Is Pay-Per-Click Efficient? An Empirical Analysis of Click Values

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ABSTRACT

Current sponsored search auction adopts per-click bidding. It implicitly assumes that an advertiser treats all clicks to be equally valuable. This is not always true in real world situations. Clicks which lead to conversions are definitely more valuable than those fraudulent clicks. In this work , we use post-ad-click behavior to measure a click's value and empirically show that for an advertiser, values of different clicks are highly variant. Thus for many clicks, the advertiser's single bid does not reflect his true valuations. This indicates that the sponsored search system under PPC mechanism is not efficient, or does not always give a slot to the advertiser who needs it most.

Categories and Subject Descriptors

H.4.m [**Information Systems**]: Miscellaneous

General Terms

Design, Experimentation

Keywords

Internet Monetization

1. INTRODUCTION

Sponsored search has become one of the most profitable components for search engine. When a user issues a query, the system will choose a list of advertisements matching the keywords and display them on the webpage. The order of the advertisements is determined by the bids corresponding advertisers submit. The bid is usually the average value of all clicks. The advertiser uses the same bid even though clicks may be of different values. This may lead to a problem when the variance of the click values is high: the advertiser may bid a higher value on an invaluable click. From game theory perspective, the pay-per-click mechanism may not be efficient: since we do not know the advertiser's true valuation of a click, we cannot guarantee that the system gives a slot to an advertiser who needs it most.

The goal of this work is to provide a empirical analysis of the click values and motivate the mechanism design researchers to think about a refined and more efficient mechanism beyond the currently used PPC mechanism. We use a user's post-ad-click behavior as a surrogate for the value of his click on an advertisement. We propose two assumptions on click values and empirically validate them to imply that the value variance is typically high for many advertisers and that the currently adopted PPC mechanism may not be efficient.

We propose the two assumptions in section 2 and validate them in section 3.

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2. ASSUMPTIONS ON CLICK VALUES

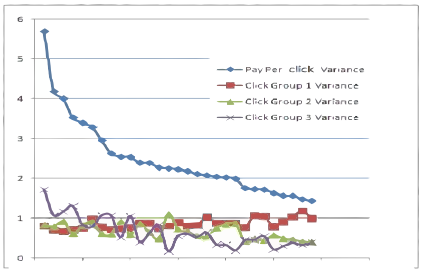
We use a user's post-ad-click behavior [2, 3, 1] to measure the value of his click on the advertisement. ***Post-ad-click behavior*** is defined to be the user's subsequent online behavior on the advertiser's website after the click. In this section, we look into click values from two perspectives:

- ***Click value variability:*** We assume that the variance in click value is very high and that if we group clicks according to their values, the variance in each group is significantly reduced. Advertisers always would like to submit a bid for a click group of low value variance. Therefore, if the variance is high, an advertiser has the incentive to differentiate users and provides different bids for different groups.
- ***Advertiser evaluation variability:*** We assume that different advertisers have different business strategies and thus different valuations of a click from the same user. A click that is valuable to one advertiser may be worthless to another advertiser. Enabling advertisers to differentiate clicks and place different bids can make the system more efficient and increase advertisers' satisfactions.

3. EMPIRICAL ANALYSIS ON CLICK VALUES

In this section, we will use the toolbar log to validate the proposed assumptions. We totally collect a set of 29 advertisers $\mathcal{A} = \{a_1, a_2, ..., a_{29}\}$ on computer games. In the dataset, We denote by $U_i = \{u_{i1}, u_{i2}, ...\}$ the set consisted of users who clicked a_i's advertisements, and denote by $t(u_{ij})$ the dwell time of the user u_{ij} on the advertiser website. In the dataset, many users clicked different advertisers' ads.

Figure 1: Click group variance compared with pay-per-click variance



We assume that an advertiser uses dwell time to evaluate the value of a click. Therefore, for each ad a_i, we rank clicks according to their dwell time. We then let the top 10% clicks form a click group U_i^1, the top 11% - 50% ones form U_i^2, and the remaining ones form U_i^3.

3.1 Click Value Variability

We use the relative standard deviation of the dwell time to measure click value variability. Specifically, given a set of clicks and their dwell time $T = \{t_1, ..., t_m\}$, we calculate the mean $\mu(T)$ and the variance $\sigma(T)$ of the dwell time. The relative standard deviation $rsd(T)$ is the quotient between $\sigma(T)$ and $\mu(T)$.

For each advertiser a_i, we calculate the relative standard deviations $rsd(T_i)$, $rsd(T_i^1)$, $rsd(T_i^2)$, $rsd(T_i^3)$ on four click groups, i.e., U_i, U_i^1, U_i^2, U_i^3. We plot four curves C_0, C_1, C_2, C_3 in Figure 1 where $C_j = \{(i, rsd(T_i^j))\}$

We can see from the Figure 1 that the relative standard deviation on the click set $\{T_i\}$ is very high, up to 5.8 for an advertiser. It indicates that the variance in click value is high. However, after the clicks are grouped into three groups, the relative standard deviation in each group is significantly reduced. Figure 1 shows that the relative standard deviation in each group is decreased by more than 50% percentage for most advertisers. Therefore, an advertiser may prefer a system which enables him to bid differently on each group.

3.2 Advertiser Evaluation Variability

In this section, we empirically prove that different advertisers have different criterions to determine which group a click belongs to. Recall that advertiser a_i divides clicks into three groups. Let $\theta_i^3 = \max\{t(u_{ij}), u_{ij} \in U_i^3\}$ and $\theta_i^2 = \max\{t(u_{ij}), u_{ij} \in U_i^2\}$. We construct three intervals $[0, \theta_i^3]$, $[\theta_i^3, \theta_i^2]$, and $[\theta_i^2, \infty]$ correponding to the dwell time intervals for groups U_i^3,U_i^2, and U_i^1 and assume that a_i determines a click c's group by finding the interval which c's dwell time falls into.

Thus, for each advertiser, we plot the three intervals to be a colored horizontal bar in Figure 2. Intervals of click group 3, 2 and 1 are in blue, red and green respectively. Different advertisers correspond to different bars. It is clear from the figure that the click valuations of different advertisers are significantly different.

In order to make the conclusion more solid, we give a definition for ***effective user*** as follows:

DEFINITION 1. *We say that u is a effective user for advertiser a_i if*

1. Besides a_i, u has also clicked other advertisers' ads.
2. There exists at least one other advertiser a_j such that the user u's clicks on the two advertisers' ads belong to different click groups.

Figure 3 illustrates the proportion of the effective users and the proportion of the ineffective users for 29 advertisers. We can see that every advertiser has over 40% effective users, which validates the assumption about advertiser evaluation variability. Therefore, if the mechanism allows an advertiser to define its own click group, the sponsored search will be more effective and can allocate the slot to the advertiser which needs it most.

Figure 2: Different evaluations of clicks by different advertisers

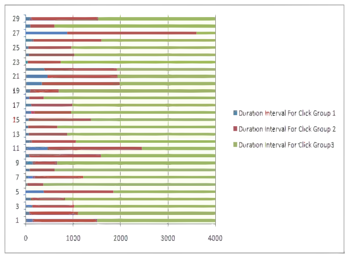
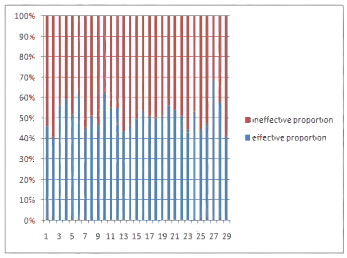


Figure 3: The proportion of effective users Of advertisers



4. CONCLUSION

We conducted an empiricaly analysis of the click values. We proposed two assumptions, click value variability and advertiser evaluation variabiltiy and verified them on the toolbar log data. Experimental results implied the necessity to enable advertisers to define their click groups and submit a separate bid for each group.

5. REFERENCES

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