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Optimizing Market Segmentation Granularity in RTB Advertising: A Computational Experimental Study

Rui Qin, Yong Yuan*, *Member*, *IEEE*
The State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing, China
Qingdao Academy of Intelligent Industries, Qingdao, China
Beijing Engineering Research Center of Intelligent Systems and Technology, Beijing, China
Email: rui.qin@ia.ac.cn, yong.yuan@ia.ac.cn (Corresponding author)

Fei-Yue Wang, *Fellow*, *IEEE*
The State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing, China
Research Center of Military Computational Experiments and Parallel System, National University of Defense Technology, Changsha, China
Email: feiyue.wang@ia.ac.cn

***Abstract*—Real Time Bidding (RTB) is a novel business model of online computational advertising with the integration of Internet economy and big data analysis. It can help advertisers achieve the precision marketing through the market segmentation strategies of Demand Side Platforms (DSPs). Based on a mathematical programming approach, this paper studied DSPs' strategies for market segmentation, and established a selection model of the granularity for segmenting RTB advertising markets. We proposed to validate our model using the computational experiment approach, and the experimental results show that: 1) with the increasing refinement of the market segmentation granularity, the total revenue has a tendency of a rise first followed by a decline; 2) the optimal granularity of market segmentation will be significantly influenced by the number of advertisers on the DSP, but less influenced by the number of ad requests. Our findings show the crucial role of market segmentation on the RTB advertising effect, and indicate that the DSPs should adjust their market segmentation strategies according to their total number of advertisers. Our findings also highlight the importance of advertisers as well as the characteristics of the target audiences in DSPs' market segmentation decisions.**

***Keywords*-real time bidding; computational advertising; market segmentation; demand side platforms; computational experiment**

I. Introduction

With the rapid development and integration of Internet economy and big data analysis, Real Time Bidding (RTB) has been widely-recognized as the main-stream business model of online advertising markets [2, 3], and it can help advertisers reach their target audiences via big-data-driven real-time matching and auction-based dynamic pricing. As such, RTB has the potential of improving the market efficiency as well as advertisers' revenue.

As a central part in the RTB ecosystems, Demand Side Platforms (DSPs) serve as agencies making decisions on behalf of their advertisers (i.e., the demand side), and the key decision for DSPs is designing effective strategies for market segmentation. In advertising research, the targeting accuracy is a major concern of the advertisers, and many targeting approaches have been proposed, in which user segmentation is regarded as the most effective way to improve the target accuracy for the advertisers [12]. User segmentation aims to divide the users into multiple distinct groups, such that the users in the same group have similar interests, while the features among different groups are quite distinguishing [13]. Generally, the online behavior of the users can well characterize various kinds of users [15], thus many behavior-based user segmentation approaches were proposed [1], in which the search behavior [10, 4, 14] and the evaluative behavior [9] are the two most widely used online behavior.

As for DSPs' market segmentation strategy, however, related research is still nonexistent. Usually, the market segmentation granularity is a key parameter that can partly determine both the competition degree among advertisers and their valuations of ad impressions. On one hand, fine-grained market segmentation can improve the precision of advertiser-audience matching and also advertisers' value-per-ad-impression in each niche market. This helps increase the average price of RTB ads. On the other hand, however, with the increased segmentation granularity, the number of advertisers in each niche market, and also the resulting competition among them, will be reduced. This will decrease the RTB ad price according to classical auction theory [6]. Obviously, there exists a dilemma for DSPs in choosing the granularity of market segmentation in pursuit of better ad prices and revenue. Therefore, it is extremely urgent to study the market segmentation problems, and provide a feasible market segmentation strategy for DSPs, so as to maximize the marketing effect of advertisers in RTB markets.

In this paper, we aim to study the market segmentation problem for DSPs. We define this problem as an issue of seeking for the best market segmentation granularity, and establish a mathematical programming model for optimizing the market segmentation granularity. Considering the market complexity, we utilize a computational experiment approach

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and design experiments to validate the effectiveness of our proposed model. Experimental results show that the market segmentation granularity has great influence to both the total revenue of all advertisers and the expected revenue for each advertiser. With the increasing refinement of the market segmentation granularity, the total revenue has a tendency of a rise first and followed by a decline. Moreover, the optimal market segmentation granularity can be influenced by the number of advertisers on the DSP, but less influenced by the number of ad requests.

The remainder of the paper is arranged as follows. In Section II, we first introduce our problem briefly, and then propose our market segmentation model and its solution algorithm. In Section III, we propose to use a computational experiment approach to solve our proposed model, and design numerical experiments to validate our model. Section V concludes our efforts.

II. Model and Solution

A. Problem Statement

For simplicity, we use "strategy" and "granularity" in the following sections to represent "market segmentation strategy" and "market segmentation granularity", respectively.

In RTB markets, DSPs typically label the target audiences (or users) with various kinds of tags, and each tag can divide the audiences into multiple groups (e.g., Figure 1). With the increasing of the number of tags, a hierarchical structure of the audiences can be obtained. For example, suppose there are M tags dividing the audiences into $t_1, t_2, \cdots, t_M$ groups, respectively. Then we have a $(M+1)$-layer structure of the audiences with none tag in the top level, and one more tag from the upper level to the lower level, as shown in Figure 2. Obviously, the granularity increases from the top level to the bottom level, and correspondingly the number of users in each niche market decreases, resulting in better matching and targeting for advertisers.

For DSPs, each level corresponds to one of their strategies. A DSP has to choose the best strategy, so as to maximize the marketing effect for all advertisers.

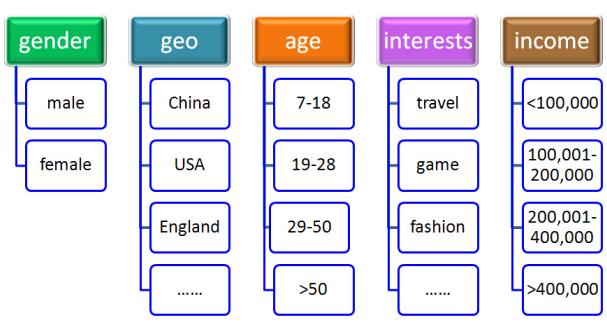

Figure 1. An illustrative example of the tags used in a DSP to characterize the target audiences

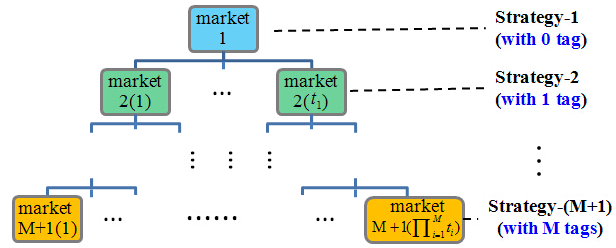

Figure 2. The $(M+1)$-layer user structure in the DSP

B. Notations

Consider the scenario that there are K competing DSPs in the RTB market, i.e., the winning advertiser in one DSP will obtain the ad impression only if he/she defeats the winning advertisers on other DSPs.

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.

With these tags, DSP can segment the RTB market with diverse granularities, and thus lead to different number of niche markets. For example, if the DSP chooses none tag, then there is no segmentation to the market. In this case, there is only one market; if the DSP chooses the tags $\{T_1, T_2, \cdots, T_i\}$, then the market will be divided into $\Pi_{j \le i} t_j$ niche markets. Denote all the possible 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 $\Pi_{j \le i-1} t_j$ niche markets. Thus, L_i can be represented by an i dimension function $F_i(f_1, f_2, \cdots, f_i)$, where $f_i \in \{1, 2, \cdots, t_i\}$. Thus, $F_i(\cdot)$ has $\Pi_{m \le i-1} t_m$ values, each corresponding to a niche market under granularity L_i. Denote $y_i = (1, 2, \cdots, \Pi_{m \le i-1} t_m)$, then $y_{i,m} = m$ represents the mth niche market under granularity L_i. Corresponding to the $M+1$ granularities, the DSP has $M+1$ strategies to segment the market.

For a certain time period, suppose there are S ad requests, denoted as $Q = \{q_1, q_2, \cdots, q_S\}$, and for each request $q_j \in Q$, the reserve price is ρ_j. Each ad request is labeled by many tags, and it falls into only one niche market under each granularity. For simplicity, denote the niche market of ad request q_j under granularity L_i as $y_{i,h_1(j)}$, where $h_1(j)$ is a function on j, and it takes the values in the set $\{1, 2, \cdots, \Pi_{m \le i-1} t_m\}$.

Denote all the advertisers on the DSP as $U = \{u_1, u_2, \cdots, u_N\}$, and their total budgets as $B = \{B_1, B_2, \cdots, B_N\}$. Under each granularity L_i, the advertiser $u_k \in U$ should choose his/her best matched niche market through function $F_i(\cdot)$. Denote the niche market matched with advertiser u_k as $y_{i,h_2(k)}$, where $h_2(k)$ is a function on k, and it takes the value in the set $\{1, 2, \cdots, \Pi_{m \le i-1} t_m\}$.

Let $\sigma_i(k, j) \in \{0, 1\}$ be the matching probability between the advertiser $u_k \in U$ and the ad request $q_j \in Q$ at

granularity L_i. Then $\sigma_i(k,j)=1$ if and only if advertiser u_k and ad request q_j fall into the same niche market under granularity L_i, i.e., $y_{i,h_1(j)} = y_{i,h_2(k)}$. Generally, the matching probability is a measurement for the matching degree of the ad request (and also the audience) with the advertiser. The advertiser u_k will participate in the auction of q_j under granularity L_i only if $\sigma_i(k,j)=1$.

Denote the value function of the advertiser $u_k \in U$ for ad request q_j under a granularity L_i as $v_i(k,j)$. According to the equilibrium outcome of Vickrey auction mechanism [6], we can assume that the bid for advertiser u_k for ad request q_j is also $v_i(k,j)$.

C. Market Segmentation Model

Under each granularity L_i, we first locate the corresponding niche market $y_{i,h_1(j)}$ for ad request q_j, and the corresponding niche market $y_{i,h_2(k)}$ for each advertiser $u_k \in U$. Then the matching probability $\sigma_i(k,j)$ of advertiser u_k and ad request q_j can be computed as follows

$$\sigma_i(k,j) = \begin{cases} 1, & \text{if } y_{i,h_1(j)} = y_{i,h_2(k)} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

The set of advertisers on the DSP bidding for ad request q_j can be computed as follows

$$U_i(j) = \{u_k | u_k \in U, \sigma_i(k,j)=1, b_i(k,j-1) \geq v_i(k,j)\}, \tag{2}$$

and the advertisers with the highest bid and the second highest bid can be obtained by

$$u_{k^*(i,j)} = \underset{u_k \in U_i(j)}{\text{argmax}}\, v_i(k,j) \tag{3}$$

and

$$u_{k'(i,j)} = \underset{u_k \in U_i(j)/u_{k^*(i,j)}}{\text{argmax}} \quad v_i(k,j), \tag{4}$$

respectively.

Denote the highest bid for ad request q_j on all the other DSPs as $v^{''}(j)$. According to the RTB auction mechanism, the advertiser with the highest bid wins the auction, and he/she needs to pay only the second highest bid [7].

Define advertiser $u_{k^*(i,j)}$ on the DSP wins (or not) ad request q_j under granularity L_i with the following indicator function

$$I_i(k^*(i,j),j) = \begin{cases} 1, & \text{if } v_i(k^*(i,j),j) > v^{''}(j) \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

Thus, if $I_i(k^*(i,j),j)=1$, then advertiser $u_{k^*(i,j)}$ wins the auction, and the cost is

$$c_i(k^*(i,j),j) = \max\{v_i(k^{'}(i,j),j), v^{''}(j), \rho_j\} I_i(k^*(i,j),j), \tag{6}$$

and the remaining budget for advertiser u_k after ad request q_j is

$$b_i(k,j) = \begin{cases} b_i(k,j-1) - c_i(k^*(i,j),j), & \text{if } k = k^*(i,j) \\ b_i(k,j-1), & \text{otherwise,} \end{cases} \tag{7}$$

where $b_i(k,0) = B_k$.

Assume the revenue of the advertiser from an ad request 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 request q_j. Denote the revenue of all advertisers on the DSP from ad request q_j under the granularity L_i as $r_i(j)$, then we have

$$r_i(j) = v_i(k^*(i,j),j) I_i(k^*(i,j),j). \tag{8}$$

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

$$g(i) = \sum_{j \in Q} r_i(j). \tag{9}$$

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

$$\max_{L_i \in L} g(i). \tag{10}$$

With the above analysis, we can formulate our market segmentation model as follows:

$$\begin{cases} \max\limits_{L_i \in L} g(i) = \sum\limits_{j \in Q} v_i(k^*(i,j),j) I_i(k^*(i,j),j) \\ \text{subject to:} \\ \sigma_i(k,j) = \begin{cases} 1, & \text{if } y_{i,h_1(j)} = y_{i,h_2(k)} \\ 0, & \text{otherwise} \end{cases} \\ U_i(j) = \{u_k | u_k \in U, \sigma_i(k,j)=1, b_i(k,j) \geq v_i(k,j)\} \\ u_{k^*(i,j)} = \text{argmax}_{u_k \in U_i(j)}\, v_i(k,j) \\ u_{k_i^{'}(j)} = \text{argmax}_{u_k \in U_i(j)/u_{k^*(i,j)}}\, v_i(l,j) \\ I_i(k^*(i,j),j) = \begin{cases} 1, & \text{if } v_i(k^*(i,j),j) > v^{''}(j) \\ 0, & \text{otherwise} \end{cases} \\ c_i(k^*(i,j),j) = \max\{v_i(k_i^{'}(j),j), v^{''}(j), \rho_j\} I_i(k^*(i,j),j) \\ b_i(k,j) = \begin{cases} b_i(k,j-1) - c_i(k^*(i,j),j), & \text{if } k = k^*(i,j) \\ b_i(k,j-1), & \text{otherwise} \end{cases} \\ b_i(k,0) = B_k \\ \text{for } i = 1,2,\cdots,M+1, j = 1,2,\cdots,S. \end{cases} \tag{11}$$

Solving the above model, we can obtain the optimal granularity L_{i^*}, and the corresponding optimal revenue is $g(i^*)$.

D. The Solution

The proposed model (11) is difficult to solve since it contains a lot of complex iterative processes for each granularity and each ad request. Moreover, the iterative processes for each ad request is highly depend on the result of the previous request. Thus, the numerical solution of model (11) can hardly be obtained exactly.

In order to find the optimal granularity, we should first compute the revenue of the advertisers from each ad request at each granularity, then the total revenue in each granularity can be obtained by adding up the revenues from all the ad

requests. Finally, we can obtain the maximized revenue and the corresponding optimal granularity by comparing the total revenues at all the granularities. Thus, the detailed solving processes of model (11) can be described as follows:

Step 1: At each granularity L_i, compute the matching probability $\sigma_i(j,k)$ for each ad request q_j with each advertiser u_k according to formula (1), and find the set of advertisers $U_i(j)$ on the DSP bidding for ad request q_j according to formula (2).

Step 2: Find the advertisers with the highest and the second highest bids $u_{k^*(i,j)}$ and $u_{k'(i,j)}$ on the DSP for ad request q_j from the advertiser set $U_i(j)$ according to formulas (3) and (4).

Step 3: Check if advertiser $u_{k^*(i,j)}$ wins or not ad request q_j by comparing his/her bid with the highest bid of all the winning advertisers on other DSPs, according to formula (5).

Step 4: Compute the cost $c_i(k^*(i,j),j)$ of advertiser $u_{k^*(i,j)}$ for ad request q_j according to formula (6), and update the remaining budget $b_i(k,j)$ of each advertiser u_k according to formula (7).

Step 5: Compute the revenue on the DSP from ad request q_j at granularity L_i according to formula (8).

Step 6: Get the total revenue $g(i)$ on the DSP by adding up the revenues from all the ad requests $q_j \in Q$ according to formula (9).

Step 7: Find the maximized total revenue $g(i^*)$ and the corresponding optimal granularity L_{i^*} according to formula (10).

III. Computational Experiments

A. Computational Experiments Design

The computational experiment approach is first successfully used in solving economic issues by Kydland & Prescott [5] in 1996. After the innovative ACP (Artificial Societies + Computational Experiments + Parallel Systems) theory proposed by Wang [11], computational experiments has been recognized by researchers and widely used in dealing with various kinds of socio-economic problems with success.

Due to the essential complexity of online RTB markets, it is difficult to validate our proposed model and strategies with online field experiments. Fortunately, computational experiments can serve as an alternative way. In the following sections, we will design two experimental environments with the computational experiment approach, to validate our model. The purpose of the first experiment is to validate how market segmentation influence the advertising effect of all the advertisers on a DSP, and seeking for the best granularity; and the second experiment is to explore the influential factors of the optimal market segmentation granularity.

B. Computational Experiment I: Finding Optimal Granularity

Suppose there are 2 DSPs in the market, and the winning probabilities of them are the same. There are 13 tags in all to characterize each ad request, and each tag can divide the ad requests into 2 groups. With these tags, the DSP has 14 feasible strategies, with the number of tags as 0 to 13, as shown in Figure 3. The numbers of niche markets under these strategies are $2^0 = 1, 2^1 = 2, 2^2 = 4, \cdots, 2^{13} = 8192$, respectively. The purpose of the DSP is to find the optimal granularity to maximize the total revenues of the advertisers.

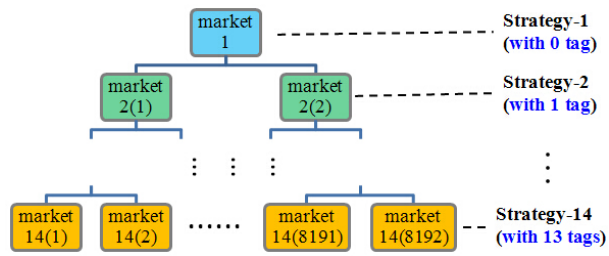

Figure 3. The 14 strategies of the DSP and the corresponding niche markets

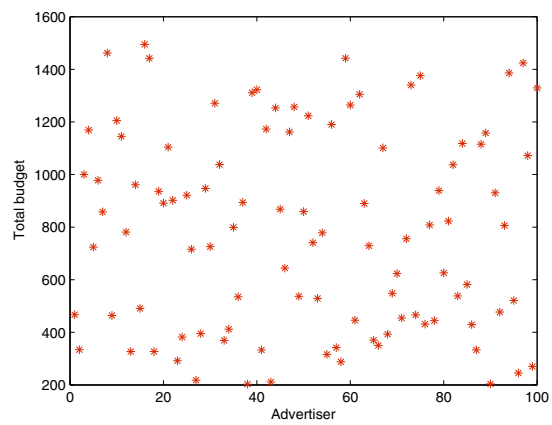

Figure 4. The total budget of each advertiser under strategy-14

To evaluate the 14 strategies, we construct a computational experiment with 2 DSPs, 2000000 ad requests and 100 advertisers. The ad 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 strategy, and it is generated randomly from these niche markets. Figure 6 randomly generates the above data in our experiment.

Since advertisers' values of ad impressions typically increase with the accuracy of matching [8], we can assume that the CPMs of the advertisers increase with the granularity. Suppose the CPMs of each advertiser under strategy-1 is

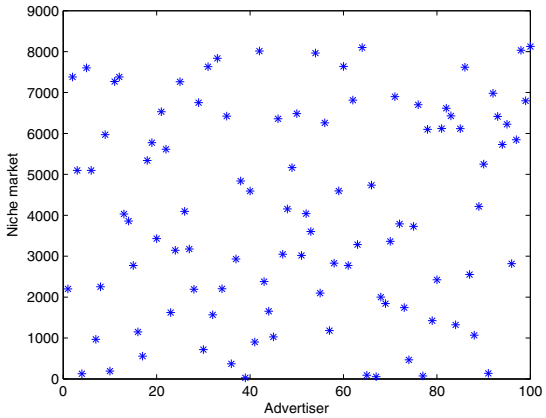

Figure 5. The target niche market of each advertiser under strategy-14

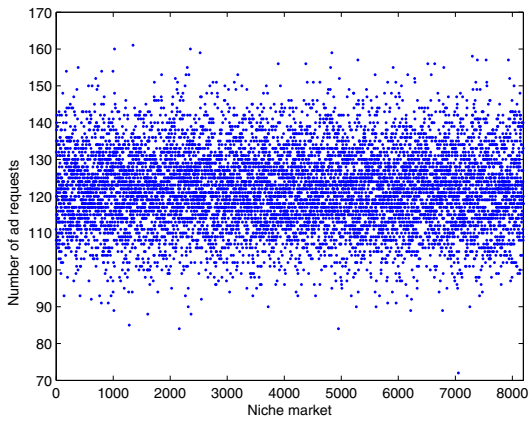

Figure 6. The total number of ad requests in each niche market under strategy-14

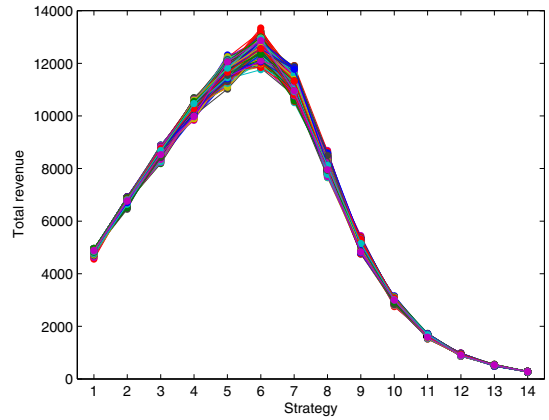

Figure 7. Comparisons of the total revenue for the advertisers on the DSP in 2000 experiments

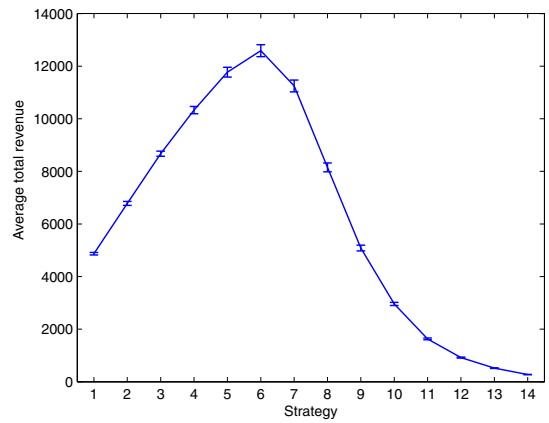

Figure 8. The average total revenue with error bar for the advertisers on the DSP in 2000 experiments

uniformly distributed in $\alpha = [2.00, 5.00]$, and with the increasing of the 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 strategy also has a higher CPM under other strategies.

In order to obtain general conclusions for the optimal strategy, we conduct 2000 independent experiments, and the total revenue of the advertisers on the DSP in these 2000 experiments are shown in Figure 7. Moreover, with the standard deviation of the total revenues, we can obtain the error bar at each strategy, as shown in Figure 8. From Figure 7–Figure 8, 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 granularity. The maximum occurs at strategy-6 1996 times out of 2000 times (99.8%). It illustrates that there exists a threshold (6 in our case), when the granularity is less than the threshold, the revenues can be improved with the increasing of the granularity. However, when the granularity is larger than the threshold, the revenues will decrease sharply with the increasing of the granularity.

(2) The average total revenue for the advertisers also has a tendency of a rise first and followed by a decline, with the increasing of the granularity, and the maximum occurs at the granularity under strategy-6. It is obvious that strategy-6 is the optimal strategy for the DSP in our experiment scenario.

(3) The variation tendency of the standard deviations of the total revenues is the same with that of the average total revenue, and the maximum is also reached at the optimal strategy, which illustrates that the total revenues have larger fluctuations at the optimal strategy than other strategies.

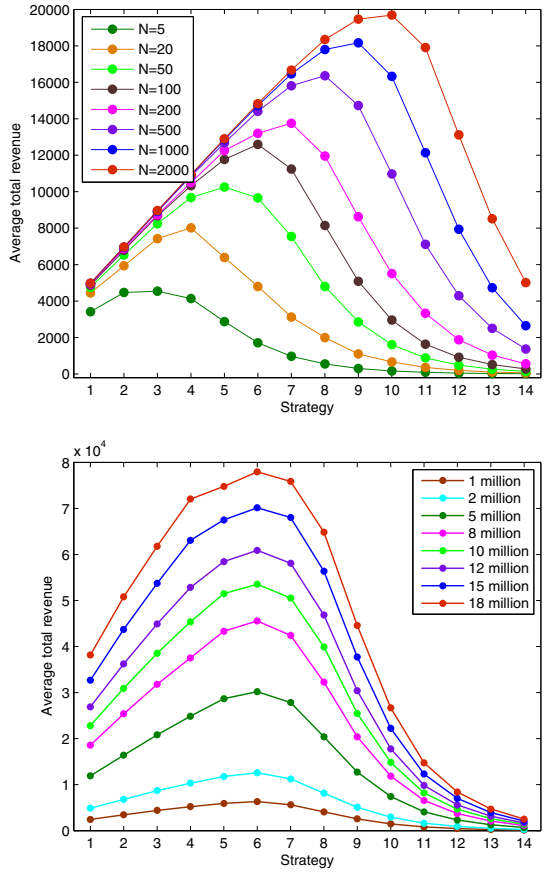

Figure 9. The effect of the number of advertisers and ad requests on the optimal strategy

C. Computational Experiment II: Exploring Influence Factors of Optimal Market Segmentation Granularity

In the following, we aim to find the influence factors of the optimal strategy. By changing the number of advertisers and ad requests, respectively, we obtain their effects on the optimal strategy, as shown in Figure 9, from which we can obtain the following results:

(1) When the number of the ad requests is fixed, the average total revenue of the advertisers on the DSP will increase with the increasing of the number of advertisers under each strategy.

(2) When the number of advertisers is fixed, the average total revenue of the advertisers on the DSP will increase with the increasing of the number of ad requests under each strategy. Moreover, the gap between the average total revenues of different number of ad requests first increases, and then decreases, with the increasing of the granularity, and the maximized gap occurs at strategy-6.

(3) The optimal granularity can be affected by the number of advertisers, and larger number of advertisers will correspond to larger optimal granularity.

(4) When the number of advertisers is fixed, the number of ad requests has little effect on the optimal granularity.

With the above results, it is clear that the DSP should segment the market according to the total number of advertisers on it. For convenience, we make more computational experiments to find the corresponding number of advertisers for each strategy of the DSP, when the number of advertisers on the DSP is between 5 and 2000, as shown in Figure 10. With the help of Figure 10, the DSPs can easily make their market segmentation decisions.

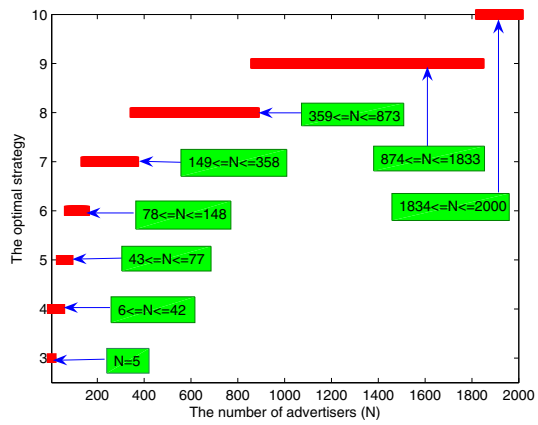

Figure 10. The corresponding number of advertisers for each strategy

IV. Managerial Insights

Our research can offer useful managerial insights for DSPs in RTB markets. First, big-data driven user targeting is the most important basis for the precision marketing in RTB advertising. For DSPs and advertisers, bigger data are usually be expected to bring higher revenues because of the higher matching quality between the advertisers and their audiences. However, our work indicates that this is not always true in RTB advertising, possibly due to the reduced competition among the advertisers. Thus, it is extremely important for DSPs to recognize that bigger data is not always better in RTB advertising, and the maximized revenues will drift away if the online big data was overused.

Second, due to the dynamics of RTB markets, the optimality of the best market segmentation strategy can be changed over different periods. In such cases, it is urgent for DSPs to explore the key factors that can influence the optimality. This work indicates that the number of advertisers on the DSP can greatly influence the optimality of the market segmentation decisions of the DSP, and the number of ad requests has little influence on the optimality of a granularity. Thus DSPs should pay more attention on the number of advertisers rather than the number of ad requests in making their market segmentation decisions, and adjust their strategies when the

number of advertisers is greatly changed. This is easy to realize for DSPs since the number of advertisers can be obtained precisely.

V. Conclusions and Future Work

Market segmentation is an important strategic problem for DSPs, and also an important guarantee for the effectiveness and efficiency of the emerging RTB advertising paradigm. In this paper, we characterized the target audiences with multiple tags, and established a model for the choice of the market segmentation granularity. This model can be used to help DSPs to determine the optimal granularity. We proposed to use the computational experiment approach to evaluate our model, and experimental results show that: 1) there is a market segmentation cap, and the advertising effect will keep rising before the cap, but quickly fall off after the cap. 2) there exists an optimal granularity, which can be influenced by the number of advertisers on the DSP, but less by the number of ad requests.

This work is a primary attempt to study the market segmentation issue in RTB markets. In our future work, we plan to extend this paper from the following aspects: 1) Analyzing the strategic behavior and the resulting equilibrium of the principal-agent games between the advertisers and the DSP; 2) extend the matching probability to an interval $[0, 1]$.

Acknowledgements

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