A Computational Experiment Research on Segmenting RTB Advertising Markets

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Abstract: Real Time Bidding (RTB) is emerged with the rise of Internet and big data, and it realized precision marketing through the market segmentation strategies of Demand Side Platforms (DSPs). This paper studies DSPs' strategies for market segmentation, and established a market segmentation model to find the optimal granularity. We proposed to validate our model using a computational experiment approach, and the experimental results show that with the increasing of the market segmentation granularity, the total revenue has a tendency of a rise first and followed by a decline.

Keywords: Real Time Bidding, Demand Side Platforms, Market Segmentation Granularity, Computational Experiments, Precision Marketing.

1 Introduction

Real Time Bidding (RTB) is emerged with the rapid development of Internet and big data, and it has become the most popular form of online advertising [2, 3]. In RTB advertising, the advertisers can reach their target audiences via an auction of real-time, better matching and pricing, thus display their advertisements to the target audiences with a higher conversion value. As such, RTB can greatly improve the market efficiency and advertisers' revenues.

In the RTB ecosystems, Demand Side Platforms (DSPs) is regarded as the central part, and it is an agency of making decisions on behalf of their advertisers. For DSPs, the key decisions are designing efficient bidding algorithms and effective market segmentation strategies. In literature, designing bidding algorithms has attracted much more interests of researchers. For instance, Ghosh et al. [4] proposed an offline bidding algorithm for DSPs considering the scenario of both the full information and the partially observable information settings. In addition, many other offline algorithms have been proposed based on the historical average winning bid prices [9], the predicted winning rates and prices [5], as well as the click-through-rates [8]. Chen et al. [1] designed an online bidding algorithm that can adjust value-based bids dynamically.

However, there are few researches on DSPs' market segmentation strategies. In our previous work [6], we preliminarily studied the market segmentation problem for DSPs, and define this problem as an issue of seeking for the best market segmentation granularity within the given alternative granularities. By establishing a programming model for the choice of market segmentation granularity, we concluded that market segmentation has great effect on the advertising effect in RTB advertising.

In this paper, we aim to extend our previous work, and find how the market segmentation strategies affect the advertising effect in RTB advertising. In practice, there are many tags to characterize the target audiences in RTB markets, and different number of tags may produce different market segmentation strategies. By introducing the tags to characterize the target audiences, we can obtain the high dimensional features for each granularity. With computational experiment approach, we obtain that with the increasing of the market segmentation granularity, the total revenue has a tendency of a rise first and followed by a decline.

The rest of the paper is arranged as follows: In Section 2, we first introduce our problem briefly, and then establish a model for the choice of market segmentation granularity. In Section 3, we propose to use a computational experiment approach to solve our proposed model, and design numerical experiments to validate our model. Section 4 discusses the managerial insights of our findings for DSPs. Section 5 concludes our efforts.

2 The Model

2.1 Problem Statement

In RTB markets, DSPs typically label the target audiences (or users) with various kinds of tags, resulting in a hierarchical structure. Fig. 1 provides an example with n tags, and each tag can divide the target audiences into two groups. Obviously, with the increasing of the number of tags from the top level to the bottom level, the granularity of market segmentation increases, and correspondingly the number of users in each niche market decreases, resulting in better matching and targeting for advertisers.

For DSPs, choosing different number of tags can produce different market segmentation strategies, and these strategies may lead to different marketing effect for advertisers. Thus, a DSP has to choose the best market segmentation strategy, so as to maximize the marketing effect for all advertisers.

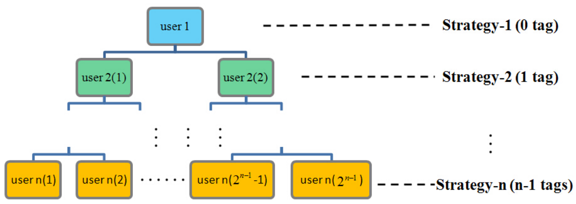

Figure 1: The user structure with n tags

2.2 The Model

In the following, we first introduce the notations, and then establish the market segmentation model.

Suppose there are M alternative tags, represented by $T = \{T_1, T_2, \cdots, T_M\}$, corresponding to the target audiences, and each tag T_i can segment the audience into t_i groups. For simplicity, we assume the tags are equally important, and we do not need to differentiate them. Then choosing different number of tags will corresponding to different market segmentation granularity, and will generate different number of niche markets. Denote the market segmentation granularities as $L = \{L_1, L_2, \cdots, L_{M+1}\}$, where L_i is generated with $i-1$ tags, and if we let $t_0 = 1$, then L_i corresponds to $\Pi_{j\leq i-1}t_j$ niche markets. Thus, L_i can represented by an i dimension function $F_i(f_1, f_2, \cdots, f_i)^T$, where $f_j \in \{1, 2, \cdots, t_j\}$. Thus, $F_i(\cdot)$ has $\Pi_{j\leq i-1}t_j$ different values, each corresponds to a niche market under market granularity L_i. Denote $y_i = (1, 2, \cdots, \Pi_{j\leq i-1}t_j)^T$, then $y_{i,j} = j$ represents the jth niche market under market granularity L_i. Corresponding to the $M + 1$ market segmentation granularities, the DSP has $M + 1$ market segmentation strategies.

For a certain time period, suppose there are S ad impression requests, denoted as $Q = \{q_1, q_2, \cdots, q_S\}$, and the reserve price of q_j is ρ_j. Each ad impression request is labeled by many tags, and it belongs in only one niche market under each market granularity. For simplicity, denote the niche market of ad impression request q_j under market granularity as L_i as $q_{j,i}$.

Denote the advertisers on the DSP as $U = \{u_1, u_2, \cdots, u_N\}$, and their budgets as $B = \{B_1, B_2, \cdots, B_N\}$. Under each market granularity as L_i, the advertiser $u_k \in U$ should choose his/her best matched niche markets through function $F_i(\cdot)$. Denote $u_{k,i}$ as the niche market matched with advertiser u_k, and $\sigma_i(k,j) \in \{0,1\}$ as the matching probability between the advertiser $u_k \in U$ and the ad impression request $q_j \in Q$, at market granularity L_i.

Denote the value function of the advertiser $u_k \in U$ for ad impression q_j under a market granularity L_i as $v_i(k,j)$. According to the equilibrium properties of Vickrey auction mechanism, we can assume that the bid for advertiser u_k for ad impression q_j is also $v_i(k,j)$.

Consider the scenario that there only one DSP in the RTB market, i.e., the winning advertiser in the DSP will obtain the ad impression. For each market granularity L_i, the remaining budget for advertiser u_k after buying ad impression q_j is

$$b_i(k,j) = b_i(k,j-1) - c_i(k,j-1), j = 1, 2, \cdots, \tag{2.1}$$

where $b_i(k,0) = B_k$, and $c_i(k,j-1)$ represents the cost of advertiser u_k for ad impression q_{j-1} under a market granularity L_i. We set $c_i(k,j) = 0$ if advertiser u_k does not win in the auction. The set of advertisers on the DSP bidding for ad impression request q_j can be computed as follows

$$U_i(j) = \{k | k \in U, \sigma_i(k,j) = 1, b_i(k,j) \geq v_i(k,j)\}, \tag{2.2}$$

and the advertisers with the highest bid and the second highest bid are

$$k_i^*(j) = \underset{k \in U_i(j)}{\operatorname{argmax}}\, v_i(k,j) \tag{2.3}$$

and

$$k_i^{'}(j) = \underset{k \in U_i(j)/i_0(l,j)}{\operatorname{argmax}}\, v_i(l,j), \tag{2.4}$$

respectively.

According to the RTB auction mechanism, the advertiser with the highest bid wins the auction, and he or she needs to pay only the second highest bid.

Thus, advertiser u_{k^*} wins the auction, and the cost is $c_i(k^*, j) = \max\{v_i(k_i^{'}(j), j), \rho_j\}$.

Assume the revenue of the advertiser from an ad impression is equal to the advertiser's value for the impression, then the winning advertiser $u_{k_i^*(j)}$ can obtain $v_i(k_i^*(j), j) I_i(k_i^*(j), j)$ revenue from ad impression j. Denote the revenue of all advertisers on the DSP from ad impression j under the market granularity L_i is $r_i(j)$, then we have

$$r_i(j) = v_i(k_i^*(j), j) I_i(k_i^*(j), j). \tag{2.5}$$

Thus, under market granularity L_i, the total revenue of the advertisers on the DSP from all the ad impression requests is

$$g(i) = \sum_{j \in Q} r_i(j). \tag{2.6}$$

The DSP aims to choose the best market granularity from L_i to maximize the total revenue of all the advertisers, i.e.,

$$\max_{L_i \in L} g(i). \tag{2.7}$$

Solving the above model, we can obtain the optimal market granularity L_{i^*}, and the corresponding optimal revenue is $g(i^*)$. Thus, choosing $i^* - 1$ tags is the best choice for DSP.

3 The Experiments

Due to the essential complexity of online RTB markets, it is difficult or even impossible to validate our proposed model and strategies with online field experiments. Fortunately, computational experiments [7] can serve as an alternative way. In this section, we utilize the computational experiment approach to validate our model.

3.0.1 The Computational Experimental Scenario

Suppose there are only one DSP in the market, and nine tags can be used to characterize each ad impression request. Each tag can divide the ad impression requests into two groups. With these tags, the DSP has ten feasible market segment strategies, with the number of tags as 0 to 9, as shown in Figure 2. The numbers of niche markets under these market segment strategies are $2^0 = 1, 2^1 = 2, 2^2 = 4, \cdots, 2^9 = 512$, respectively. The purpose of the DSP is to find the optimal market segmentation granularity to maximize the total revenues of the advertisers.

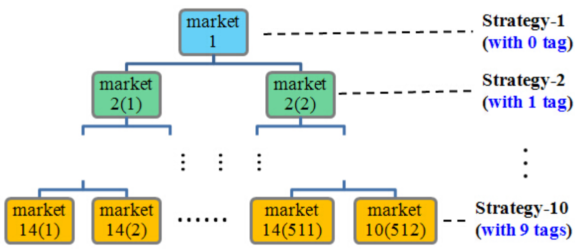

Figure 2: The 10 market segmentation strategies of the DSP and the corresponding niche markets

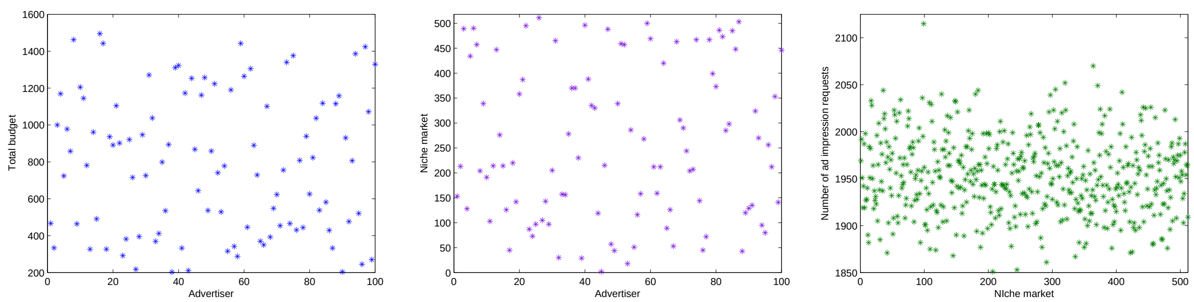

Figure 3: The total budget of each advertiser, the target niche market of each advertiser and the total number of ad impression requests in each niche market under Strategy-10

To evaluate the ten market segmentation strategies, we construct a computational experiment with 1 DSP, 1000000 ad impression requests and 100 advertisers. The ad impression requests are randomly distributed in these niche markets, and the total budgets of the advertisers are uniformly distributed in $[200, 1500]$. For simplicity, we suppose there is only one target niche market for each advertiser under each segment strategy, and it is generated randomly from these niche markets. Figure 3 gives the above data in our experiment.

Since advertisers' values of ad impressions typically increase with the accuracy of matching, and so we assume that the CPMs of the advertisers increase with the market segment granularity. Suppose the CPMs of each advertiser under strategy 1 is uniformly distributed in $\alpha = [2.00, 5.00]$, and with the increasing of the market segmentation granularity, the lower bound and the upper bound of α will increase 1.00 and 2.00 each time, respectively. Moreover, we assume that the advertiser with a higher CPM under one segmentation strategy also has a higher CPM under other segmentation strategies.

3.0.2 The Experimental Results

In order to obtain general conclusions for the optimal segmentation strategy, we conduct 2000 independent experiments, and the total revenue and the average total revenue for the advertisers on the DSP in these 2000 experiments are shown in Fig. 4 – Fig. 5, respectively.

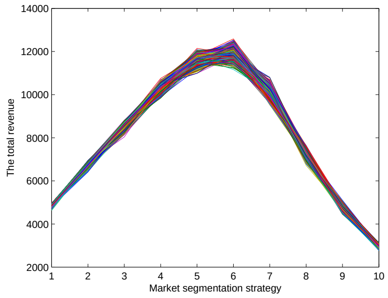

Figure 4: Comparisons of the total revenue for the advertisers on the DSP in 2000 experiments

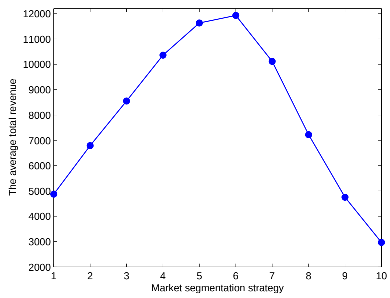

Figure 5: The average total revenue for the advertisers on the DSP in 2000 experiments

From Fig. 4 – Fig. 5, we can obtain the following conclusions:

(1) For all the 2000 experiments, the total revenues have a tendency of a rise first and followed by a decline, with the increasing of the market segmentation granularity. The maximum occurs at Strategy-6 1769 times (88.45%). It illustrates that there exists a threshold (6 in our case), when the market segmentation granularity is less than the threshold, the revenues can be improved with the increasing of the market segmentation granularity. However, when the market segmentation granularity is larger than the threshold, the revenues will decrease sharply with the increasing of the market segmentation granularity.

(2) The average total revenue for the three strategies also has a tendency of a rise first and followed by a decline, with the increasing of the market segmentation granularity, and the maximum occurs at granularity 6. It is obvious that Strategy-6 is the optimal market segmentation strategy in our experiment Scenario.

4 Managerial Insights

Our paper can offer critical managerial insights for DSPs in RTB markets.

First, there are typically lots of tags to characterize the target audiences of the advertisers on the DSP, and how to measure the effect of different number of tags on the advertising effect is a difficult task for the DSP. This work provides an feasible approach to measure the effect of market segmentation strategies for the DSP.

Second, we proved that the advertising effect has a tendency of a rise first and followed by a decline with the increasing of market segmentation granularity, thus the DSPs should segment the market with an appropriate granularity, neither too wide or too narrow.

5 Conclusions and Future Work

Market segmentation is an important problem for DSPs, and it plays a critical role in improving the precision of RTB advertising. In this paper, we considered the effect of different number of tags on the advertising effect, and established a model to find the optimal market segmentation granularity. Moreover, we utilized the computational experiment approach to validate our model, and experimental results show that the advertising effect has a tendency of a rise first and followed by a decline with the increasing of market segmentation granularity.

This work is an attempt to discuss the RTB market segmentation problem considering different number of tags. In our future work, we are planning to extend this research from the following aspects: (a) Considering the cases that different tags will divide the target audiences into different number of groups; (b) Studying the influence factors of the optimal market segmentation strategy.

Acknowledgments.

This work is partially supported by NSFC (71472174, 71102117, 71232006, 61533019, 61233001) and the Early Career Development Award of SKLMCCS (Y3S9021F36, Y3S9021F2K).

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