Displaying Ad with Optimal Real-Time Bidding

by

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A project submitted
to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
M.Engg. in Computer Science and Engineering

Department of Computer Science and Engineering
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Declaration

We are herewith stating that

1. To achieve the M.Engg. degree at Brac University we have proffered our real work.
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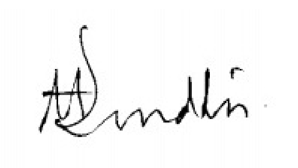

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Approval

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Of Fall, 2020 has been received as satisfying in partial accomplishment of the demand for the degree of M.Engg. in Computer Science and Engineering on December 05, 2020.

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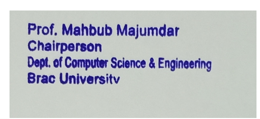

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Abstract

Real-time bidding is a new paradigm for displaying an ad. Through our research work, we have tried to find a bid optimization solution for displaying an ad in RTB. Advertisers are able to bid per impression through RTB to display their ads in publisher sites. The internal mechanism is quite complex and it correlates different parameters like user data, demographic location, culture and so on to determine the winning bid. In addition, it must be mentioned that this is different from the sponsored search auction where the bid price is related to keywords. Considering the budget, the objective of the predefined campaign and miscellaneous information collection in run time and from history is the key challenge for DSP. In our project, optimizing the bid in a programmatic manner is the desired problem. We have tried to develop a simple optimization bidding function which will be used to calculate in real-time within certain limitations. Finding non-linearity was the sole purpose of our work and it simply proves that CTR and CVR rate have that relationship with each and every estimated impression with different level of features. All the earlier works are basically focused on budget capping or reducing campaign period or prioritizing key features which are all falling in bidding with linearity.

Bidding optimally which is our mathematical derivation indicates that conventional bidding strategy should be changed from high-value low set of impression to low value set of a huge impression because firstly it is much more cost-effective and secondly and definitely increases the winning rate. Moreover, effectiveness and outperformance of our optimization framework and optimal bidding strategy have been shown by offline and online evaluation using a real dataset and production RTB system.

Keywords: Real-Time Bidding, Demand-Side Platform, Supply-Side Platforms, Ad Exchange, Optimizing Bid, Displaying Ad

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Fist of all, I would like to express my heartiest gratitude to Almighty Allah, who has given us sensible consciousness and energy for having this project work done in due time.

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Infine, honour to my Family and Friends for their motivation and explicit decent support.

Table of Contents

List of Figures

List of Tables

Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

RTB Real Time Bidding

DSP Demand Side Platform

SSP Server Side Platform

IAB Interactive Advertising Bureau

PPC Pay Per Click

CPC Cost Per Click

CPA Cost Per Action

CPM Cost Per Thousand

CTR Click-Through Rate

CVR The Conversion Rate

KPI Key Performance Indicator

ROI Return on Investment

DOOH Digital Out-of-Home

ADX Average Directional Index

POMDP Partially Observable Markov Decision Process

Chapter 1

Introduction

In recent days, RTB has surfaced as a quite innovative displaying ad paradigm. It is different from conventional sponsored search or contextual advertising because each chosen keyword's price presets by advertisers for their campaigns. Each impression submitted by an advertiser, RTB permits a little time frame, sometimes less than 100ms [8]. Ad displaying landscape has been tremendously changed by RTB for a couple of reasons. Firstly, it facilitates the buying process of the huge number of back-fill inventories by allowing per impression transaction scales and secondly, rather than contextual data, true analysing the real-time audience data and re-targeting those users make a robust impact towards buying [9]. More information about RTB can also be found in [8, 10].

1.1 Motivation

Since the inception of the Internet, the display ad market speculates one of the largest shifts in media. New and advance technologies are the central component of this change like real-time bidding, allow advertisers to dissect their precious audiences in real-time. But the key problem here is to influence the appropriate person at the appropriate time with the precise message in the accurate place in the realm of optimal bidding.

It is the DSP's responsibility to find and gather all the qualified Ad creatives from the campaign boundaries and calculate a marginal bid for each of the inbound bid request. User information, language, cultural diversity, different geographic location, organization size, position indication all are combined to determine the qualification of the expected Ad creative and campaign. It helps pre-filtering the rules before starting any bidding process. Both behavioural and contextual [3] data are used by DSP to determine a bid. Here, individual search, personal browsing history, discrete purchase history, occupational diversity, earnings source, attitude, viewpoint and so on all are fall in the behavioural category and specific domain and related web page, striking keywords, specific date and time, geographic location and weather, diverse cultures like language and prayer and platform-independent browser and operating system are fall in the contextual group. That's why it is normal and usually, advertisers are inspired to buy user interest parts from the third-party data providers [9]. There are different pricing model fostered in RTB such as Cost Per Mille (CPM), Cost Per Click (CPC), Cost Per Acquisition (CPA) and so on. We would like to say that, in our project, we limit our work within the CPM model which is fairly approved in RTB.

The most critical problem for a DSP is calculating the bid. Defining an acceptable bidding strategy is the ultimate solution to this problem. For decisive opponents in second-price auctions, [46] truth-telling is the predominant tactics for advertisers to bid their special values [21]. In general, DSP will assess each impression value of each bid request to determine the CTR/CVR rate and increase it by the value of click or conversion [35]. Usually, bid values are set by the advertisers [40, 35] and continue till the end of the campaign's lifetime. However, the bidding aspect, total budget and the campaign's remaining lifetime must be considered as practical constraints while computing a bid. The decent combination and consideration of these characters tend toward the DSP's overall optimized performance of a campaign and this is usually referred to as Key Performance Indicator (KPI). Total clicks number, conversion rate, total revenue all are using in stochastic methods rather than anticipating strategic advertisers with their personal, per impression true value [12].

1.2 Research Problem

Nowadays, real-time bidding is buzzed by everyone, especially for a paid search campaign which worth needing investigation. It's not only going to be revolutionary but also expands diversely soon when more and more merchants start funding in RTB. In general, advertisers require to pay a fixed rate varying number of impressions to display ad and that's the way of working in media buying. According to static bidding model, buyers need to purchase in a bucket of thousands of impressions at a flat or fixed average charged within that bucket. Generally, it's known as CPM or cost-per-thousand. But the impressions are quite less efficient at specific times of day time is the key flaw of this model.

Undoubtedly, real-time bidding is going to be the future of displaying the digital ad. It will be a dynamic and vibrant way for advertisers, where they can manage their available ad inventories maintaining their predefined campaigns through RTB. By observing the key behaviours already manifested online or investigating the user key preference data, advertisers surely can lean up their target markets. It's open and there is no restriction where the buyer can differently evaluate each possibility to buy an ad impression in real-time observing the miscellaneous platforms. Allowing or declining any distinct add impression of any buyers media plan can be considered as an example here.

Visiting a publisher webpage by any user usually triggers an ad auction for the specific slot of that page which is in RTB dynamic model creates a bid request for a particular targeting campaign. Now it's DSP's responsibility whether to take part any auction or not considering the provided bid request with different features like auction and user information, ad and ad-context and so on. Now, if the DSP participate any auction it must return a bid for the participating auction. Determining the realistic bid is the key issue here because it depends on too many factors. Key Performance Indicator (KPI) or predicted key performance indicator (p-KPI) value is not the only substantial for the ad impression being auctioned like the Click Through Rate (CTR) and Conversion Rate (CVR) which are the primary achievable target of all advertisers. But these are linked with many other key factors such as budget limitation, action winning probability, feature and cost of a specific ad impression. In our work, generating real-time bids optimally has been considered as a functional optimization problem and propose a novel optimization framework by considering all the above-mentioned factors into account. In fine, we have explained and showed how it leads to a practical bidding function.

1.3 Aims and Objectives

To enrich and at the same time flourishing the RTB marketplace by providing restriction-free industry standards for better interaction between traders of publisher inventory and consumers of advertising is the key mission of this project. As we mentioned earlier, open industry standards have diverse aspects but not limited to actual RTB protocol, taxonomic information, online and offline configuration and relative synchronization and so on.

Here, individual impression estimation to the bid value has linked through formulating the impression level-bidding procedure as a function. We have proposed a novel optimized functional framework withing the given budget constraint, the lifetime of a campaign and many more discrete statistics like auction winning probability, impressive features to prior distribution and many more.

So, from our analytical solution, we have found that a critical role has played by the auction winning function towards shaping the bidding function, whereas the division of the features is less irrelevant. The desired outcome originated from practical bidding data using the simple winning function are the form of non-linearity and concavity. It's not like the linear functions proposed previously [40], our defined function boosts too much higher bids for impression with a low estimated value, increasing the winning chances with a more cost-effective way comparing the higher evaluated ones is the main target. After experimenting offline and online data, it's been found that our proposed bidding methodology outshine the strong baseline as we predicted. Below is the summarization of our contributions -

- A novel optimized functional framework has proposed to determine the optimal bidding in RTB to display the ad.
- To our knowledge, defining the non-linearity and concavity form, against the KPI of each impression based on using the action winning function has never been explored in previous literature on RTB ad display.
- The realistic effectiveness of suggested bidding approach has been validated by conducting extensive offline and online tests.

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1.4 Organisation of the Report

We have orchestrated this report in the following manner - A brief overview with research objective has been delineated in section I. In section II, we have tried to explain the concepts related to the subject matter in detail. In section III, previous studies have been shortly described. Afterwards in section IV, we have shown problem definition with optimal solutions and in section V, experiment setup has been described with related dataset and training. Finally, we have wrapped up with the offline and online evaluation results and some future scopes of this research in section VI, VII and VIII respectively.

Chapter 2

Background Study

2.1 RTB Basics

In RTB, programmatic instantaneous auction is used to buy and sell advertising inventory considering each impression which is closed to financial markets. With RTB, buyers of ad bid on an impression and upon winning the bid it is immediately displayed on the pre-defined publisher's site. Besides, RTB helps to manage and optimize different ads from different ad-networks facilitating to create and launch required ad campaigns, defining network priority and allotting percentage of of unsold inventory which is also known as back-fill.

RTB is different from static auctions and easily perceptible. In a simple term, RTB is a per-impression basis bidding strategy whereas combination of up-to several thousand of impression is the fundamental concept of static auctions. Considering the advertising inventory sold statistics from both publishers and advertisers side RTB has been promoted more practical and efficient than static auctions, though execution methods and local circumstances play notable role to change the desired outcome.

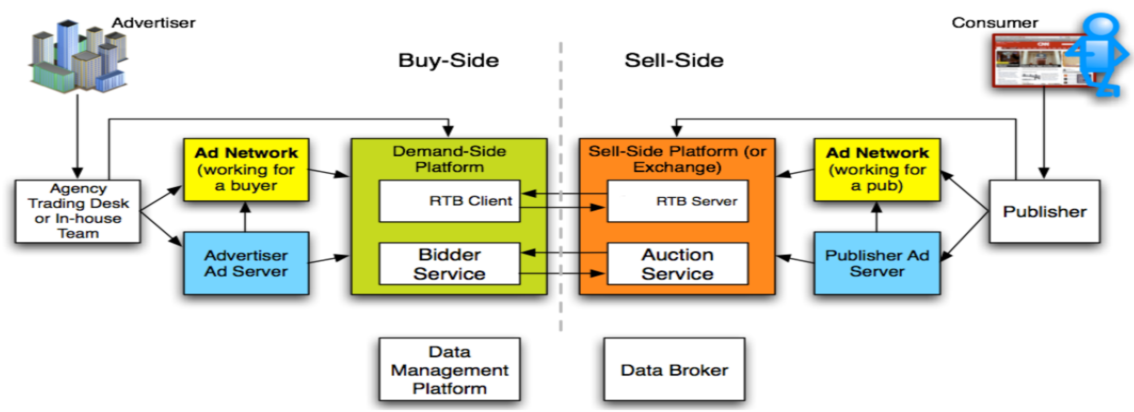

Figure 2.1: Eco-system of RTB from top-level communicative entities [45].

2.2 Publisher's Content Management

When we start visiting a publisher's website or a particular web page, a complex process of content selection and delivery begins. Publishers generate content such as news, music, video, information, sports and other entertainment. This content draws an audience and the publisher sells ad space to advertisers who want to reach that audience. It's the browser responsibility to establish a connection with the publisher's server when any user visits the publisher's web page. When the requested HTML content sends back by the DSP, the publisher server gets busy assembling that content. The browser begins to interpret and render that HTML to display an ad within it. There's a URL that tells the browser where to go to retrieve that add content.

2.3 DSP, SSP and Ad Server Sync Process

The publisher has an ad server that uses built-in logic to choose what happens next by considering a series of important questions. That will help to decide which advertisers should get this opportunity if the ad space isn't reserved for any specific advertiser. The publisher ad server connects to an SSP (Supply-Side Platform) that the publisher uses to monetize its programmatic ad inventory. For sending the ad request to an ad exchange, the SSP applies additional logic to it. Meanwhile, the ad exchange has been busy connecting to and communicating with potential buying systems. These systems include DSPs (Demand-Side Platforms) networks and even other exchanges in the same way that we can tell a stockbroker. The winning DSP passes instructions to the exchange for retrieving the ad creative. The exchange passes those instructions to the SSP. The publisher ad server gets the request from SSP and after doing some internal processing, it replies to the still open HTTP connection telling the browser to go to the agency ad server for the ad. An ad performance

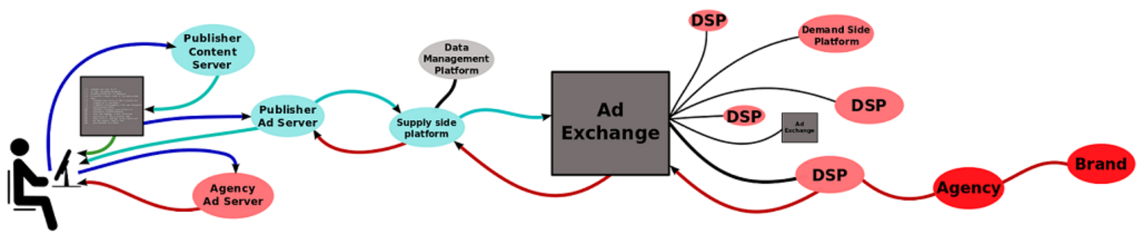

Figure 2.2: Online advertising serving process [48]

for advertisers is tracked down by the agency ad server. Moreover, when DSP generates an ad request with the winning bid, the ad agency server stores that request as an impression. Now, the browser responsibility to finally render the ad within the web page content resulting in the delivery of an ad most appropriately matched. The digital landscape is complex even more so far explain and this entire process depending on internet speeds can happen in a fraction of a second.

2.4 RTB Request Response Activity Flow

Upon visiting a publisher site by a user initiates the journey of a typical transaction. In other words, it triggers a bid request including various pieces of information like user's liking and disliking, demographic info, geo-location, cultural diversity, browsing data and loaded page history. After that, this request with various information goes to an ad exchange from the publisher. Now, it's an ad exchange responsibility to submit that request to multiple advertisers who place their ads by automatically offering bids in real-time. So, all advertisers have to bid on each ad impression, the highest bidder won the impression and finally, the winning ad is displayed on the publisher page.

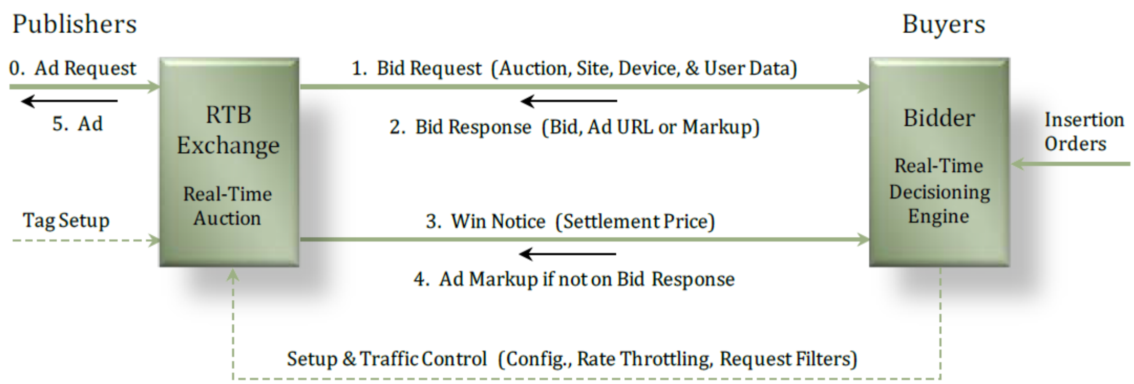

Figure 2.3: Real-Time request response sequence [47]

The above figure demonstrates the RTB inter-communications between the desired exchanges and its target bidders. At first, publisher site originates an ad request. Then, for every inbound ad request corresponding bid requests are disseminated to bidders, general auction rules are applied for evaluating responses, the notification goes to the winner and finally winning ad markup is returned. Critical data communication with the bidders possible only when the win notice URL and ad markup able to contain several macros standard.

Needless to say that there is no specific prerequisite for notification lost due to significant amount of system and bandwidth cost. However, accepting the offline procedures or enduring separate process outside of the request-response protocol. Focusing bid request, response and winning notice is the key RTB specification.

An advertising campaign's maximum bids and budgets are set by advertisers with the event of an automatic bidding process. Bidding criteria sometimes get complexed based on different types of consumers as well as detailed behavioural exchanged data.

2.5 Demand Side Platforms

Buyers can access varied inventory sources directly through Demand Side Platforms (DSPs). The simplifying workflow and reporting are typically streamlined the ad operations. DSPs are keen to the advertisers. DSP and ad exchange both empowered by the technology. In one hand, technology helps to build the foundation for a DSP and on the other hand, strengthening an ad exchange by permitting the combined power between advertising campaigns. An ad network and a DSP is different in many ways. Determining the individual impression value on real-time based on the user's history is the key capability of DSPs [48].

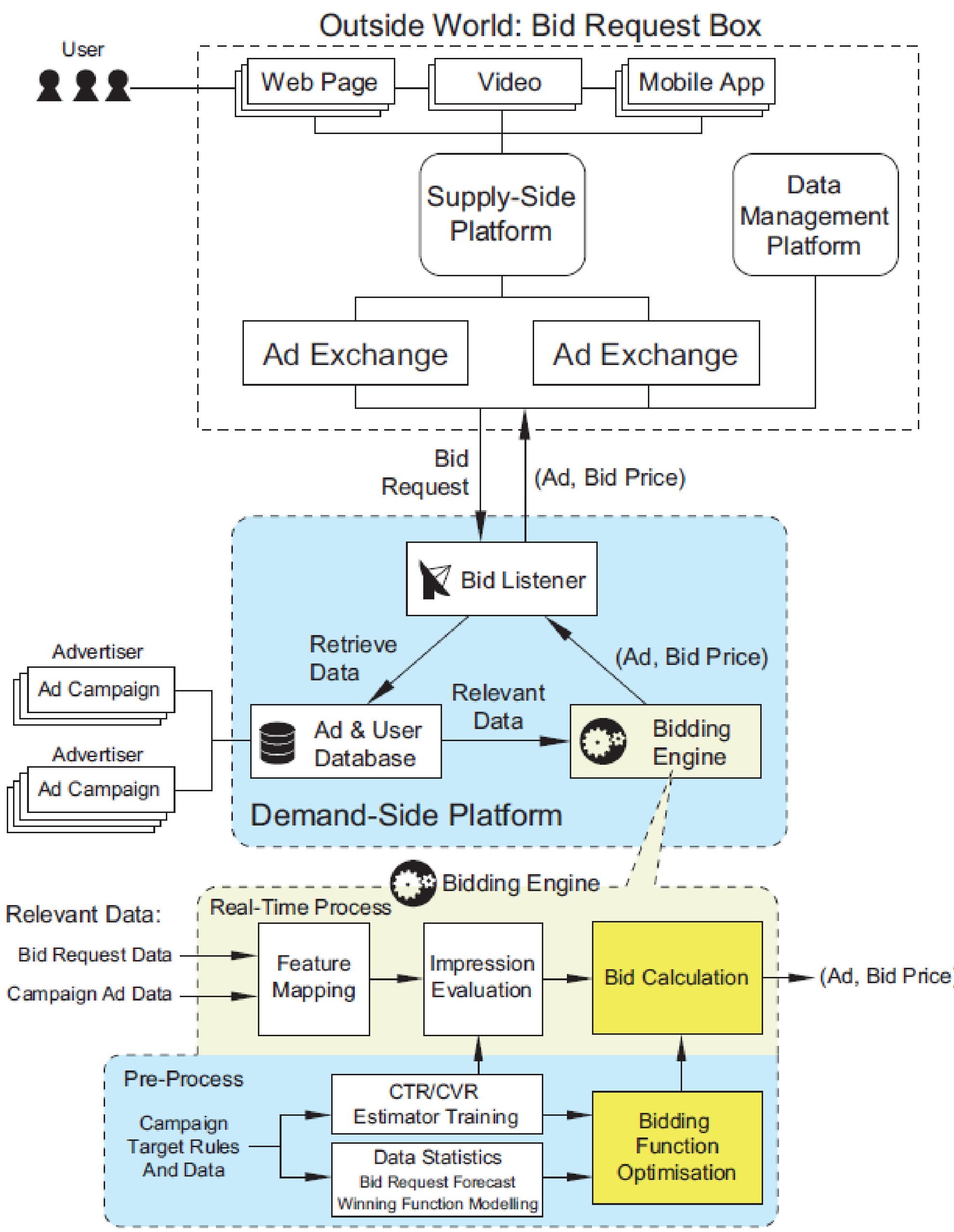

Figure 2.4: DSP and Bidding Engine [5].

2.6 Supply Side Platforms

Sometimes publishers handle more than one ad networks and yield diverse advertising with the help of SSPs. Data produced from impression-level bidding is used by these SSPs to assist tailoring the campaigns of advertising. Moreover, often applications bundled into supply-side platforms to control miscellaneous ad operations. Both SSP and DSP interfaces on the advertiser and the publisher side respectively. Firstly, advertising networks and exchanges are interfaced by SSP on the publisher side and later it turns this interface towards the advertiser side through the DSP. Generally, advertising networks are buyers oriented whereas SSP renders assistance for publishers, for example - app, website, DOOH owners and so on. Besides, sometimes SSP merged into advertising structure and ad providing organizations and ad exchanges which in turn work for both DS (i.e. advertisers) and SS (i.e. publishers) [49].

2.7 Ad Exchange

To buy and sell ad inventory from multiple ad networks there needs some kind of technology platform for making bridges to facilitate this process. An ad exchange is that kind of technology platform aiding the buying and selling different ad inventory from different ad networks. It's the RTB's responsibility to determine every inventory price. It does not consider the old historical approach where negotiation happens in the eve of determining the price on media inventory, rather follow fully technology-driven approach. All these representing fields are usually defined by the Interactive Advertising Bureau (IAB), and publications of the trade advertisers [50].

Chapter 3

Related Works

From the inception of online advertising, a range of critical problems have been identified and explored to find better solutions. Optimising bid one of the well-studied problems must need to be addressed [23, 24, 29, 40]. Nonetheless, it's been found that in the sponsored search context most of the research so far has been conducted limiting to the keyword auction [1, 21, 37]. Before optimising advertiser's objectives certain optimisation process needs to be performed like estimating cost and volume, the utility of each keyword and so on [2, 32, 14, 26]. Besides, one thing needs to aware is that typically all pre-setting bids keywords need to be considered under each scenario rather level of impression. Optimising budget problem is defined as performance-optimizing of the advertiser based on the upper bound cost of a given campaign budget [23, 39]. Sometimes bid price is related to keywords, leveraging the features of the query language broadly inferring keyword matching. In that sense, some authors concentrate on both the bid generation and optimization based on the above keyword matching criteria [4, 22]. Moreover, third-party or sponsored search under the different campaign for keyword-level bid optimisation and campaign level budget optimisation altogether have been proposed by some authors [13].

The auction price of the pre-setting keywords and they're periodic changes have been considered in some recent works. Needless to say, remaining campaign lifetime and budges also has been taken into account here. For example, keyword tuning for defining bid price online [12, 28], Markov decision method has been utilized where remaining budget and bid plays two distinct roles. Remaining budget and auction volume exploit as states and price of bid setting act as auctions. Some authors propose that within the lifetime of campaign bid allocation should be estimated [32] and also mention that bid price on each keyword should be defined considering a different discrete-time unit with market competition and ad position through CTR. But unfortunately, per-impression evaluating auction in SS has been missing in all the previous works. Also, advertisers and their corresponding agencies are scarcely granted for their impression and key level features. Moreover, there are two roles played by the SS during bid optimisation such as - keyword setting for bids and hosting the required auctions. Overall revenue optimisation through the search engine could also be diverted functional objective [11, 20, 33, 27], comparing individual advertisers campaigns performance.

To display ad in RTB with the optimised bid is quite different. This is the most difficult part in DSP and its RTB engine to calculate the optimal bid for displaying an ad. First of all these bids are not resolved by the keywords which are previously set or defined [8] but are based on impression-level features. So, what's happening here is, firstly, all advertisers generally need to introduce their own target rules, estimating every ad impression value to auctioned in real-time and returning that bid price per auction. Secondly, CPM costing is used by default in RTB [8]. Now, DSPs and advertisers directly optimise the conversion and click whereas impression winning undeviatingly related to the cost. That's why different dependencies like constraints of budget, CPM (Click Through Mil), eCPC (estimated Click Per Click) and so on should be investigated to find the various fruitful dimensions within a single framework. An ad displaying auction based on full or partial information has also been studied [24] where an algorithm proposed by the authors to learn winning bid distribution. According to the authors, this algorithm helps to make bid decision within the given budget constraint to obtain the most desirable offering. Some study shows that maximizing the revenue of the publisher's end is the ultimate target by adjusting the bid price from an individual campaign in real-time [16]. We have found a linear relationship to ad impression with the predicted click-through rate (CTR) in one of the most recent and relevant works. Here [40], bid price being return by DSP having a linear relationship to predicted pCTR where auction been taken place for each ad impression.

But the ultimate goal is to find a bidding function which will be non-linear and concave. In that context, the optimized functional framework offered from our analytical clarification confirms the non-linearity of the optimal bidding function. Auction winning probability and this non-linearity is nearly related but poorly coupled with earlier distributed impressive features. Digital advertising is a new paradigm and hence different RTB related issues also have been exposed and explored. The spacing problem in RTB has been discussed here [34] where placidly remitting campaign budget was the ultimate target. Defining reverse price is a different concept while ad auctioning in RTB paradigm. Considering the SSP viewpoint, the setting of the reverse price also been studied in [42]. Similar to reverse pricing, sparsity problem is explored in [35] where conversion model has been introduced for estimating the exchange rate considering different levels of selected hierarchy. Ad displaying performance evaluation also been studied in [19] where authors investigation reveal that site visiting aims robust proxy in term of normal user clicks. Moreover, communication perplexity on ad exchange also been studied in [15, 38]. In fine, RTB related more research, exploration, discussion and study also be found in [8].

Chapter 4

Problem Definition

4.1 Formulate the RTB Problem

Now its time signify the RTB problem in terms of mathematics. To formulate RTB problem mathematically we need to consider different key characteristics like relevant set of rules and budget. First of all, for displaying add launching a campaign is mandatory and next, it's advertisers responsibility to upload their desired creative ad sets with targeting rules and campaign lifetime within that budget. Here targeting rules means defining place, time, user segmentation with the corresponding budget and campaign.

Notation	Description
n	Total bid requests.
$p_n(n)$	The probability density function of n.
$\beta(n)$	Winning auction's predicted KPI.
$p_\beta(\beta)$	Probability density of KPI β.
B	Total budget of the campaign.
N_T	Total bid requests of T lifetime.
$bid(\beta(n), n)$	The bidding strategy function bid(), where $n \rightarrow \beta \rightarrow bid$; So $bid(\beta(n), n) \equiv bid(\beta(n))$.
$win(bid(\beta(n)), n)$	Winning probability with respect to bid request n and bid price $bid(\beta(n))$. Dependency assumption: $n \rightarrow \beta \rightarrow bid \rightarrow win$; So $win(bid(\beta(n)), n) \equiv win(bid(\beta(n)))$.

Table 4.1: Notations and corresponding descriptions.

After setting the target rules, the advertisers do not jump into an immediate bidding process rather allocate a tiny budget to acquire some statistics by random bidding impression. After analysing these statistics the advertiser dive into bid optimisation. For example, budget limitation and prevailing setting are usually used to estimating auction statistics when the forecast module of auction volume is employed [5, 6, 18]. We already defined an estimated bid request number N_T for targeting rules within the lifetime T. Here, n represents the featuring vector of a large dimension for each bid request. There are two sets of characteristics for each entry, the first one is imposed from the campaigning ad and the second is linked with the impression being auctioned. Matching the target rules of the campaign, we use $p_n(n)$ to indicate earlier feature vectors smooth distribution. Historic bidding can be used by the advertiser for the discrete campaign and analysing the feedback data of the auctioning ad impression help to predict the KPI. Predicted KPI of a bid request has been denoted n as $\beta(n)$. We should keep in mind that different KPIs can be considered by different advertisers. For instance, if maximising the straight visits is an ultimate campaign goal, i.e. increasing the click numbers then $\beta(n)$ indicates the pCTR for that impression. Estimating CTR, we do suggest to follow this study [5, 25, 41]. If there is any campaign targeting conversion, in that case, $\beta(n)$ points to predicted conversion (pCVR) for those impressions. Besides, predicted KPI of each bid request of earlier distribution is denoted by $p_\beta(\beta)$. All the used notations and their corresponding descriptions are addressed in table 4.1.

4.2 Devise an Optimal Bidding Strategy

We have accumulated the necessary statistics which was the first problem and now devising a strategy for optimal bidding is the second problem. The solution of the second problem is to find an optimal solution in such a manner where a particular KPI objective will be maximized over the budget. For keeping everything simple, considering click number as our desired objective while natural extension as alternative KPIs. Detail experimental results are provided in later subsequent Sections 6.5. We have tried to formulate the optimally bid generation problem as the problem of functional optimisation in terms of mathematics.

$$bid()_{ORTB} = \frac{argmax}{bid()} N_T \int_n \beta(n) win(bid(\beta(n), n) p_n(n) dn \tag{4.1}$$

directed to $N_T \int_n \beta(n) win(bid(\beta(n), n) p_n(n) dn \leq B$, where $bid(\beta(n), n)$ indicates the desired bidding function we are going to achieve. To resolve the winning function, predicted CTR $\beta(n)$ and feature vector n are required. Expected winning rate denoted by bin(bid,n) for n feature of the auctioning impression for a bidding price (bid) [5]. Clic probability for an auctioned impression created by the Eq. (4.1), which is the product of $\beta(n)$ and win(bid,n). Anticipated click per impression auction yields marginalising over the feature space. We have to keep in mind, in real scenario auction for every impression appear in synchronous order i.e sequentially. As a result, persistent bidding rule can potentially be made by anyone for feedback looping and optimised dynamic model manipulating like Partially Observable Markov Decision Processes (POMDPs) [7]. As in our illustration, a bid decision must be returned quickly within maximum 100ms time-frame as well with a small budget. So, in general, the above model is not achievable in our case due to quite high computational expense. As a result, we have to develop a different strategy like a two-stage approach for learning statistic such as $p_n(n)$ and N_T and then comes the bid optimisation phase. We examine the simple static model without ignoring the single generality and enduring broadly allowing judgment of the earlier bid optimisation work [28, 16]: each time the feature vector is independently generated from an identical distribution.

The anticipated cost of an upper bound is the reason behind the confinement. Normally second-price auction is applied by RTB because usually in terms of price, it pays the second-highest bid. Nonetheless, the second-highest bid sometime happens to quite low due to reserve price set [42, 8]. So, considering the cost of winning $bid(\beta(n), n)$ as the upper bound can be used as the desired bid price in our case. Expected each impression cost within an auction can be produced by winning rate and cost of the product. However, we have to keep in mind that the total budget cost B cannot be less than the overall expected cost of a time-frame. In other words, multiplying N_T with the feature space yielding cost must not be greater than the budget B. Besides, eCPC must be minimised by maximising the number of clicks within the budget restriction which is crucial in measuring display ad [5].

4.3 Rewriting the Optimization Problem

Now it's time to solve the above problem. We are going to make below subsequent postulate by considering synchronous variable dependency within each auction -

- Lets predict $bid(\beta(n), n) \equiv bid(\beta(n))$, where n $\rightarrow \beta \rightarrow$ bid. This helps us broadly for determining optimisation decision by reducing functional decision space as well as earning impression features through the KPI calculation $\beta(n)$. We found related dependency in an earlier work [38, 5] where bid depends only on CTR.
- Lets predict win(bid,n) $\equiv$ win(bid), where the winning rate is solely influenced through the bid generation of the feature n. Here, n $\rightarrow$ β $\rightarrow$ bid $\rightarrow$ win. According to our sensible prediction, we found that (shown in Section 5.1), the bid price has higher dependency than bid request features. In some earlier works [28, 13, 5], where winning keyword within ad slots also been predicted for bid optimisation.

Now we can re-write our optimisation problem as follows:

$$bid()_{ORTB} = \frac{argmax}{bid()} N_T \int_n \beta(n) win(bid(\beta(n))) p_n(n) dn \tag{4.2}$$

subject to $N_T \int_n \beta(n) win(bid(\beta(n))) p_n(n) dn \leq B$

Moreover, as we are aware that, n and $\beta(n)$ have a deterministic association so from that association probability density is also be determined by solving the above equation.

$$p_\beta(\beta(n)) = \frac{p_n(n)}{||\nabla \beta(n)||} \tag{4.3}$$

So, by performing substitutional integration we can more focus on β

$$\begin{aligned}
&\int_n \beta(n) win(bid(\beta(n))) p_n(n) dn \\
&\qquad = \int_n \beta(n) win(bid(\beta(n))) p_\beta(\beta(n)) ||\nabla \beta(n)|| dn \\
&\qquad = \int_{\beta(n)} \beta(n) win(bid(\beta(n))) p_\beta(\beta(n)) d\beta(n) \\
&\qquad = \int_\beta \beta win(bid(\beta)) p_\beta(\beta) d\beta
\end{aligned} \tag{4.4}$$

and the related exchange for similar substitution $\int{}_n bid(\beta(n)) win(bid(\beta(n))) p_n(n) dn$. However, we get the final functional optimisation problem by re-writing the integration with respect to β which is as follows:

$$bid()_{ORTB} = \frac{argmax}{bid()} N_T \int_\beta \beta win(bid(\beta)) p_\beta(\beta) d\beta \tag{4.5}$$

subject to $N_T \int_\beta \beta win(bid(\beta)) p_\beta(\beta) d\beta \leq B$

4.4 Finding Optimal Solutions

To find the optimal solution we need to introduce the Lagrangian objective function which (Eq. (4.5)) is

$$L(bid(\beta), \eta) = \int_{\beta} \beta win(bid(\beta)) p_{\beta}(\beta) d\beta - \eta \int_{\beta} bid(\beta) win(bid(\beta)) p_{\beta}(\beta) d\beta + \frac{\eta B}{N_T} \tag{4.6}$$

where the Lagrangian multiplier refers to η. Considering the diverse distinctions of mathematical calculation, we can define the Euler-Lagrange form of $bid(\beta)$ as

$$\beta p_{\beta}(\beta) \frac{\partial win(bid(\beta))}{\partial bid(\beta)} - \eta p_{\beta}(\beta) \left[win(bid(\beta)) + bid(\beta) \frac{\partial win(bid(\beta))}{\partial bid(\beta)} \right] = 0 \tag{4.7}$$

$$\eta win(bid(\beta)) = \left[\beta - \eta bid(\beta) \right] \frac{\partial win(bid(\beta))}{\partial bid(\beta)} \tag{4.8}$$

from the above equation, we can find that $p_{\beta}(\beta)$ which is the probability density of KPI has dropped. Now, winning function $win(bid(\beta))$ stands as the only dependency for the bidding function $bid(\beta)$. Taking the combination over the allocation of $p_{\beta}(\beta)$ for the objective and constraint is the key reason. Different optimal bidding functions are the outcome of different winning functions. To fit the standard and the trajectories of real-world data, we are going to introduce two winning functions and at the same time originating corresponding optimal bidding functions [5].

4.4.1 Winning Function 1 & Corresponding Bidding Function 1

After sampling on real data, we have shown in Figure 5.1 that the estimated concave shape is the constant outcome of the winning rate win(bid). We also find that winning rate increases by adding up a little bid price which is a little bit more than zero and less than already been two high. So, the simple form of this winning function as follows -

$$win(bid(\beta)) = \frac{bid(\beta)}{c + bid(\beta)} \tag{4.9}$$

here, c is a constant. When c's value changes, our winning function produces different output and that meets our desired expectation. In Figure 5.3(a) we have provided a detail representation of the winning function with changes of given c's value.

Getting a derivative concerning to the bid provides:

$$\frac{\partial win(bid(\beta))}{\partial bid(\beta)} = \frac{c}{(c + bid(\beta))^2} \tag{4.10}$$

Considering Eq. (4.9) and (4.10) with Eq. (4.8) provides:

$$\frac{c}{(c + bid(\beta))^2} - \eta \left[\frac{bid\beta}{c + bid(\beta)} + c \frac{bid\beta}{(c + bid(\beta))^2} \right] = 0 \tag{4.11}$$

$$\left(bid(\beta)^2\right) = c^2 + \frac{\beta c}{\eta} \tag{4.12}$$

Finally, we can derive our expected optimal bidding function by resolving the above equations:

$$b_{ORTB1}(\beta) = \sqrt{\frac{c}{\eta}\beta + c^2} - c \tag{4.13}$$

4.4.2 Winning Function 2 & Corresponding Bidding Function 2

There are different types of campaign targeting different publisher with diverse high reserve price or huge campaign budget. Regardless of these parameters, we would like to say, when the bidding price tends to zero, winning chances will not increase quickly. So, when the bid price starts to increase the winning probability also starts to increase excitingly. But this is not the norm, usually happens within the ad slots of high-profile [13]. That's why in quest of achieving this feature from our proposed winning function we need to tune it slightly, i.e.

$$win(bid(\beta)) = \frac{bid^2\beta}{c^2 + bid^2(\beta)} \tag{4.14}$$

where c is the curve controlling parameter, i.e. increasing or decreasing the curve shape depends on the c's different value. Figure 5.4(a) provides an illustration of this concept.

Taking the exact similar token, we have solved Eq. (4.8) using the winning function in Eq. (4.14), i.e.

$$b_{OTB2}(\beta) = c.\left[\left(\frac{\beta + \sqrt{c^2\eta^2 + \beta^2}}{c\eta}\right)^{\frac{1}{3}} - \left(\frac{c\eta}{\beta + \sqrt{c^2\eta^2 + \beta^2}}\right)^{\frac{1}{3}}\right] \tag{4.15}$$

Solving $\eta = 3.25$ x 10^{-7}, considering different c's value within the bidding function expecting output has shown in Figure 5.4(b). Undoubtedly, $b_{ORTB2}(\beta)$ is a concave function.

4.4.3 Measuring the Optimal η

From our earlier equations we notice that, η is one of the key parameters for both bidding function in Eq. (4.13) and (4.15). Lets explicitly signify these as $bid(\beta, \eta)$. Now to measure the optimal η, applying the Euler-Lagrange condition of η from Eq. (4.6) is

$$\int_{\beta} bid(\beta, \eta) win(bid(\beta, \eta)) p_{\beta}(\beta) d\beta = \frac{B}{N_T} \tag{4.16}$$

The optimal resolution of η can be found by applying the formula of $bid(\beta, \eta)$. However, the study shows that there is absent of analytic solution of η, though applying our winning function in many different cases. Moreover, we have found that sometimes final outcome depends on $p_{\beta}(\beta)$. It's found that bidding log data have been used to find numeric solutions as well as solving efficient numeric calculation. In our work, we have re-targeted η as a tuning parameter as part of the pragmatic approach for the bidding functions with a view to learning from the data. From Eq. (4.13), (4.15) and (4.16), we can easily observe that, when η decreases the value of $\int_{\beta} bid(\beta, \eta) win(bid(\beta, \eta)) p_{\beta}(\beta) d\beta$

steadily increases. Therefore, the solution of η tends to smaller correspondence with the larger budget B/N_T which usually points to a high volume bid price. Optimal η trend in respect to different per-case budget B/N_T is the ultimate demonstration of our experiment.

Chapter 5

Organizing the Experiment

Our proposed optimised bidding framework is examined both under offline and online evaluation. In Section 6, we have shown the evaluation of our method employing the real-world dataset and in Section 7, we have applied the industrial DSP with authentic advertisers and impressions. Now, in this section, we are going to describe the organization of the research and summarise the outcomes from our data investigation.

5.1 Equipping Dataset and Essential Analysis

5.1.1 Source and Specification of Dataset

We have tried to use the feedback records from the actual bidding history and, for this real-world dataset, a renowned DSP company was our primary candidate. This DSP company has released their dataset on the website http://data.computational-advertising.org. More than 13 million impressions of more than 10 days in 2019 have been recorded along with real-world users feedback from 10 campaigns' of diverse advertisers. The information for each bid request within the log includes miscellaneous information such as - the user segmentation or the user, the ad creative format and size or the advertiser, page domain and URL, ad slot, reserve price for the auction or the publisher, operating system and browser, region and time or the context and so on. Every auction winning bid price is associated with a distinct bid request. Later on, after winning the auction by the advertiser, each click and conversion in terms of the user feedback will be recorded. These dataset are shown in details in Table 5.1.

5.1.2 Data investigation on succeeding bids

Figure 5.1 is the delineation of the winning rate vs. the bid price concerning campaigns one through six. Due to the quite similar outcome, campaigns seven to ten are not provided here. After careful observation, we do find that, similar patterns are the outcome for all the campaigns. We find dramatic rise of winning rate for the campaign with the acceleration of the corresponding bid price. But winning rate stalls down when the bid price grows larger that is more than 100 and eventually it converges to 1. That's why it's prudent to apply the concave functions like Eq. (4.9) and (4.14) with a view to model the above associations. We have introduced a constant parameter c to fit the winning functions to generate the real curve with the tiniest square error for every campaign.

The winning bid prices and the bid request features' internal dependency also have been studied. It is also familiar with market prices in [12]. The box plot pattern [36] can also be visualized from the Figure 5.2, where we can see the winning price deal against the diverse characteristics such

	Overall Impressions, Clicks, Cost, CTR, CPM and eCPC for a Particular Campaign Period					
Campaign#	**Impressions**	**Clicks**	**Cost**	**CTR**	**CPM**	**eCPC**
1	2,585,150	2,554	252,000	0.081%	98.82	186.15
2	2,240,120	2,157	210,940	0.076%	92.57	178.32
3	1,893,765	1,720	170,463	0.073%	81.16	119.10
4	1,547,810	1,476	140,394	0.070%	76.73	115.12
5	1,270,530	1,127	116,082	0.065%	86.22	101.19
6	1,170,360	1,061	10,715	0.058%	69.35	97.90
7	989,651	957	88,641	0.037%	73.60	87.84
8	787,514	643	68,172	0.034%	79.28	77.17
9	512,433	496	45,578	0.031%	80.72	64.25
10	352,237	320	32,467	0.028%	63.25	44.11
Total	13,349,570	12,511	1,135,632	0.078%	82.78	110.25

Table 5.1: Overall Dataset statistics.

as hour of the day, day of the week, different browsers used by the users, various operating systems and miscellaneous geographic regions of bid requests to campaign 1. Needless to say all other campaigns in our experiment follow the alike pattern. Figure 5.1, shows that the clear comparison with the bid price and corresponding deviated relation. Figure 5.2, confirms that certain feature values do not have any impact on the winning price distribution. It implies that to influence or maximize the winning rate in corresponding campaign's auction, the bid price is the fundamental factor . The winning rate is petty receptive to the other bid request traits when the bid value is identified. Hence, it is pragmatically plausible to clarify win(bid,n) ≡ win(bid) as recommended in Section 4.

5.1.3 Training & Analysis Distribution

We have conducted 2:1 training and analysing data distribution by the sequence of time for every campaign. The key reason behind using this training data is to tune the parameters of the bidding function along with the CTR estimator. Sometimes, DSP bidding strategies are compared for evaluation with these experimental data.

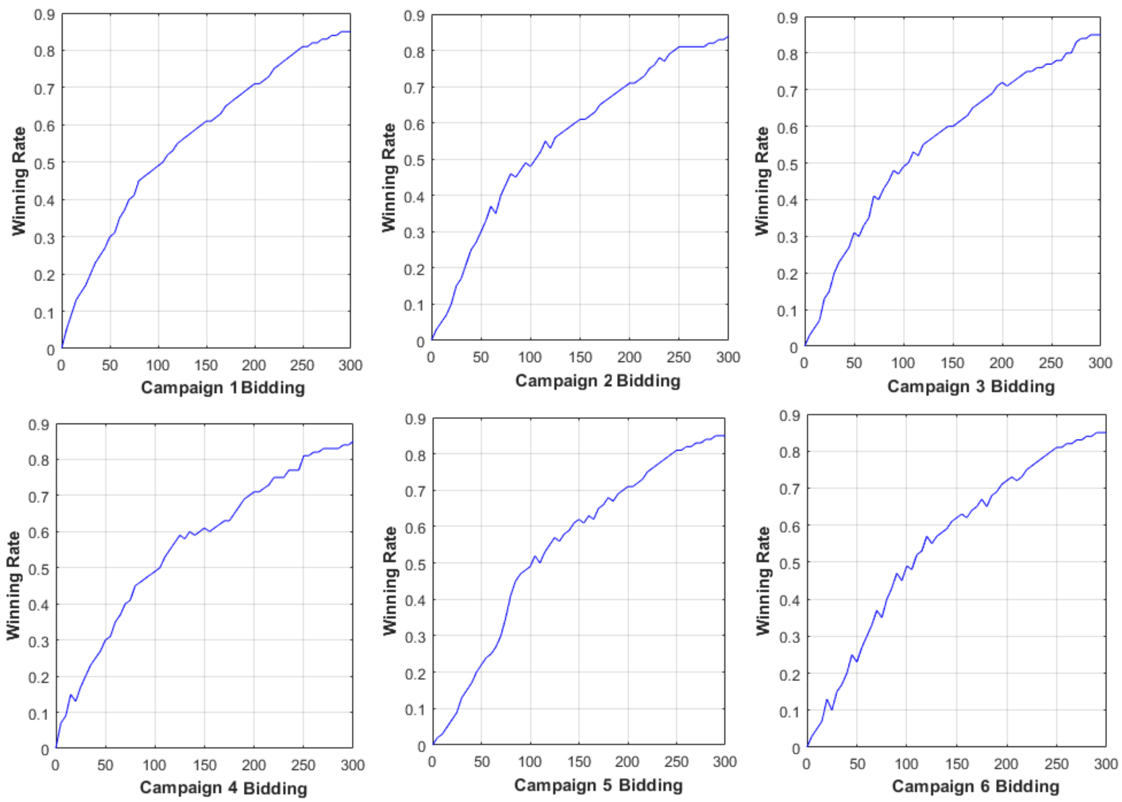

Figure 5.1: Winning rate vs. bid value in respect to different campaigns.

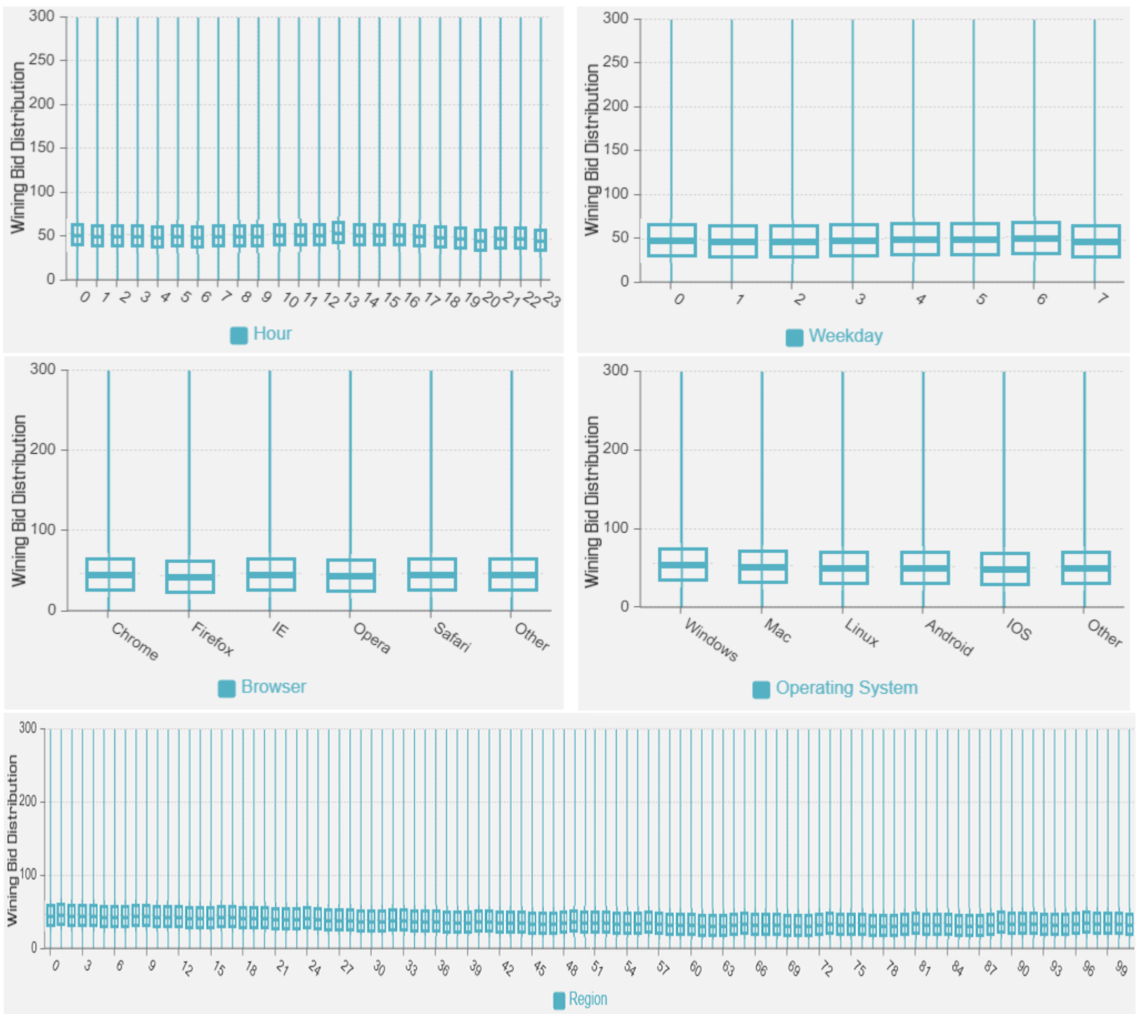

Figure 5.2: Winning bid allocation toward various characteristics for campaign 1.

5.2 Analysis of Winning & Bidding Function 1

According to the prediction of winning function 1 and mathematical form of Eq. (4.9), we find that the optimal bidding function $b_{ORTB1}(\beta)$ produces the concave shape: a functional form of a square root. With the changes of c's value, this bidding function also produces different concave shapes which is illustrated in Figure 5.3(b), fixing the $\eta = 3.25 \text{ x } 10^{-7}$.

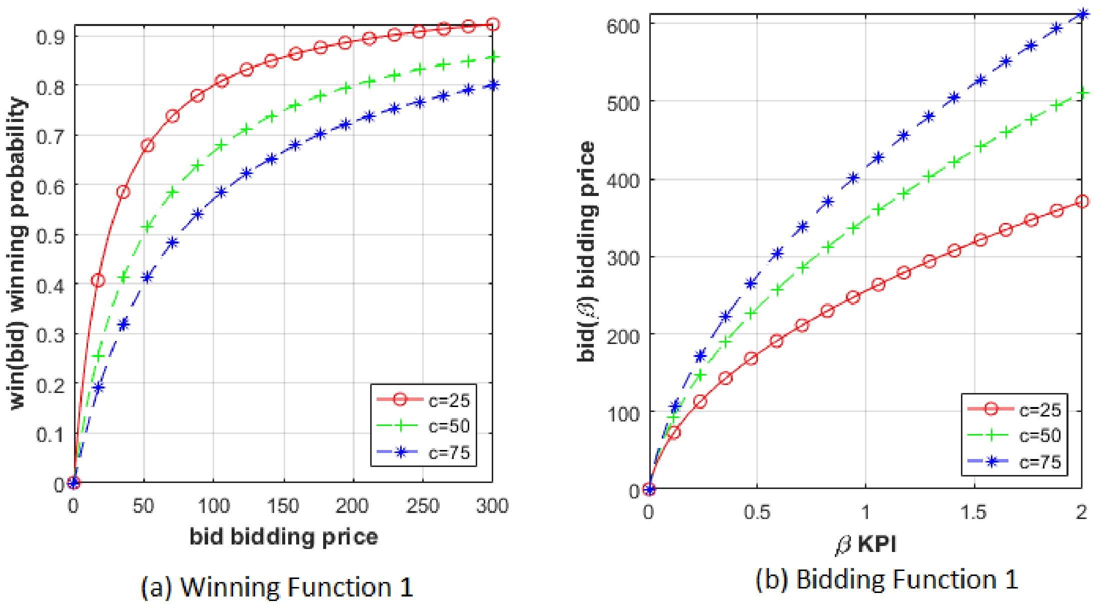

Figure 5.3: Winning and corresponding bidding function $b_{ORTB1}(\beta)$.

5.3 Analysis of Winning & Bidding Function 2

Our bid optimisation framework is a comprehensive one. From Eq. (4.8) we can see clearly that, different optimal bidding functions are the outcome of different winning functions. The proposed framework can conform to numerous ad markets with diverse winning functions. We limit our study only withing RTB markets and execute the winning function experiment grasping real data (Figure 5.1).

5.4 Analysis of Optimal Bid Functions

All the previous study of bidding functions shows the linear form [40, 35] (denoted as Lin). In our obtained optimal bidding functions, Eq. (4.13) and (4.15) provides both non-linearity and concave form which is novel one. Moreover, under different budget restriction for RTB, it shows a quite positive mapping from CRT prediction to the pre-defined bid value. Now we are going to show some comparison with other bidding frameworks. Figure 5.5 shows, ORTB bids higher compared

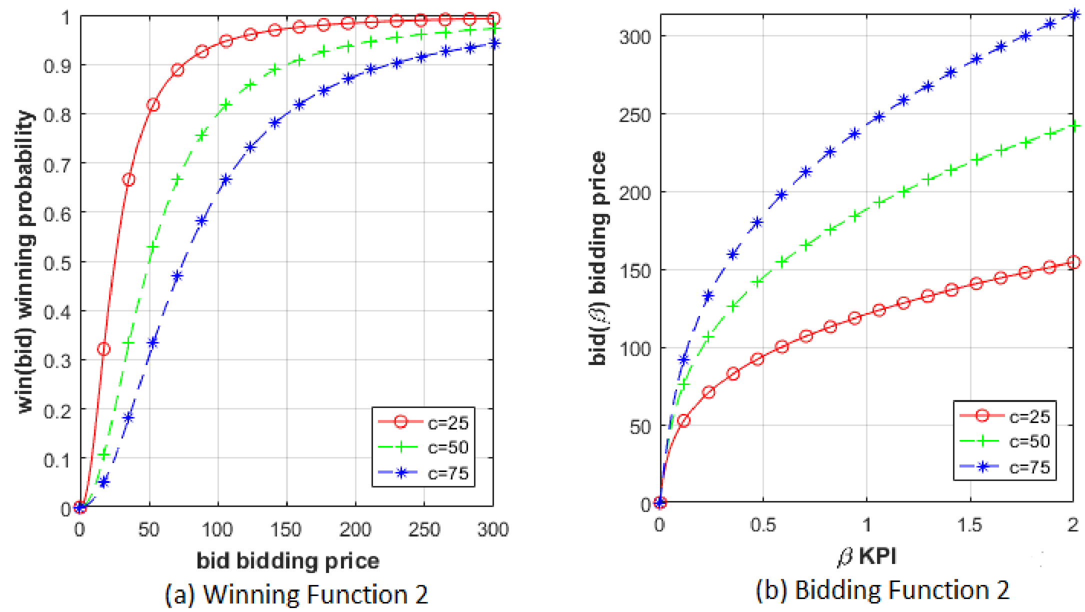

Figure 5.4: Winning and corresponding bidding function $b_{ORTB2}(\beta)$.

with Lin when the predicted KPI is moderate. That implies, on the low reward and low-cost cases, ORTB allots more budget.

So, the bidding technique for more low-cost impressions ultimately derive from the form of the winning functions. From Figure 5.1 we notice that the high growth rate of winning probability depends on the slight increase of bid price from zero. Afterwards, the winning rate starts to converge to 1 when the bid price exceeds a particular area. According to ORTB strategy with the moderate CPM increase winning probability goes higher because of the concavity of winning rate respective with the corresponding bid price.

5.5 Assessment Projection of Different KPI

Optimising the KPI of every campaign withing the sanctioned budget is the key responsibility of the DSPs. Therefore, the KPI is the fundamental evaluation criterion in our investigation. Although CPM and eCPC statistics are also observed, clicks have been regarded explicitly as our fundamental KPI. Moreover, a combination of obtained clicks and conversions have also been considered as an alternative test parameter of KPI, which is discussed in Section 6.5.

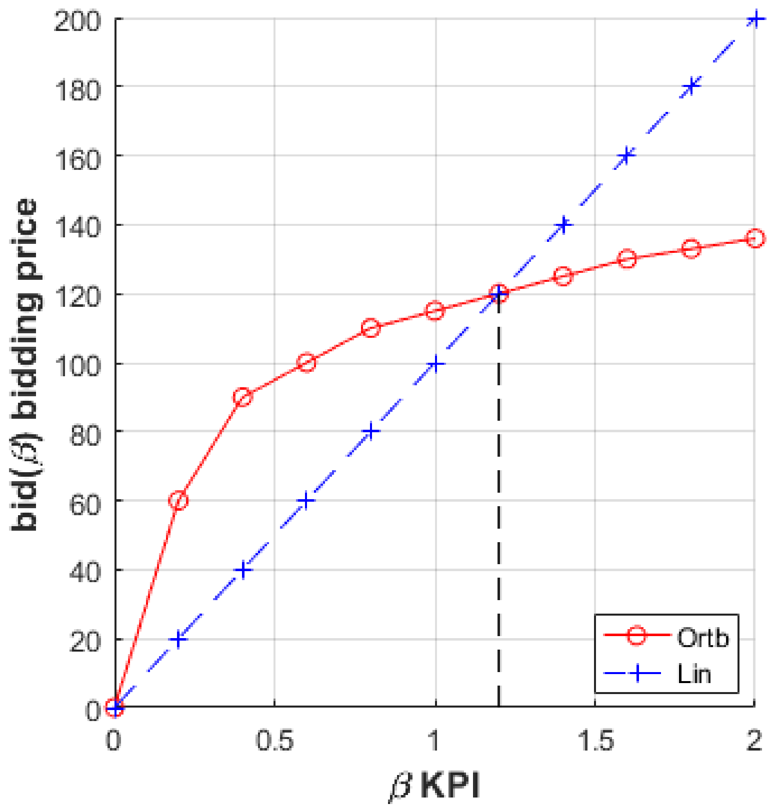

Figure 5.5: Concave bidding function's winning probability with respect to pCTR.

5.6 KPI Prediction Exercise

Each campaign consists of a combination with some key attributes like impression, click, conversion, cost unit, duration or lifetime and so on. To train the KPI estimator we use distinct campaign's log data of impression, click or conversion for each bid request. Especially, when KPI is ticked, then it directs to the well recognise CTR calculation [25, 41]. An arbitrary forest and inclination raising regression tree can be implemented here as part of the Regression models. As our work predominantly converges on the bidding tactics instead of the KPI evaluation model, we employ the Logistic regression as our CTR evaluation as it is a broadly adopted option [41]. The ground truth and estimated click probability which is the result of the loss cross-entropy also been considered. In our analysis for an alternative KPI, we have evaluated another KPI exercise which is discussed in Section 6.5.

To train and shape the CTR assessment model miscellaneous features have been deduced from the various logged data. Precisely, we obtain 27,325 first-degree binary characteristics and based on that produce 546,645 second-degree binary traits, which produces the cumulative 573,970 characteristics for our practice.

5.7 Probing Assessment Frameworks

5.7.1 Assessment Progress

Figure 5.6 delineates the assessment progress. We can look through the evaluation data of a distinct campaign after analysing the bidding tactics and corresponding budget for the examination tenure. Here, the array of records refers to the experiment data. Information of users feedback, winning price of an auction and bid request all are key attributes of a record. Particularly, any record tagging with a timestamp within incoming bid request characteristics does generate a bid price following the bidding tactics. If the budget is too low to the bid price, then it simply discards the waiting bid request and returns 0. However, if the record's auction winning price is lower than the bid price then that auction is wined by the campaign and displayed in the respective publisher site. Therefore, related feedback of the user and record's charged price are used respectively as a reference to update the cost and performance. When no-bid requests are left in the experiment data, the assessment comes to an end and concluding review delivered. Having an assessment using

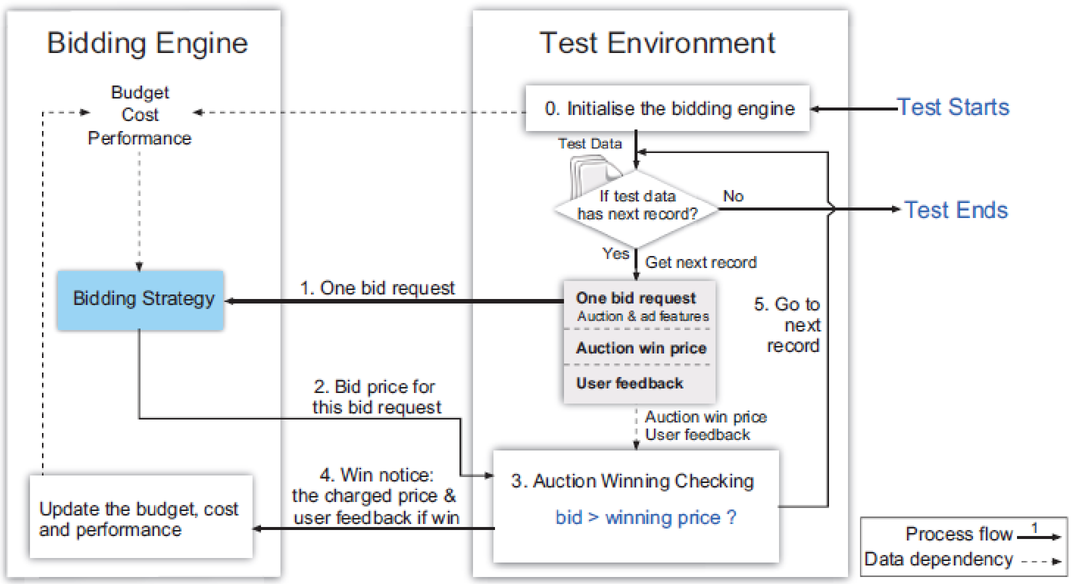

Figure 5.6: Assessment Progress Chart [26].

logs from user feedback has certain limitations. In this situation, user feedback simply happens for the winning auctions. In other words, producing ad impressions in case of winning otherwise losing bids creates empty user feedback. So, considering our offline test we can not confirm whether the user is going to click or convert even bidding high enough then originally expected. In our project, offline assessments have been considered from paid search [25], the pre-defined standard system [31] and search in the web [17], which are the related objects (auctions) with hidden user feedback are overlooked. To round off the offline assessment, online analysis execution has been conducted on a production DSP in Section 7.

5.7.2 Budget Restrictions

If we decide to fix the budge equivalent to total primary expense in the experiment records, it just starts to bid too high satisfying every state and consequently will deplete the budget by getting an entire bundle of logs clicked. In our experiment, we decide the budget cost in the following manner - 1/2, 1/4, 1/8, 1/16, 1/32 and finally 1/64. We assessed to determine the performance considering miscellaneous budget restrictions for the distinct campaign. Besides, all the experimental assessment conducted sequentially accepting the initial entire cost in the experiment log as the budget.

5.8 Compare Different DSP Bidding Approaches

In our research, some standard and advanced bidding approaches have been analysed. The parameters of the individual bidding procedure are harmonised managing the experimental data. So, compared bidding tactics are - Constant bidding (Const), Random bidding (Rand), Bidding below max eCPC (Mcpc), Linear-form bidding of pCTR (Lin) and finally Optimal real-time bidding (ORTB1 and ORTB2).

Const - Within a campaign, every bid request uses a constant value. Here, the bidding price is constant with a particular parameter.

Rand - Within a provided scale a bid value has to determine randomly. Here, the specification is the higher bound of the stochastic bidding range.

Mcpc - From the discussion in [35], maximum eCPC is the ultimate goal for advertisers, where CPC is the topmost bound. The bid price for an impression is measured by augmenting the maximum eCPC and pCTR. Maximum eCPC derived for an individual campaign by splitting its cost and obtained the number of clicks in the experimental data. In this bidding methodology parameter is needles.

Lin - The bid price is linearly equivalent to the pCTR which is found in an earlier work [40]. The general form of that formula is as follows -

$$bid_{Lin}(\beta) = bid_0 \frac{\beta}{\beta_0} \tag{5.1}$$

where β_0 is the median CTR following a defined situation and bid_0 is the fundamental bidding value for this objective state. bid_0 has been harmonised in our investigation.

ORTB1 and ORTB2 - Needless to say, these are our determined optimal bidding approaches in our framework. From Eq. (4.13) and (4.15), we can observe that parameter c is determined by adjusting the winning probability and η is attuned practising the exercise data.

Table 5.2 compiles the properties of the distinct approaches. As Mcpc consumes the entire budget, definitely it is not budget-conscious. Impression-level assessments are done by Mcpc, Lin and ORTB respectively for conduction required bidding. ORTB is the most instructive approach considering the winning functions into the reckoning. In Section 6 the decisive achievement for the

Bidding Approaches	Const	Rand	Mcpc	Lin	ORTB
Budget Restriction Observation	√	√		√	√
Per Impression Value Assessment			√	√	√
Winning Function Evaluation					√

Table 5.2: Key attributes for bidding approaches.

corresponding attribute's impact has been investigated.

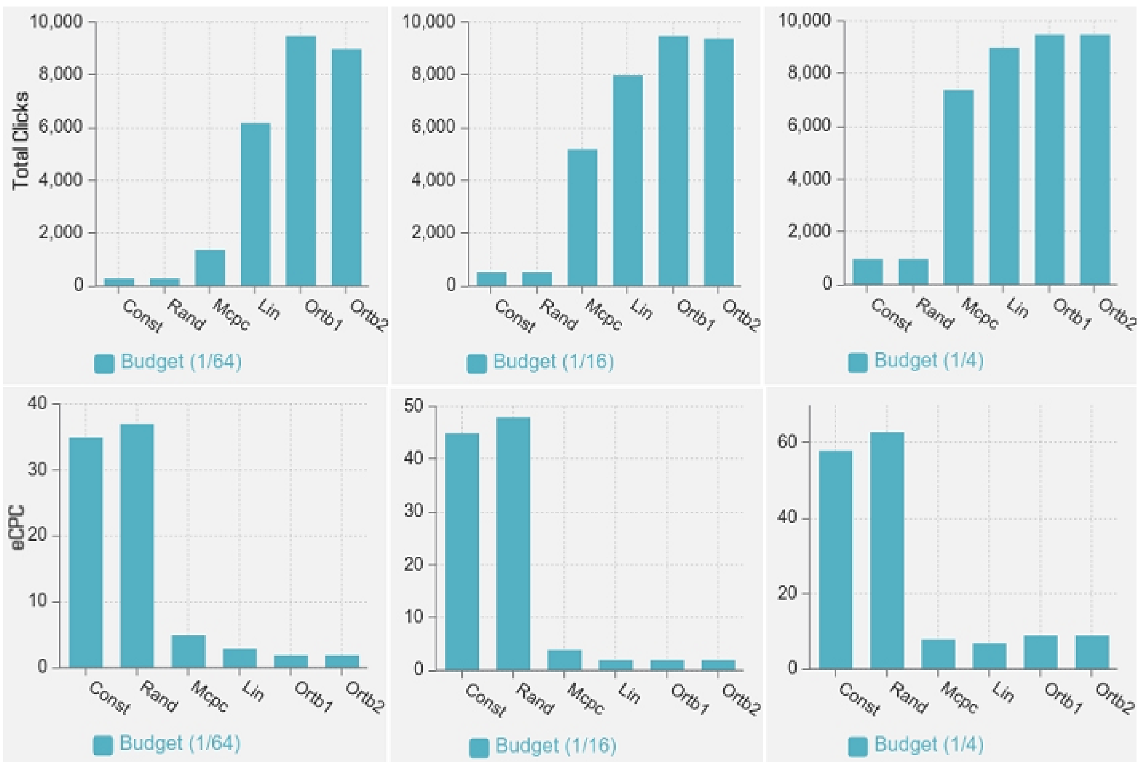

Figure 5.7: Overall performance comparison for bidding approaches with respect to budget.

Chapter 6

Offline Assessment

Through our investigation, we have tried to show the outperformance of our proposed optimal bidding function as well as parameter impacts on this performance concerning different budget conditions.

6.1 Performance Comparison

Figure 5.7 is the concrete visualisation of achievement comparison between total eCPC and clicks under various budget limitations. What we have perceived here is as follows -

1. Proposed bidding approaches, ORTB1 and ORTB2 have shown the outstanding accomplishment under every budget on total clicks and confirms the effectiveness of the derived non-linear forms of the bidding function.

2. Lin is the second-best algorithm extensively adopted in DSP bidding manoeuvrings [38].

3. Mcpc is capable of dynamically changes its bid value according to the predicted CTR. However, Mcpc has zero adjustability to various budget limitations comparing to ORTB and Lin. For instance, if the budget sets to minimal for the distinct bid request, Mcpc still will take the max eCPC for the bidding, whereas ORTB and Lin will show their adaptive traits and reduce the bid to acquire the impressions and clicks with bigger ROI.

4. Poor performance has been shown by Const and Rand under various budget provisions no matters how many ways their parameters are harmonised.

5. To obtain one-click, Rand and Const spending too much money than the aware of case value policy of Mcpc, Lin and ORTB.

The advantage of real-time bidding to display ad infer by the last two points. Assessing the cost for every bid request performs a vital role in the achievement. Table 6.1 provides comprehensive performance enhancement on entire clicks of ORTB1 over Lin following various campaigns and budget provisions. Among the recorded 52 perspectives, ORTB1 prevails Lin in 47 (87.5%) perspectives, ties in 3 (4.8%) perspectives, and lose in 2 (5.2%) perspectives. From the above statistics, ORTB1 is reasonably robust and the outperformance is steady.

	Different Budget Restriction					
Camp#	**1/2**	**1/4**	**1/8**	**1/16**	**1/32**	**1/64**
1	0.25%	1.35%	1.34%	-0.76%	1.37%	0.98%
2	0.91%	0.68%	2.38%	0.54%	0.15%	0.80%
3	1.10%	5.50%	1.43%	2.45%	1.33%	28.16%
4	2.74%	0.16%	2.54%	2.19%	-1.19%	25.46%
5	1.32%	2.82%	4.17%	0.63%	0.75%	51.54%
6	2.57%	4.67%	-1.19%	8.13%	48.19%	85.07%
7	0.40%	2.97%	5.27%	17.50%	41.10%	87.67%
8	0.55%	0.49%	1.33%	7.82%	29.78%	51.23%
9	0.45%	0.99%	1.53%	6.72%	21.78%	57.45%
10	10.29%	29.82%	61.75%	107.71%	121.25%	435.65%

Table 6.1: Click augmentation of ORTB1 over Lin for every campaign under diverse budget restrictions.

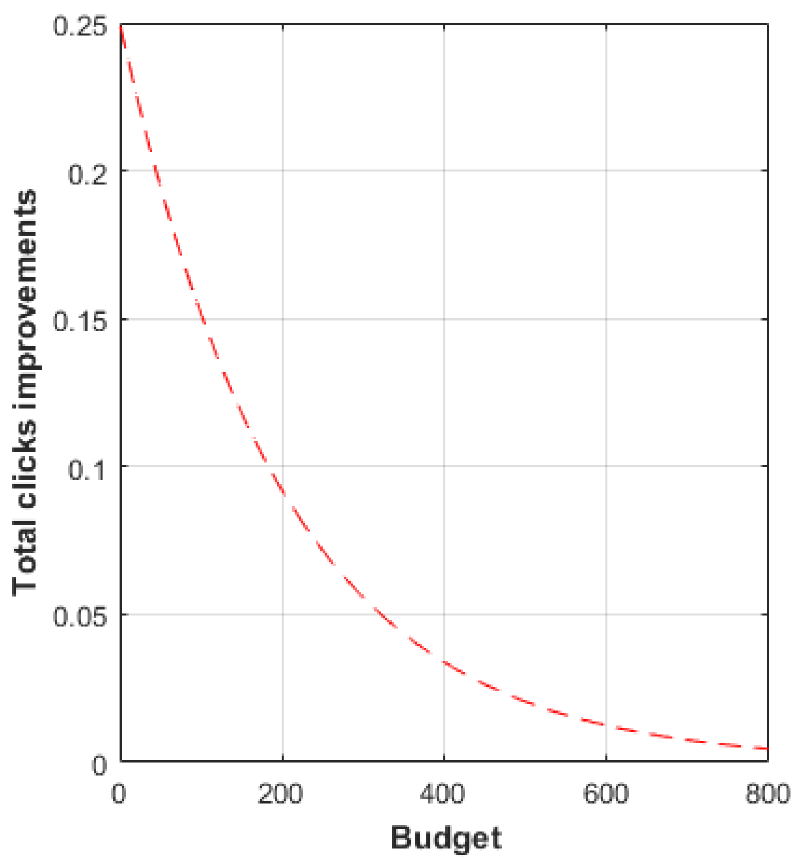

Figure 6.1: Click augmentation of ORTB1 over Lin under various budget restrictions.

6.2 The Consequence of Budget Restrictions

Investigating the adaptation of the swerving budget restrictions by the bidding approaches is quite exciting. We have introduced 1/2, 14, 1/8, 1/16, 1/32 and 1/64 as our experiment budget of the initial overall cost respectively. We can see from Figure 6.1 that ORTB1 has certain percentage increase on overall clicks over Lin for the pre-defined budget limitations. In the case of click improvement for considerably under budget (i.e. only 1/64 of the initial whole cost), ORTB1 over Lin is pretty impressive which is more than 47%. This means our offered bidding method is outperforming especially under quite poor budget provisions. In general, better bidding approaches should consume comparatively low on every bid request when the budget is pretty poor. Due to concavity nature, ORTB1 designates additional budget for lower cost events and we can see it from Figure 5.3(b)). This is logical because considering the functions of the highest winning rate in Figure 5.1 we came to know that winning probability does not decrease by lowering the pricy bid. However, the winning probability rises slight highering the low bid. The improvement ratio becomes leaner when the experimental budget grows fattier. This is obvious because, with the rise of the budget, budget reallocation happens from low-cost to high-cost cases properly by the optimised strategy. Hence, the trajectory of the concave degree Figure 5.3(b) will be minimal. The change is zero when the experiment budget set equal to the initial total experimental cost which is an exceptional scenario. The reason for this is, all bidding approaches bidding too highly to deplete the budget soon enough by getting each impression and click in the experimental data.

6.3 Click Versus Impression

Click and eCPC are two key attributes of every bidding method. We have shown the entire clicks and eCPC for every bidding approach in Figure 6.2(a) and 6.2(b). The campaign budget rises when both the number of clicks and eCPC rise. We have already observed that in case of low budget, good bidding methods tends to grab the low-cost cases and in the same manner in case of a higher budget distribute to costly cases which ultimately increased the eCPC. Although, Mcpc does not care about the condition of the budget and it's eCPC variation entirely rely on the data. The eCPC of Mcpc is higher than Lin and ORTB when the budget is quite minimal (i.e. 1/64, 1/32, 1/16 of the starting cost) and the eCPC of Mcpc begins to lower than Lin and ORTB when the budget rises over 1/4 of the opening cost. Whole impressions and CPM of distinct bidding method can be visualized from Figure 6.2(c) and 6.2(d). Our ORTB method not only produces the maximum clicks but also generated promising amounts of impressions compared to other methods. This is profitable for advertisers who want to aggrandize their clicks as well as adjusted their healthy expressions.

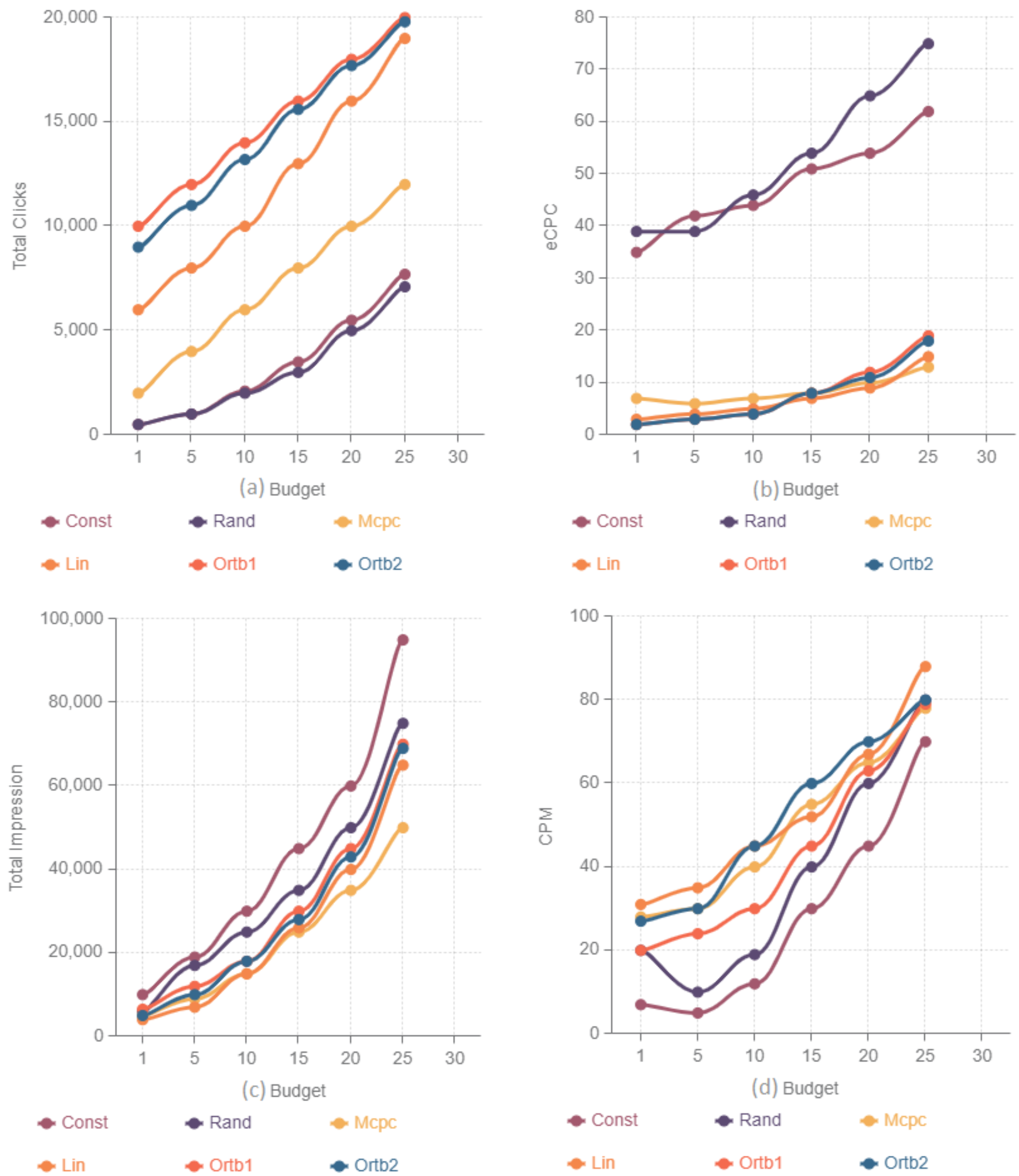

Figure 6.2: Performance on different measures with different budget conditions.

6.4 η Tuning of ORTB1 & ORTB2

We described earlier by simple mathematics we can resolve parameter η but honing the performance we have tunned every campaign utilizing the experimental data in our work. Click improvement related to ORTB1 and ORTB2 have been depicted by harmonising η parameter. With the combination of η and distinct value of c parameter for levity checking by making various points to every n-value. However, for the distinct campaign parameter c suits perfectly in the winning rate data. When the offered budget is lean, the optimal cost of η is huge which is sensible. We can apprehend from Eq. (4.13) and (4.15) that the usual range of the bidding cost is handled by the η parameter: the bid price gets lower when η is higher. So, the bidding cost level should get linear when the respective budget is more insufficient which response to the upper optimal value of η.

6.5 An Alternative KPI and Related Outcomes

An Alternative KPI and it's related outcome has discussed in Section 4. Our optimisation goal is various KPIs can be consolidated in our adaptable framework at ease. Click number is the main target of this project but we also evaluate alternative KPI by aggregating the number of click and number of conversion along with parameter k managing the consequence of exchange:

$$KPI = NumberofClick + k * NumberofConversion \tag{6.1}$$

This intention is reasonably beneficial [43] because measuring the advertisers [40] this conversion plays a key role. Moreover, the sparsity obstacle of conversion calculation [35] can also be pointed by linear blending. From our dataset, we find enough conversion records within campaign 3 and 7. Therefore we take them as our optimising operations and we introduced k = 3 in our investigation. To study and predict two logistic regression patterns have exercised. For every bid request, the CTR (pCTR) and CVR (pCVR) have predicted and proceed to measure pKPI, such as pKPI = pCTR + k * pCVR, which is the bidding function's β value.

Figure 6.3 provides the overall KPI achievement and the explicit number of clicks or the number of conversions received by individually bidding tactics. Comparing the standards bidding approaches, ORTB strategies are outperforming and their effectiveness has confirmed by the alternative optimisation of KPI. ORTB2 delivers more distinguished KPI and exchange numbers than ORTB1 especially, on 1/64 budget provision because the winning function 2 meets these two optimised campaigns better than winning function 1.

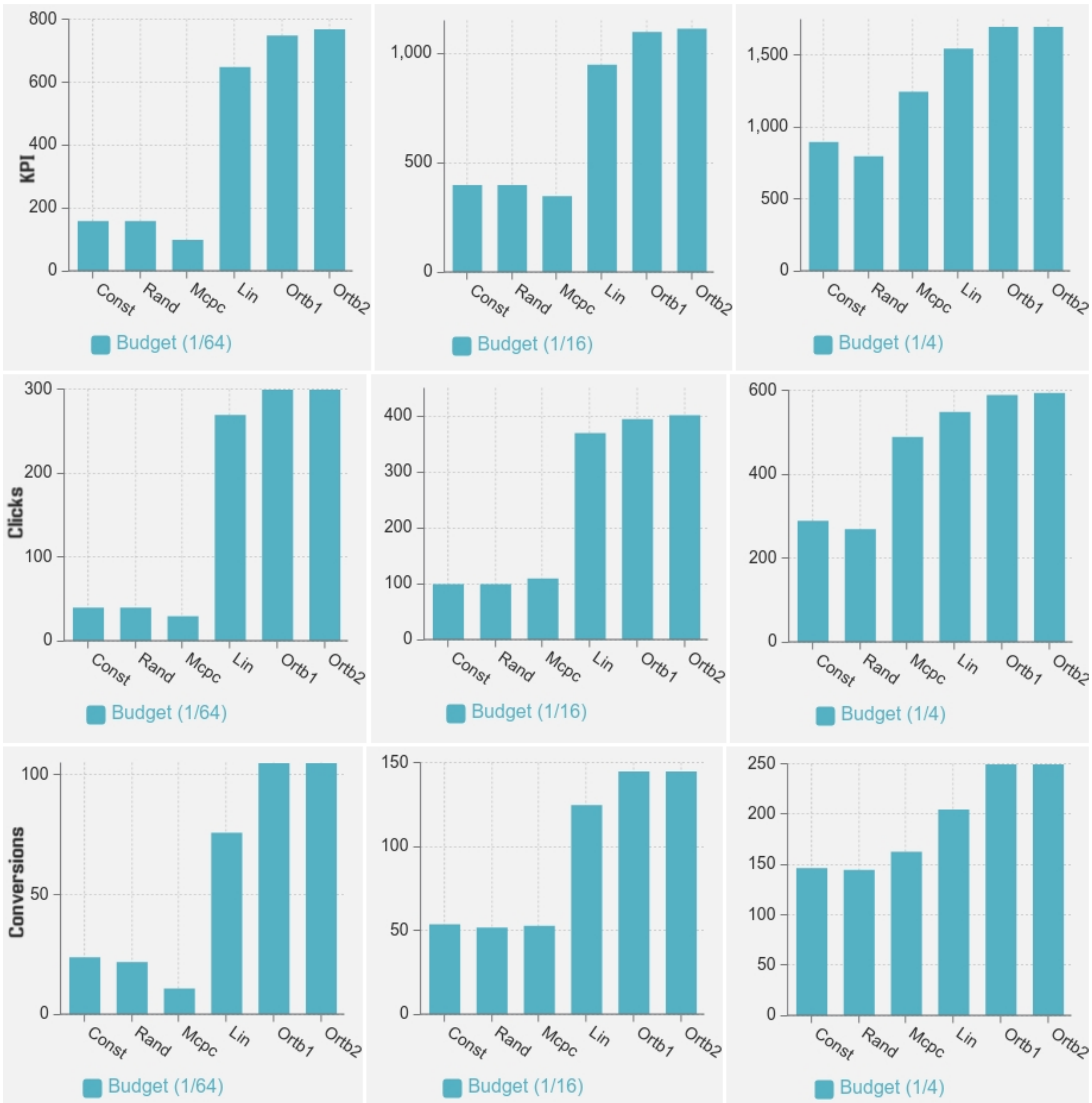

Figure 6.3: Comparing outcomes with an alternative KPI.

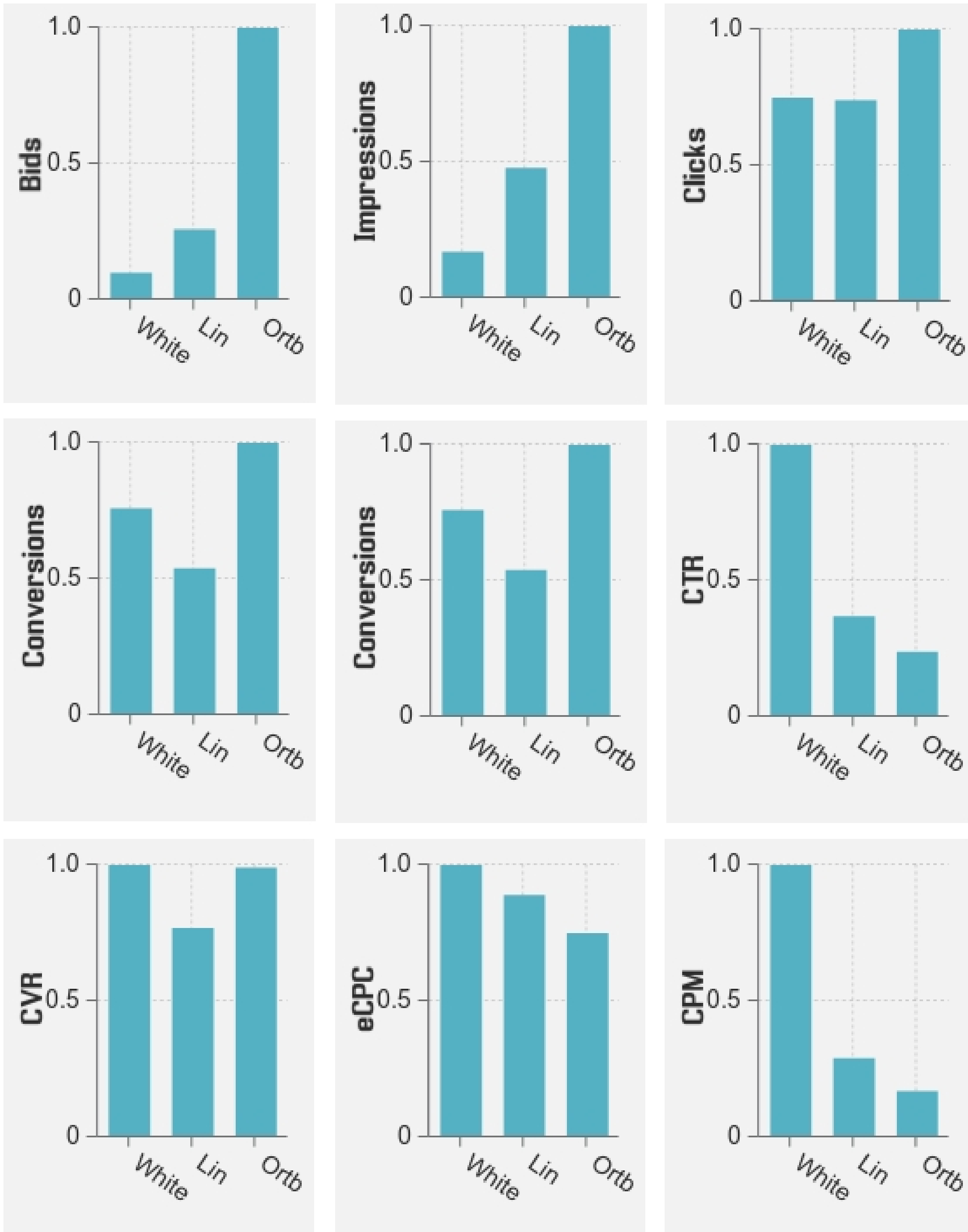

Figure 6.4: Corresponding achievement for online assessment.

Chapter 7

Online Assessment

To accept the non-linear strategy and more influence on marginal CPM impression we have carried out an online investigation on iPinYou Optimus program which is nowadays the biggest DSP all over the world [44]. In November 2020 three consecutive campaigns have been conducted. White is considered as the new comparing bidding approach which holds feature rule and bid list extremely large. Click is the optimisation measure scale for the targeted KPI. White performs as a stepping function in [33] compared with Lin. So, for specific bid request, all the three algorithms show equivalent opportunity to execute the bidding of iPinYou DSP. Figure 6.4 delineates the achievement association with diverse propositions. We assist [13] here to only show the pertinent performance here due to data delicacy.

Bellow are our observation from the different method's comparison -

- Comparing Lin and White, ORTB's bidding rate is much higher and accepts the maximum impressions, clicks and conversions. Moreover, ORTB gains the meanest eCPC, which shows it as the most practical technique.
- ORTB receives the most economical CPM. This confirms ORTB designates more funds to reasonable events. That's why ORTB bids larger events with the leanest CPM.
- Due to flat CPM on inexpensive pCTR events, ORTB has it's dominating auction winning rate. But it's not relevant since the total number is our ultimate goal.
- White bids only on the high subset of events resulting in shallow bidding statistics and unusual CPM. Based on the whitelist, the events matching this whitelist contains larger CTR.
- Essentially fair performance has shown by Lin which is as usual expected.

In fine, our suggested optimised bidding approaches do satisfy online assessment which distributes sufficient budget on the cost-effective events to accelerate extra bids with moderate CPM.

Chapter 8

Future Work & Conclusion

No doubt, in recent time with the advancement of technology RTB has emerged as a new paradigm for displaying online advertisements. We are planning to investigate the bidding function covering direct bid request features rather key performance indicator only as our future work. Besides, as an extension of our optimization framework we are aiming to cover the following three situations -

- Bidding risk and ambivalence should be modelled and the uncertainty in click-through forecast, bidding approach and auction operation should be handled delicately to construct risk-aware and budget restrain bidding tactics [5].
- Tuning bid with dynamic approaches [12] with respect to the distinct prevailing achievement will be analysed within the proposed optimisation framework.
- Finding optimized overall performance over several advertisers of DSPs or Ad agencies. Our functional optimization framework would probably produce a reliable solution coupling with auction theory [46].

Finding the steady-state RTB approach to show ad is our proposed unique functional optimization framework. Considering the predicted Key Performance Indicator (KPI), both non-linearity and concavity characteristics have been shown by the determined adaptive bidding functions. Our bidding approaches have been analyzed correlating with standard and cutting-edge approaches within a diverse budget restriction and KPI frames. From the theoretical perspective, our advised methods not only have proved its acceptability but also after having both offline and online assessments it reveals it outperformance and the most substantial effectiveness.

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