International Journal of Advance Research in Science and Engineering
Volume No.07, Special Issue No. (03), January 2018
www.ijarse.com
IJARSE
ISSN: 2319-8354

Real Time Bidding With Comparative Study of Various User Responses Prediction Models

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ABSTRACT

Real Time Bidding is the fastest growing area in the online advertisement market. It has changed the way of advertisement from traditional advertising to target audience buying. It is just similar to financial market where the auction determines who gets to buy the impression and the bid winner advertisement will be displayed on publishing site. So, it acts as an interface between the buyer and seller of the ads.

In this paper we will discuss the current RTB trends, various techniques of RTB and the challenges associated with it.

Keywords: Real-time bidding, Machine learning, bidding strategy, Impression, Target Audience.

I.INTRODUCTION

Real-time bidding (RTB) is considered as the new era of digital advertising [1]. Digital advertising is one of the main means of monetizing user data. RTB is a growing trend in today's market which compromises many different components requiring to effectively delivering intelligent real time purchasing of advertisements

RTB has changed the way of advertising from traditional advertising to target audience buying [2]. In traditional advertising, the cost of advertisement is previously negotiated between buyer and seller but in RTB price is not previously fixed between advertiser and publisher, it depends on the bid which is submitted by the advertisers.

Real time bidding used cookie based online big data analysis for collecting and identifying the interests and aspects of targeted audience and then shows ads that are suitable for them.

In this, the total numbers of impression clicked by the user on any website are mapped with any advertiser using bidding process. It allows advertiser to bid for slots available in web pages when user launch the application. This advertisement is placed on user's webpage only for few milliseconds. This process is very complex as there are huge applications available in the market. So, mapping the correct application with correct advertiser on the basis of the content of the application is a difficult task.

RTB is becoming the key to target marketing where it could optimize advertiser's expectations drastically [3].

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Fig 1: RTB acts an interface:

It acts as an interface between advertisers and user's of the websites and makes the match that what advertisement is shown to user according to his interest so that it can generate maximum number of impressions.

RTB is the real time process which gives only less than 120 ms for deciding the price of bid [3]. So, it is not useful for that practices which takes more time in decision making.

II.BUSINESS MODEL OF REAL TIME BIDDING

Under this section, we will give detailed overview about key roles and business flow of RTB process.

2.1 Key Roles Of Real Time Bidding Markets

In this section we will give detailed explanation about roles of various RTB entities such as advertiser, publisher, DSP, DMP and Ad exchange.

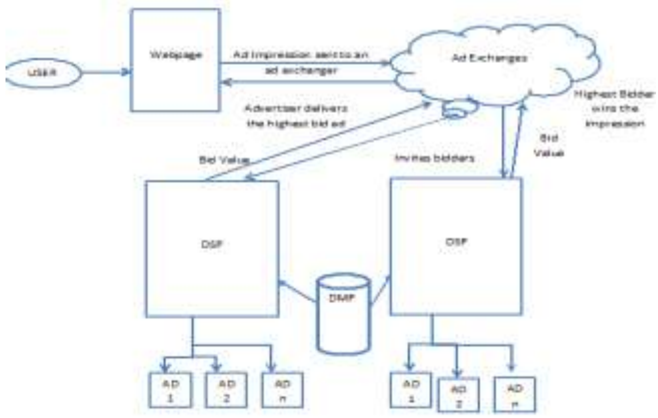

Fig 2: RTB ecosystem Key role in RTB markets:

The role of various entities in RTB markets are as follows:

Advertiser: is the buyer of ad slots on which their ad will be displayed. They participate in ad auction and bid according to their budget, market goals etc. the advertiser who bids highest amount wins the ad impression.

Demand side platform (DSP): it helps advertisers in buying the appropriate ads from ad exchange in very efficient way. It provides match on the basis of big data analysis, audience targeting etc.

Ad Exchange: it acts as an interface between user and DSP. It displays ads according to the interest of the user.

Publisher: is the owner of the website searched by the user. When a user launched the ad of advertisers who wins the ad auction will displayed on the ad slots.

Data management platform (DMP): is a data warehouse and store, merge and label user information which is useful to advertisers and DSP. This information is collected by cookie synchronization method.

In cookie sync method, when a user opens a webpage and goes without closing it then a third party tracker tracks the user's activities and stores the information in DMP.

2.2Business Flow Of Rtb Process

As seen in fig 2 the detailed flow of RTB process is given as follows:

- Firstly any user on internet visits the webpage and this webpage is owned by a publisher.
- If on this webpage ad slots are available then publisher send this information to ad exchange with user's information, number of slots and demanded price.
- Ad exchange then forwards it to all DSP's.
- Each DSP parses the information given by ADX. DSP ask DMP for more information about the user such as location, age, sex, shopping interest etc. after finding information it places an auction among all the advertisers which are associated with DSP. The information about the winner of the auction is provided to AdX.
- ADX is connected to several DSPs and receive winner from each DSP. Then it again starts an auction among all winners of DSPs, if the bid of advertisers is less than the publisher's demanded price then it terminates the process else it notifies the DSP to the winner. Then it plays the advertisement of winner in the ad slot of the user.

III.LITERATURE SURVEY

Various RTB techniques have been proposed for bidding strategy. The different techniques are described below: Myerson et al [4] proposed an optimal mechanism. In optimal mechanism the bidder who bids highest price wins the auction but gives only second highest price. There are two stages in auction process. First is DSP advertisement and second are advertisement exchange/ DSP stage. There is no incentive given to the DSP who truthfully submits the bids to all of its advertisers. This leads to decrease in adv. exchange revenue.

Mansour et al [5] prove that the optimal second price forces all the advertisers to truthfully submit their price as we are not making highest winning price available to advertisers. So, there is less information available to advertisers about winning price. They bid their higher price in order to win the bid. So, in this way loss of adv. Exchange will be reduced.

Claudia et al. [16] purposed a bid optimization Researcher introduced hybrid BIN TAC mechanism for increasing the revenue of ad exchange [6]. In this impressions are auctioned by win using buy it now price. If only one advertiser can give that price, then he/she wins the auction. If many advertisers want to purchase that impression, than a second auction is held between them. If there is no advertiser who can afford that price, then a take a chance auction is held between top L advertisers. The impression is randomly given to any advertiser at L+1 st price.

Yuan et al [7, 16] proposed time dependent model for evaluating the ad performance. It observed the ad impression, click and conversion rate for evaluation.

Rogers et al. [8, 18] have suggested a probabilistic model by considering the users behavior and advertisers. This model focusses on bidding strategy and find out most reasonable bid value for each auction and also determines how we can achieve maximum number of impressions.

Hegeman et al. [9] have suggested the standard for the bidding strategy. It considers the past value of impressions, total allocated budget, presence of social functionality, chances of advertisement selection and total available budget etc. It considers the past results in which DSP wins the auction and estimate the bid price of its current auction. In some other research bidding strategy was made by best using values of budget and price of the bid.

Chakraborty et al. [10, 17] suggested the optimization framework. In this framework, they combined online algorithms and stochastic models. They proposed Bayesian decision framework with constraint of type of bandwidth. In Bayesian framework we display advertisements according to the content of the web page which is searched by the user.

Li et al [11] tries to forecast bid value by taking an impression at lowest cost. They use logistic regression model for forecasting winning price and win rate model for forecasting win rate. After combining both the models, they tried to estimate bidding strategy.

R. Schapire el at [12, 13, and 14] has proposed one high level approach which is based on machine learning. This approach uses data of ad exchangers as training data for win rate estimation model. This data can be either negative or positive. By using this data, a toolkit for generating bid price for further advertisements is made.

Chen et al. [15] proposed impression level bid price issue as a constraint optimization problem as there are many constraints such as limit of budget, availability of inventory for maximizing revenue. Their bidding algorithm is based on linear programming this algorithm proposed detailed impression valuation and consider the constraint for suggesting real time bid value.

This is an online algorithm which guarantees to give provide same level of knowledge as offline optimization.

Technique which is based on supervised learning and second price auction theory. This approach gives effective results in matching the impressions to audience. This approach is used in Media6Degree platforms.

IV. RTB AUCTION MECHANISM

In online marketing buyers and sellers do not know the exact price for an ad impression in market. In such situation, auction is held among buyers of ad impression. Auction is fair, simple, widely used and transparent way in which buyers and sellers are agreed on a price quickly in order to increase their sales outcome.

In auction we offered the item which we want to sell to bids and give that item to that buyer who pays the highest price. Different auction schemes are as follows:

The second price auction model: in this, many advertisers bids for an ad impression if anyone from them wins the bid then he/she should give only second highest bid price.

For example there are 4 advertisers (P, Q, R, S) who are bidding for same ad impression with bidding amount 10$, 8$, 9$, 16$ respectively. The fourth advertiser will win the auction and give only 10 $ as bidding price. The second bidding price becomes the sealed price or market price.

Winning probability: In the above model we calculate the market price per ad impression basis but in this we calculate the market price distribution per campaign basis.

In this we use winning probability for click through rate estimation.

Bid landscape forecasting: in this, we estimate the performance of different ad groups in different ad scenario. It is basically used for bid optimization process. Suppose your ad is running from few weeks in a certain ad slot but it is becoming more costly week by week.

Now you want to see the effect on your ad impression by reducing bid price a little. You want to see effect on number of clicks, cost etc.

You also want to see that you are getting enough impression after reducing your price as well or not then bid landscape forecasting helps you. It tells us that by seeing past responses of ads.

V. BIDDING STRATEGY

A bidding strategy refers to the selecting the accurate bid price for an ad impression so that the probability of winning an auction will be increased. The design of optimal bidding strategy is most difficult and important work in RTB.

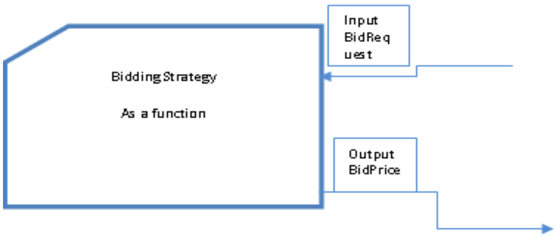

Fig 3: bidding strategy as function

Bidding strategy is an optimization function. We can assume biding strategy as a function which takes bid request (user information, ad page on which ad is displayed, context) as input and provides the bid price as output. Various types of bidding strategies are as follows:

Quantitative biding in RTB: in performance driven environment each advertisement is quantified by utility and cost.

Utility is the chances of a user clicked on ad or not. Cost is cost spent in winning the ad impression.

Strategy for profit maximization: the main motive of any business is to earn profit. So we want a bidding strategy which makes maximum profit from daily business operations.

Profit is calculated as difference between revenue and cost. If the difference is more than the profit is also more and it's vice versa. But only if our bidding price is higher than our chances of winning an auction is increased.

Strategy for revenue maximization: In this, we try to maximize revenue. An advertiser places a bid according to first price auction mechanism which means it maximize its bidding price in such a manner that it cannot lose money.

Strategy for profit and revenue maximization: In this, we try to maximize both profit as well as revenue. So we mix both of the above function together and use a weight alpha to control the strategies. When we placed a bid then we can adjust alpha value for controlling the importance of profit vs. revenue. This strategy can change value of alpha in real time depends on performance of bidding system.

5.1Prediction Of User's Response

Learning and predicting user's response is most difficult in online marketing. In this, we have to learn how to estimate user response such as clicks conversion, readings etc.

We have to predict user response accurately so that profit of the advertiser can be maximized. We can use CTR

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and CVR prediction for performance driven marketing. Various approaches for predicting user response are as follows:

Table 1: Comparison of different Types of User Response Prediction Model

Type of model	**Purposed By**	**Method**	**Usage**	**Issues**
Bayesian probit regression	It is purposed by Grapetet et al., in 2010. It is also called a Bayesian learning model	It is a linear model.	It can easily implement with high efficiency.	They learn with very few features pattern and they are inefficient for catching high order patterns. Solution: This issue is solved by non linear model such as factorization machines.
Factorization machines	It is purposed by Rendle in 2010.	It directly explores features and interactions among them and mapped these features and relationship in low dimensional space.	It is very useful in collaborative filtering as it is an extension matrix factorization.	CTR estimation for mobile advertisement is a problem. Solution: This problem is solved by extending FM to HIFM (hierarchical importance aware factorization machine).
Decision tree	It is purposed by Breiman et al., in 1984.	It is a non linear supervised learning method.	It is used for CTR estimation.	Addition and deletion of specific feature is a problem. Due to small change, tree will break in parts. Solution: its solution is ensemble learning.
Ensemble learning	It is purposed by Friedman et al., in 2001.	In this, many decision trees are combined together for solving problem of splitting and avoiding over fitting in data. It uses two techniques for that which are as follows: bagging and boosting.	It is useful for decreasing variance and over fitting of data.	It helps with increasing the volume of training set but predictive force of model will not improve. It requires less correlation between trees.

Bagging	It is purposed by Breiman in 1996	It is more powerful and useful than boosting. It is also known as bootstrap aggregating. In this we will take bootstrap samples and train each sample. After training we will estimate the average of prediction of these different algorithms.	It is useful for decreasing variance and over fitting of data.	It helps with increasing the volume of training set but predictive force of model will not improve. It requires less correlation between trees.
Boosting:	It is purposed by Breiman in 1996.	In this the output of many weak predictions are combined so that a strong prediction is produced. It works iterative manner.	It also gives higher stable model by reducing variance:	It does not help in protecting over fitting.
User Look alike	It is purposed by Zhang et al., in 2016, Mangalanpalli et al. (2011).	RTB has the ability to make user profiles and detects user interest via tracking user's behavior by history, clicks and conversions.	It provides high targeting accuracy which results more number of conversions by the user.	In this building of user interest segment is performed independently which results it has less attention towards prediction of ad response.
Transfer of learning process from browsing of web to ad clicks	It is purposed by Pan and Yang in 2010.	Here we learn by transferring the knowledge from other related tasks. It is related to multi-task learning. In RTB training data is transferred by two resources. One is user behavior and other is ad response by user. User behavior estimation is task of collaborative filtering and ad response prediction is task of CTR.	It solves the problem of classification, regression and collaborative filtering. It is useful in that situation where training data for learning process is very expensive and quickly outdated.	The amount of observations are very large it is quite promising to deal with this large amount of data.

5.2Attribution Model

The user's interaction on a particular ad is tracked by the number of clicks. The particular ad item is purchased by user or not is determined by the touch points. So credit of conversion is allocated over touch points. We have to make good conversion attribution in online marketing. Two different types of models are as follows:

Heuristic model: In this model, various rules are created by human by suing their past business experiences. Example of such type of heuristic model is Google Analytics.

Data driven probabilistic model: There are two types of data driven probabilistic model are as follows:

Bagged logistic regression: It tries to predict user's behavior in terms that he/she is converting ad touch event or not. It does not consider repeated touch of same user. The user's ad touch event is given as input to the regression process and output is a binary value which determines user's response in yes or no.

Simple probabilistic model: it uses both types of conditional probabilities for credit allocation.

VI. CONCLUSION

Real Time Bidding helps to simplify the bidding process and help marketers to take their revenues to new heights. In this paper, we have briefly introduced RTB marketing model and summarize the related work undergoing in this field. It is connecting many platforms such as desktop, mobile web and social media. But here are many open issues in this field. In this, we have dealt with various auction mechanisms and bidding strategies. We also read about comparisons between various user response models. There are many issues in RTB, one such issue is the tradeoff between the innovations in procedures of advertisement and security of the user's personal data.

REFERENCES

[1] Real Time Bidding in Online Digital Advertisement Shalinda Adikari and Kaushik Dutta National University of Singapore, Singapore, Singapore

[2] A Survey on Real Time Bidding Advertising Yong Yuan1,2, Feiyue Wang1,2,\ Juanjuan Li1,\ Rui Qin1,3 The State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing, China Qingdao Academy of Tntelligent Industries, Qingdao, China Beijing Engineering Research Center of Tntelligent Systems and Technology, Institute of Automation, Chinese Academy of Sciences, Beijing, China

[3] Real Time Bidding in Online Digital Advertisement Shalinda Adikari and Kaushik Dutta National University of Singapore, Singapore, Singapore

[4] Muthukrishnan, S., Ad exchanges: Research issues. Internetandnetwork economics, 2009: p. 1-12.

[5] Mansour, Y, S. Muthukrishnan, and N. Nisan, Doubleclick Ad Exchange Auction. Arxiv preprint arXiv: 1204.0535,2012.

[6] L.Elisa c., et al., Buy-it-now or Take-a-chance: A New PricingMechanism for Online Advertising. Working Paper, 2012.

[7] Yuan, S., J. Wang, and X. Zhao. Real-time bidding for online advertising: Measurement and analysis. in 7th Internationa Workshop on Data Mining for Online Advertising,A DKDD 2013 -Held in Conjunction with

SIGKDD 2013,A ugnst II,2 013 –August 11, 2013. 2013. Chicago, IL, United states: Association for Computing Machinery.

[8] Rogers, A., David, E., Payne, T.R., Jennings, N.R.: An advanced bidding agent for advertisement selection on public displays. In: Proceedings of the 6th International Joint Conference on Autonomous Agents and Multiagent Systems, p. 51. ACM (2007)

[9] Hegeman, J., Yan, R., Badros, G.J.: Budget-based advertisement bidding, US Patent US20130124308 A1 (2011)

[10] Chakraborty, T., et aI., Selective call out and real time bidding.Internet and Network Economics, 2010: p. 145-157.

[11] Li, X., Guan, D.: Programmatic Buying Bidding Strategies with Win Rate and Winning Price Estimation in Real Time Mobile Advertising. In: Tseng, V.S., Ho, T.B., Zhou, Z.-H.,Chen, A.L.P., Kao, H.-Y. (eds.) PAKDD 2014, Part I. LNCS, vol. 8443, pp. 447–460. Springer, Heidelberg (2014)

[12] Schapire, R., Stone, P., McAllester, D., Littman, M., Csirik, J.: Modeling auction price uncertainty using boosting-based conditional density estimation. In: ICML 2002 (2002)

[13] Wellman, M., Reeves, D., Lochner, K., Vorobeychik, Y.: Price prediction in a trading agent competition. Journal of Artificial Intelligence Research 21, 19–36 (2004)

[14] Putchala, R., Morris, V., Kazhanchi, R., Raman, L., Shekhar, S.: kavayaH: A trading agent developed for TAC-02. Tech. Rep., Oracle India (2002)

[15] Chen, Y, et al. Real-time bidding algorithms for performance-based display ad allocation. 2011. ACM.

[16] Claudia, P et aI,., Bid Optimization and Inventory Scoring in Targeted Online Advertising, in The 18thACM SIGKDD Conference on Knowledge Discovery and Data Mining. 2012: Beijing, China.

[17] Chakraborty, T., Even-Dar, E., Guha, S., Mansour, Y., Muthukrishnan, S.: Selective callout and real time bidding. In: Saberi, A. (ed.) WINE 2010. LNCS, vol. 6484, pp. 145–157. Springer, Heidelberg (2010)

[18] Ghosh, A., McAfee, P., Papineni, K., Vassilvitskii, S.: Bidding for representative allocations for display advertising. In: Leonardi, S. (ed.) WINE 2009. LNCS, vol. 5929, pp. 208–219. Springer, Heidelberg (2009)

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