC_u = \frac{CTR \text{ of user } u}{\text{Average } CTR \text{ of } u\text{'s group}}$ ,  
where the average  $CTR$  is calculated for each user group and users are grouped together based on the total number of ads they have seen.
- ▶ We can also derive other user-specific click feedback features (EC, COEC, NV, NCLI) at the user, user-query, and user-ad levels.

## 6. Experiments

- ▶ The training and testing data were sampled from the Yahoo! sponsored search traffic logs for a period of 2 months.
- ▶ Online performance comparison: for online testing we selected the model with user and user-ad features.

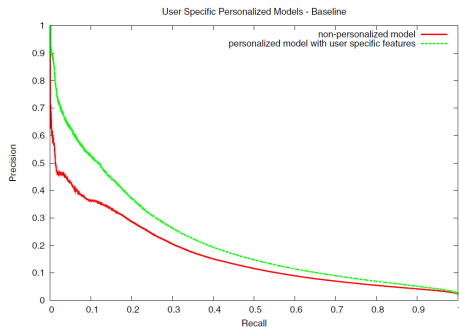


Figure 3 : Online performance of the personalized model.