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Predicting Hourly Internet Traffic in the RTB System – Panel Approach

Summary

The aim of this article is to provide a method allowing to control the costs in the real time bidding system related with the bid request traffic. Hourly limits of expenses are predicted based on the historical data. This approach allows to diversify the costs through the whole day, instead spending them immediately at the beginning of the day. To improve the accuracy, a proposed method includes a panel econometric model, where hours are panels. Results are evaluated on the basis of off-line comparison tests between the panel (fixed effects estimator) and non-panel model (ordinary least squares estimator). It turns out, that in most cases the panel method gives more accurate predictions.

Keywords: real time bidding, fixed effects estimator, panel data, bid request

JEL Classification Codes: C13, C23, C5

1. Introduction

Real Time Bidding (RTB) is a common method of providing an online advertise in the real time. The number of shown advertisements each day all around the world is counted in billions. Specialized companies called Demand Side Platform (DSP) prepare campaigns offering online advertisements of the product in the specific geo-region. In the bidding process, econometric models are involved to predict the probability of click, scroll or conversion. Nevertheless, even the low probability has some chance of buying the offered space for the advertisement. Given the volume of Internet traffic, this can lead to loss of large sums of money in just a few minutes.

Often used solution is some kind of filter of the Internet traffic. For example using software solutions, only the small percentage of the offered bids are

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considered. Difficult to predict users behaviour together with fast changing auction prices due to the competition strategies require the use of mathematical models to predict the volume of Internet traffic, which should be (or is worth to) responded. This volumes must by high enough to generate a profit and low enough to limit the risk of spending available money in few minutes or hours.

The aim of this article is to provide a method allowing to predict, based on the historical data, limits of hourly Internet traffic to be skipped. To improve the accuracy, a proposed method includes a panel econometric model, where hours are panels. Results are evaluated on the basis of off-line comparison tests between the panel and non-panel model. The methods are used to proportional distribute spending money throughout the day. For many reasons, it is better to spent small parts of the budget planned on different hours of a day, not at once immediately at the beginning of the day.

This paper is composed of five sections. The brief description of the real time bidding is in Section 2. Section 3 presents the proposed methods of the bid request traffic control, including the one based on the panel data. In Section 4 there are the description and the results of the empirical experiment involving the comparison between the suggested models. This paper ends with the summary in Section 5.

2. Real Time Bidding

Real Time Bidding is considered as a new (invented in 2009) way of digital advertising. The idea is to show the personalized advertisement to the user in the real time. This advertisement is placed on the website by the winner of an auction[2]. Players in that kind of auction are so-called Demand Side Platforms (DSPs) and the whole auction process takes around 100 ms. With every available placement on the website, one auction is connected. DSPs give their prices (bid response) for the given place (bid request) based on the data they have about the user and the website. There is a lot of information given in the bid request about the user (e.g. geolocation, language, user's IP, browser, operating system, device) and the website (e.g. URL, the size of the placement, location on the website). Richer information may by pull out from the historical data. Based on

[2] It is usually a second-price auction: the highest bidder pays the price bid by the second-highest bidder.

the websites visited by the user, often it can be deduced user's sex, age, interests, and many others. More information about RTB and auctions in that system may be found for example in Bernardelli[3].

Usually, profit for the DSP is proportional to the number of actions performed by the user after seeing the advertisement. No user action means the loss of bidding money. On the other hand, click, scroll, willingness to buy the advertised product – any interest of the user is translated to the profit. Due to the short time for the DSP's decision, it is impossible for the human to take part in an auction. RTB is about the automated systems, specialized algorithms, and powerful hardware. The better system (compared the competition), the higher profit.

A bid is a value, that the DSP is willing to pay for the placement on the specific website at a given time for a particular user. At the same time, other DSPs are estimating the value of the same bid request. From sending a bid request, through the evaluation of the bid request by DSPs, to the time when the auction is over, it's just a hundred milliseconds. The whole process is repeated for each advertisement. Often on a single website, there is a dozen or a few dozen of available placements. Each day every user is watching dozens and hundreds of websites. There are 3.6 billion Internet users[4]. Multiplying the numbers, we get billions of auctions every day. It means, that each second DSP has to evaluate from several hundred thousand to several millions of bid requests, depending on the signed agreements with SSPs (Supply Side Platforms) and technical capabilities.

The cost of the single bid request is rather small and valued in micro dollars, but confronting this with the unimaginable volume of bid request traffic, give a multi-billion dollar advertise market. Having in mind a small probability of profit from the single bid request, it allows comprehending how easy is to lost substantial amount of money in a short period of time, e.g. minutes. There are other aspects of this difficult business. First of all, due to the strict time limit, sophisticated methods of predicting the profitability of a bid request can't be considered. Secondly, the accuracy of the prediction involves real-time access to good input data, which in turn makes necessity to store historical data. However, an enormous volume of data is almost impossible to store (a classic example of Big Data problem). The third aspect is the need for powerful hardware solutions and well-qualified IT staff to provide immediate evaluation of the incoming bid

3 Bernardelli M. (2015), Cheater Detection in Real Time Bidding System – Panel Approach, *Roczniki Kolegium Analiz Ekonomicznych SGH* 39, Oficyna Wydawnicza SGH, Warsaw, 11–23.

4 In 2017, according to the report of Cisco company from 2013 (Cisco Visual Networking Index. Global Mobile Data Traffic Forecast Update, 2012–2017, www.cisco.com).

requests. And finally, it is worth to emphasize, that there practically aren't any articles available concerning effective methods of bidding from the DSP's point of view. This is because of the advantage they give over the competition. One available article by Lee et al.[5] includes constrains optimization using on-line performance indicators, which is a step further to the problem given in this article. To be precise, there are articles about optimization of budget based on the conversion (or any other action) performance, see e.g. Lee et al.[6] or Perlich et al.[7].

In this paper we consider only one aspect of the RTB system, that is the controlling of the bid request traffic. This is an extremely important issue for a DSP. Getting to much traffic to evaluate, may cause timeouts of the computers – the system will be overload and unable to respond to any bid request on time. This will be really a disaster for the company. On one hand, we have costs in terms of waste of computers and people's work. On the other hand, we have no potential profit from the conversions come from the winning auctions. One possibility of solving this problem is to upgrade the IT system. Usually, this is only a short-time solution. DSP in practice can't effort to buy or evaluate the whole bid request traffic. The only reasonable solution, therefore, is to restrict somehow the flow of the bid requests. Technically it means that for some part of the traffic DSP sends so-called NO BID response. This kind of response doesn't involve the evaluation of the bid request. The remaining question is to decide, how large part of the traffic should be skipped from bidding. The description of methods used to restrict the traffic is given in the next section.

3. Bid request traffic control methods

To calculate the hourly limits of the bid request traffic, a model-based approach was chosen. Two models were considered: one build on time series input data, and the second exploring the panel structure of data. Both of model were based

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5 Lee K.C., Jalali A., Dasdan A. (2013), Real Time Bid Optimization with Smooth Budget Delivery in Online Advertising. Proceedings of the Seventh International Workshop on Data Mining for Online Advertising (ADKDD '13). ACM, New York, 1–9.

6 Lee K.C., Orten B., Dasdan A., Li W. (2012), Estimating Conversion Rate in Display Advertising from Past Erformance Data, Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining, Beijing.

7 Perlich C., Dalessandro B., Hook R., Stitelman O., Raeder T., Provost F. (2012), Bid Optimizing and Inventory Scoring in Targeted Online Advertising, Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Beijing.

on the costs from historical data. At the beginning of this section, the characteristic of the available data is presented. After that, two class of econometric models are described. At the end of this section, there is a procedure of using models to control the costs related to the bid request traffic presented.

It is common in the RTB system to gather the data about the costs and number of impressions (won bids). Let us assume that data have hourly granulation. Usually, interests are rather towards the control of expenses, not the number of bid requests itself. This is the reason why we use costs in this paper. Of course, the idea may be straightforwardly applied to the number of impressions. Profit of the DSP is diversified between many products offered in a number of countries. Each product and each country have its own specificity (prices, people's day characteristics, and preferences, etc.). Therefore, in general, RTB system in the DSP is divided into so-called flights limited to a particular region and product. The DSP's strategy, model parameters, and all statistics are gathered per flights.

For the costs of the particular flight at the specific hour h of the day t we use notation $c_{h,t}$. We define the transformed variable

$$z_{h,t} = \frac{c_{h,t}}{\sum_{i\in\{0,1,\ldots,\,23\}} c_{i,t}}, \tag{1}$$

where the sum is calculated through all hours of day t. This variable has an easy interpretation as a percentage of daily costs per given hour. Exemplary percentage of costs per hour for one week (7 days) is given in Figure 1. The goal is to predict with the reasonable accuracy the percentage of costs per hour for the next day. We use $z_{h,t}$ as a explained variable, whereas as explanatory, three variables were chosen:

- $z_{h,t-1}$ – percentage of costs at the same hour, but the previous day,
- $z_{h,t-7}$ – percentage of costs at the same hour, but the previous week,
- $\tilde{z}_{h-1,t}$ – estimated percentage of costs at the previous hour (of the same day or the previous day in case of an hour 0); estimation is necessary, because the denominator in the formula (1) is not known yet. At hour h we know only costs till that hour, so we use them to calculate the estimation of $z_{h-1,t}$

$$\tilde{z}_{h-1,t} = z_{h-1,t}\,\frac{\sum_{i\in\{0,1,\ldots,\,h-1\}} z_{i,t}}{\sum_{i\in\{0,1,\ldots,\,h-1\}} z_{i,t-1}}. \tag{2}$$

The reason for choosing such set of variables is simple. The pattern of the costs, related to the bid request traffic, is usually repeated each day (compare

Figure 1) – this explains the use of $z_{h,t-1}$. There are also visible differences between individual days of the week. For example, on weekends most of the people don't work and their behavior in the Internet tend to be more irregular comparing to the weekdays (shifted hours, more or less time spend in the Internet, different websites, etc.). This is an explanation of the use of the variable $z_{h,t-7}$. The volume of traffic sometimes changes a lot in just a minutes. Reasons can be many: new SSP, a new set of available for advertising websites, higher bidding prices, etc. It is extremely important for the DSP to be able to adjust quickly to the changing situation – this is why the variable $\tilde{z}_{h-1,t}$ is used.

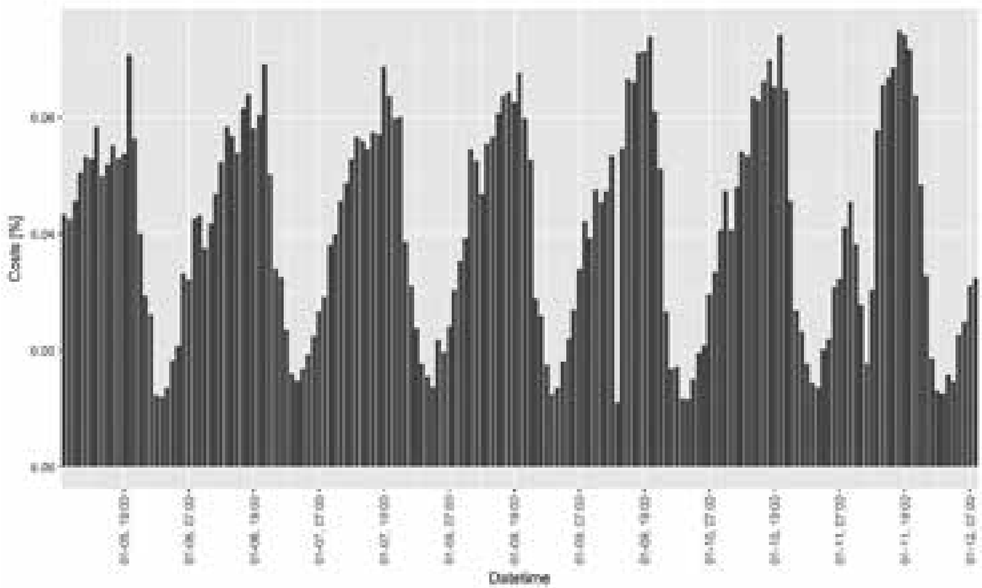

Figure 1. Percentage of costs per hour for one week for a particular flight.

Source: own calculations.

In this article, we present two class of models. The first one is the classic linear regression model

$$z_{h,t} = \beta_0 + \beta_1 z_{h,t-1} + \beta_2 z_{h,t-7} + \beta_3 \tilde{z}_{h-1,t} + \varepsilon_{h,t}, \tag{3}$$

in which variables are treated as they would have the hourly granulation (time series). Model parameters are determined using ordinary least square method (OLS). The second model is based on panel data exploring the nature of both cross-sectional and time series data. A typical model based on panel data could be presented in the form

$$z_{h,t} = \beta_1 z_{h,t-1} + \beta_2 z_{h,t-7} + \beta_3 \tilde{z}_{h-1,t} + \alpha_{\mathrm{h}} + \varepsilon_{h,t}, \tag{4}$$

where:
$h = 0, 1, 2, \ldots, 23$ – hours,
$t = 1, 2, \ldots, T$ – time index (days),
β_k – parameter related to the k-th variable,
α_h – unobserved time-invariant individual effect,
$\varepsilon_{h,t}$ – error term for hour h at time t.

This model belongs to the class of fixed effects models (FE), where it is assumed that the unobserved effect α_h is the same for all observations for that individual. Detailed information about the panel data econometrics, including estimation of the model parameters, may be found for example in Hsiao[8] or Wooldridge[9]. In this article for estimation of the model parameters so called within-groups method is used.

The basic difference between models (3) and (4) is that in the latter some common parts for each hour are assumed, whereas in the first model all hours are treated the same (so in fact only one index t should be used instead a pair of index h and t, but for ease of comparison with the model (4), both indexes have been left). Of course, there aren't any proofs that model (4) is superior to the model (3). Probably in some situations (for particular flights) predictions based on model (3) will be more accurate. The goal is rather to choose a method, which is empirically more effective.

Using any of the presented models, it is possible to plan to spend money from the daily budget for the particular flight. The key aspects of this plan are:

- do not exceed the budget,
- buy only such part of the hourly traffic that is more or less proportional to the pattern characteristic for a specific flight.

An approach that takes into account such two requirements allows spreading the costs over time. Otherwise, without any limits, the whole daily budget would be spent at the beginning of the day.

Let's assume, that we have a daily budget per flight equal K dollars. We use one of the models to predict the percentage cost each hour of the next day:

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8 Hsiao Ch. (2003), Analysis of Panel Data, Cambridge University Press, New York.
9 Wooldridge J.M. (2013), Introductory Econometrics: A Modern Approach, South-Western.

$z_{0,t}, z_{1,t}, \ldots, z_{23,t}$. Also we need estimated percentages of costs at the previous hours: $\tilde{z}_{23,t-1}, \tilde{z}_{0,t}, \ldots, \tilde{z}_{22,t}$. At the beginning of each hour h we

1. calculate how much was spent until that hour

$$K_{spent} = \sum_{i=0}^{h-1} c_{i,t}, \tag{5}$$

2. calculate how much should be spent until that hour according to the prediction

$$K_{spent}^{predict} = K * \sum_{i=0}^{h-1} z_{i,t}, \tag{6}$$

3. calculate the prediction of $z_{h,t}$ from the chosen model,
4. estimate available budget for hour h based on prediction $z_{h,t}$

$$c_{h,t} = z_{h,t} * K * \frac{K_{spent}^{predict}}{K_{spent}}. \tag{7}$$

Costs may change during the day – assumed limits per hour may be not achieved. In this case, we can spend more for the remaining hours of the day. For that is the correction $K_{spent}^{predict} / K_{spent}$ in the formula (7). The steps of the procedure, presented above, allow to control the costs each hour. The effectiveness of this method is based on the accuracy of the prediction $z_{h,t}$. Empirical experiment carried out to verify suitability of the method to the bid request traffic control is described in the next section.

4. Prediction of the hourly bid request traffic

The key part of the method of controlling the cost related to the bid request traffic, which was described in the previous section, is the model used in the third step of the procedure. In this paper, two different kinds of models are considered. One is given by the formula (3), and the second is defined by the formula (4).

To verify the usefulness of econometric models, a numerical experiment was performed. One hundred different flights were chosen for the experiment. For each one of them, the costs per hour were available for the first quarter of the year 2017. The steps of the experiment could be described as follows:

1. for each flight
2. for each period of four weeks, shifted day-by-day (starting from January, 1^{st}-28^{th}, ending with March, 9^{th}-30^{th})
3. for each hour h of the next day t
4. using both models (ordinary least squares estimator vs. fixed effects estimator[10]) calculate a prediction $z_{h,t}$
5. compare predictions with the real values, calculate the root-mean-square error (RMSE).

From the description of the experiment, it is clear, that in each evaluation of the model there are disjoint sets: one (learn set) consists of 4 weeks of hourly observation, and the second (test set) covers one day (24 hours). Of course, in each of these cases, there are different estimators of the model parameters computed. Computations were performed using the plm package in the R programming language. For the clarity of description, only exemplary estimations are presented.

Table 1. Estimation of exemplary OLS model parameters

```
Coefficients:
             Estimate     Std. Error     t value   Pr(>|t|)
(Intercept)  -0.0009692   0.0005888      -1.646    0.1
z_h-1_t      0.3660315    0.0252270      14.510    <2e-16 ***
z_h_t-1      0.3432265    0.0342881      10.010    <2e-16 ***
z_h_t-7      0.3137871    0.0348128      9.014     <2e-16 ***
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Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.006851 on 668 degrees of freedom
Multiple R-squared: 0.9081, Adjusted R-squared: 0.9077
F-statistic: 2201 on 3 and 668 DF, p-value: < 2.2e-16
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Source: Own calculations.

Values of the ordinary least squares estimator (OLS), formula (3), are presented in Table 1. Results for the fixed effects estimator (FE), formula (4), are given in Table 2.

[10] There are also other possible estimators, see Baltagi B.H., Bresson G., Pirotte A. (2003), Fixed Effects, Random Effects or Hausman–Taylor? A Pretest Estimator, *Economics Letters* 79, 361–369.

Table 2. Estimation of exemplary FE model parameters

Coefficients:

	Estimate	Std. Error	t-value	Pr (>|t|)
z_h-1_t	0.611999	0.030884	19.8157	< 2e-16 ***
z_h_t-1	0.064335	0.037913	1.6969	0.09020 .
z_h_t-7	0.085985	0.036121	2.3805	0.01758 *

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Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Total Sum of Squares: 0.034851
Residual Sum of Squares: 0.021004
R-Squared: 0.39732
Adj. R-Squared: 0.37303
F-statistic: 141.74 on 3 and 645 DF, p-value: < 2.22e-16
```

Source: Own calculations.

There was also performed the F test of individual effects based on the comparison of the within and the pooling model. For models from Table 1 and Table 2 results of F test are given in Table 3.

Table 3. F test for individual effects for the model from Table 2

```
F = 13.814, df1 = 23, df2 = 645, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Source: Own calculations.

In all, almost 7000 models in the experiment, 68 models (4 week periods) for each of 100 flights, F test gave always the same result – there is a basis for rejecting the null hypothesis and claim, that fixed individual effects are statistically significant. Within effects for the model from Table 2 are given in Table 4.

Table 4. Within effects (hours) for the model from Table 2

	Estimate	Std. Error	t-value	Pr(>|t|)
00	-0.0029033	0.0016589	-1.7501	0.0805726.
01	-0.0001922	0.0013633	-0.1410	0.8879278
02	0.0016954	0.0012778	1.3268	0.1850490
03	0.0012777	0.0012381	1.0320	0.3024712
04	0.0041185	0.0012769	3.2255	0.0013213 **
05	0.0075205	0.0014208	5.2933	1.649e-07 ***
06	0.0091801	0.0016476	5.5716	3.709e-08 ***
07	0.0103955	0.0019012	5.4680	6.514e-08 ***
08	0.0134704	0.0022722	5.9285	4.982e-09 ***
09	0.0109196	0.0024697	4.4213	1.151e-05 ***
10	0.0104087	0.0025677	4.0537	5.657e-05 ***
11	0.0102310	0.0026230	3.9004	0.0001061 ***

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12     0.0124284    0.0027836    4.4648     9.459e-06 ***
13     0.0115531    0.0028585    4.0417     5.947e-05 ***
14     0.0169460    0.0030782    5.5051     5.331e-08 ***
15     0.0194270    0.0034971    5.5552     4.058e-08 ***
16     0.0192614    0.0037904    5.0816     4.907e-07 ***
17     0.0189693    0.0039918    4.7520     2.485e-06 ***
18     0.0178275    0.0040147    4.4406     1.055e-05 ***
19     0.0186572    0.0040796    4.5733     5.757e-06 ***
20     0.0187023    0.0041983    4.4547     9.902e-06 ***
21     0.0118955    0.0040089    2.9672     0.0031161 **
22     0.0017799    0.0033331    0.5340     0.5935256
23     -0.0062487   0.0023268    -2.6855    0.0074281 **
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Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Source: Own calculations.

Final results of the comparison between the two models, are summarized in Table 5 and also visualized on Figure 2 (one week of the learn set) and Figure 3 (one-day test set).

Table 5. Results of the numerical experiment: comparison between OLS and FE model (assumed significance level: 0.05)

	Statistics per flight		
	MIN	MAX	AVG [%]
RMSE for the learn set for FE estimator is less than for OLS estimator	68	68	100
RMSE for the test set for FE estimator is less than for OLS estimator	44	66	77
p-value of the F test is less than 0.05	68	68	100
Intercept in OLS model is statistically significant	0	68	68
$z_{h,t-1}$ in OLS model is statistically significant	12	68	99
$z_{h,t-7}$ in OLS model is statistically significant	68	68	100
$\tilde{z}_{h-1,t}$ in OLS model is statistically significant	56	68	100
$z_{h,t-1}$ in FE model is statistically significant	0	68	72
$z_{h,t-7}$ in FE model is statistically significant	0	68	19
$\tilde{z}_{h-1,t}$ in FE model is statistically significant	0	68	31

Source: Own calculations.

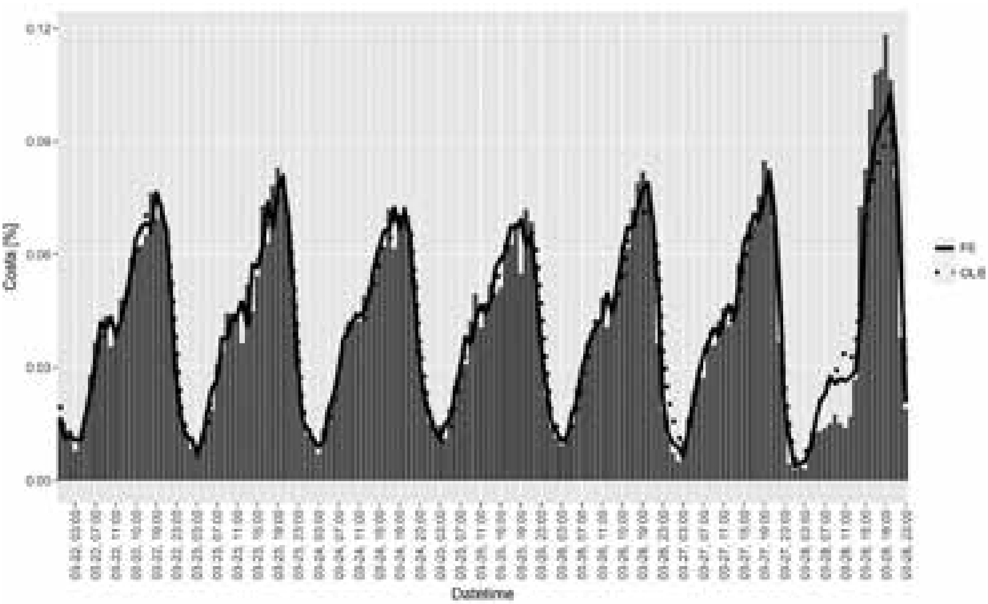

Figure 2. Exemplary percentage of costs per hour for one week with the two predictions on the learn set: fixed effects estimator (solid line) and ordinary least squares estimator (dotted line).

Source: own calculations.

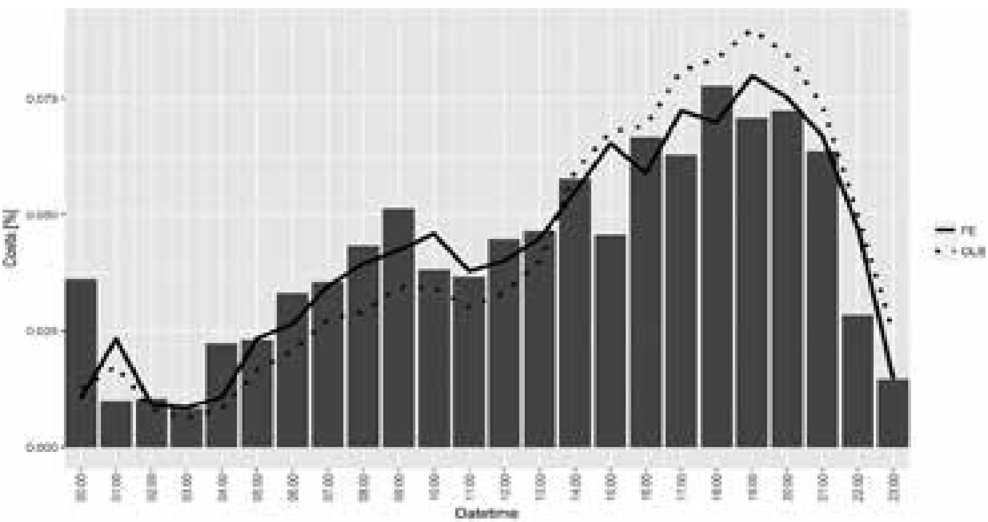

Figure 3. Exemplary percentage of costs per hour for the test set (one day) with the two predictions on the learn set: fixed effects estimator (solid line) and ordinary least squares estimator (dotted line).

Source: own calculations.

If it comes to the test set, then on average in 77% cases FE estimator gave value RMSE less than analogous value for OLS estimator. For the learn set in every case FE estimator was giving a more precise fit to the real data. All coefficients of the OLS estimator were statistically significant in the vast majority of cases. In contrast, only one coefficient, $z_{h,t-1}$, seems to be statistically significant (72% cases) for FE estimator. Other two coefficients are statistically significant only in respectively 19% and 31% of cases. Of course the difference lies in within effects (see Table 4), which for most of hours proved to be statistically significant.

Both models seem to be suitable for controlling the traffic, but taking into account the accuracy, fixed effects approach, formula (4), is better. It can be also verified by sight, looking at the Figures 2 and 3.

5. Conclusions

Controlling the traffic in the real time bidding system is the key thing for the DSP company. First of all, the massive volume of data makes in practice impossible to evaluate each bid request. This can lead to system failure and/or timeouts. Secondly, even if some daily limit is set, then it can be reached at the beginning of the day. It is, however, better to use the budget successively through the whole day.

In this article the proposition of the method allowing to control the costs in the real time bidding system related with the bid request traffic. Hourly limits of expenses are predicted based on the historical data. To improve the accuracy, a proposed method includes a panel econometric model, where hours are panels. Results are evaluated on the basis of off-line comparison tests between the panel (fixed effects estimator) and non-panel model (ordinary least squares estimator). Based on empirical experiments it is justified to draw the following conclusions:

- a method based on econometric model seems to be a solution to the described problem,
- in most cases, the panel method gives more accurate predictions than OLS estimation,
- predictions should be made per flight, taking into account the specificity of the product and the region.

It is also worth to mention that given procedure can be adapted to other, then costs, situations. For example, a number of impressions may be predicted.

In econometric models, different variables can be considered too, like information about the free or working day. Greater than hourly granulation is also possible to implement. Nevertheless, the proposed simple procedure seems to be useful in practical applications.

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Predykcja godzinowego wolumenu ruchu internetowego w systemie RTB – podejście panelowe

Streszczenie

Celem tego artykułu jest przedstawienie metody pozwalającej na kontrolę kosztów w systemie RTB, związanych z ruchem zapytań internetowych. Godzinowe limity wydatków są wyznaczane na podstawie historycznych danych. Takie podejście pozwala na rozłożenie kosztów na cały dzień, zamiast wydawania ich od razu na początku dnia. W celu poprawienia dokładności proponowana metoda uwzględnia panelowy model ekonometryczny, w którym godziny są panelami. Wyniki są oceniane na podstawie testów porównawczych pomiędzy modelem panelowym (model z efektami stałymi) i modelem opartym o szereg czasowy (estymator metody najmniejszych kwadratów). Okazuje się, że w większości przypadków metoda panelowa daje dokładniejsze prognozy.

Słowa kluczowe: real time bidding, model z efektami stałymi, dane panelowe, bid request