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CREATIVE SELECTION AND BID OPTIMIZATION IN PROGRAMMATIC ADVERTISING TECHNOLOGY

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Master's Thesis

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The thesis/dissertation titled "CREATIVE SELECTION AND BID OPTIMIZATION IN PROGRAMMATIC ADVERTISING TECHNOLOGY" prepared by Melisa ILGAR and submitted on 24/06/2023 has been **accepted unanimously** of Master of Science in Industrial Engineering Department.

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I hereby declare that this thesis meets all format and submission requirements of a Master's of Science thesis.

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I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Melisa ILGAR

Signature

DEDICATION

This thesis is dedicated to everyone who was with me during the thesis process, especially my family and my husband Tolga Mutlu. In addition, I would like to thank Assoc. Prof. Dr. Yıldız ARIKAN for supporting me during the thesis process.

ÖZET

PROGRAMATİK REKLAMCILIK TEKNOLOJİSİNDE REKLAM SEÇİMİ VE FİYAT TEKLİFİ OPTİMİZASYONU

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Tarih: Ağustos / 2023

Sayfa: 37

Bu tez, programatik reklamcılıkta reklam verenler tarafından kullanılan talep tarafı platformunun (DSP) teklif fiyatlarını nasıl optimize ettiğini ve en uygun reklamın nasıl belirlendiğini incelemeyi ve optimize etmeyi amaçlamaktadır. Üç adımda sonuçlanacak olan tez, ilk aşamasında hem reklam vereni kitlesine ulaştırabilmeyi hem de ziyaretçilerin en doğru reklamı görüntüleyebilmesini amaçlamaktadır. Bu doğrultuda temel parametrelere odaklanılacak, örnek veriler toplanıp analiz edilecek ve puanlama yapılarak bir reklam seçim algoritması geliştirilecektir. Bu doğrultuda potansiyel tüm reklam verenlerin gönderdiği reklamlar ile gerçekleştirilen açık artırma sürecinde en optimum fiyat ile satın alabilmesini hedefleyen farklı bir algoritma geliştirilecektir. Son adımda, reklam veren platformları için geliştirilmiş olan bu iki algoritmayı sürekli olarak geliştirmeye yönelik basit fakat kapsamlı bazı teknikler öneriyoruz. Sonuç olarak, bu tez, programatik reklamcılık çerçevesinde DSP'lerin teklif fiyatlarını nasıl optimize ettiğini ve en uygun reklamı belirlemeyi amaçlamaktadır.

Anahtar Kelimeler: Programatik Reklamcılık, Optimizasyon Algoritmaları, Gerçek Zamanlı Optimizasyon, Kreatif Kararı, Teklif Optimizasyonu.

ABSTRACT

CREATIVE SELECTION AND BID OPTIMIZATION IN PROGRAMMATIC ADVERTISING TECHNOLOGY

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This thesis aims to examine and optimize how the demand-side platform (DSP) used by advertisers in programmatic advertising optimizes bid prices and determines the most appropriate advertisement. The thesis, which will be concluded in three steps, aims to both reach the advertiser to the target audience and enable the visitors to view the most accurate advertisement in the first stage. In this direction, basic parameters will be focused, sample data will be collected and analyzed, and an ad selection algorithm will be developed by scoring. In the second stage, it is aimed to show the selected advertisement to the visitor in the said advertisement area. In this direction, a different algorithm will be developed that aims to ensure that all potential advertisers can buy at the most optimum price during the auction process with the ads they send. In the final step, we propose some simple but comprehensive techniques for continuously improving these two algorithms developed for advertiser platforms. In conclusion, this thesis aims to determine how DSPs optimize their bid prices and determine the most suitable advertisement in the framework of programmatic advertising.

Keywords: Programmatic Advertising, Optimization Algorithms, Real-Time Optimization, Creative Decision, Bid Optimization.

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ABBREVIATIONS

DSP	:	Demand (Advertiser) Side Platform
SSP	:	Supply (Publisher) Side platform
DMP	:	Data Management Platform
CTA	:	Call To Action
CTR	:	Click-Through Rate
CPC	:	Cost Per Click
CPM	:	Cost Per Mille
CPI	:	Cost Per Install
IR	:	Install Rate
CR	:	Conversion Rate

1. INTRODUCTION

Advertisements are very important marketing tools and mankind is exposed to them daily [1]. With the increasing importance of digital advertising and the growth in its volume, advances in faster, more efficient, safer, and easier management of advertising management have become inevitable.

According to the IAB's Full-year 2022 results April 2023 report, the increase in internet advertising continued to increase year-on-year in 2021 and 2022, reaching a total of US$ 209.7 billion, increasing by 10.8%[2]. A study of the US market was conducted by app nexus, and it was determined that 80% of digital marketing was spent through programmatic advertising in 2018 [3].

Programmatic advertising has gained such importance in this period, the importance of reaching the target audience in the shortest and most accurate way has increased for advertisers and publishers. Publishers expanded their audience’s day by day, and the number of publishers in digital media increased day by day. This has had both positive and negative consequences for advertisers. Its positive results were that it had so many options to reach the target audience. The negative results were that these processes and instant advertisement publication decisions had become too complex to be taken manually. The main purpose of these algorithms should be to maximize the number of clicks, taking into account the budgets of the advertisers [4]. It is very important to make optimizations that will increase efficiency [5].

Because of the programmatic advertising ecosystem that enables online advertising trading, it includes main components such as SSP (Publisher Platform), DSP (Advertiser Platform), and Ad Exchange (Real-Time-Bidding component where Ads are traded as a real-time auction).

Publishers (inventory owner with an audience, e.g., ad slots for a news site) make it possible to match the right advertisers with the right visitors at the right time, by targeting various types. Advertisers (brands that bring their campaigns and ads together with the audience in their publisher inventories) make various targeting. It aims to achieve the target of the campaign (call the user to action[1], increase awareness etc.) to its target audience. It pays for each impression[2] it buys in line with its target (Click, impression, conversion, [3]install etc.). Exchange platforms collect offers from advertisers [6]. It provides the right match within milliseconds, considering the targeting of these bids they collect. In addition to all these platforms, DMPs have an impact on issues such as understanding and categorizing user requests, habits, purchasing habits, which are recorded as cookies in order to create a target audience and audience [7].

It is important to bring an advertising campaign to the right user, but the most important thing is to plan the right budget and meet KPI targets while making the right payment for each impression (each user view). If these two algorithms are not used on the platform, the bidder cannot make a profit. It may incur heavy losses from the cost of winning the auction.(Markov decision) In this article, a study has been made on how the right advertisement can be selected and priced in programmatic environment and programmatic conditions. The studies carried out are aimed at optimizing the budget and unit bid, using the budget correctly, and maximizing performance by reaching the target audience when viewed by the advertiser; On the other hand, from the platform's point of view, it is to ensure the balance between choosing the right advertisement among thousands, ensuring the order of publication, consuming the budgets of all campaigns by addressing their parameters and constraints, but at the same time reaching their goals. The best way to achieve this balance is to determine relevance. Scoring the match between the page on which the ad slot is located and the creative represents relevance. Data is observed throughout the campaign process and the bid is iteratively estimated and the bid calculated [8].

Our approach will determine their relevance with the data obtained from Users, include a campaign that has not obtained performance data using learning methods over time, and campaigns with poor performance data into the system, ensuring that it wins in auctions at a certain rate, while maintaining its relevance and constantly optimizing it [9].

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[1] Ads that urge the user to take action.
[2] Viewing of the ad by visitors
[3] Rate of action intended for the user by the advertisement.

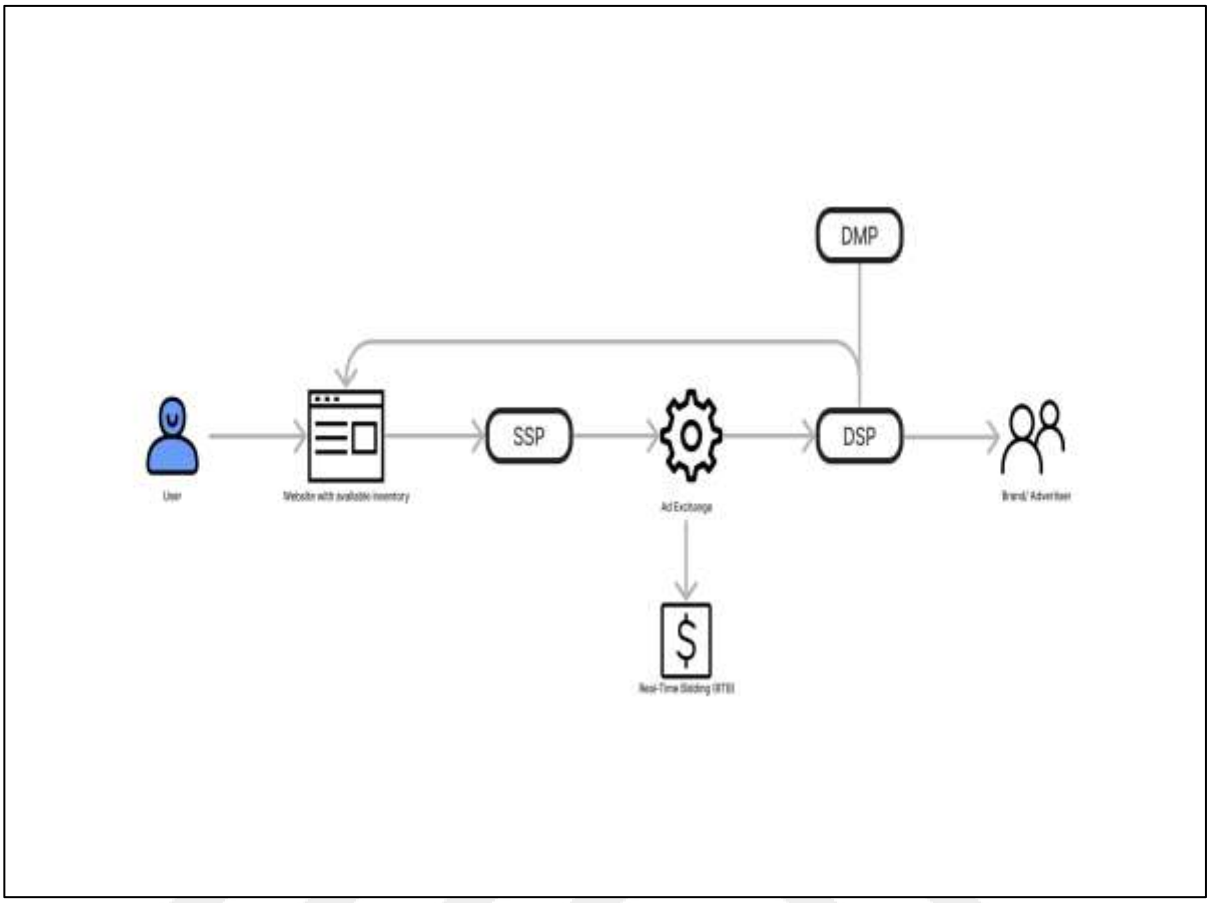

Figure 1.1: Programmatic Advertising.

2. LITERATURE REVIEW

Programmatic advertising has transformed and improved the digital advertising landscape day by day. Creative selecting and bid optimization algorithms, which are the two algorithms underlying the advertiser platform of programmatic advertising, aim to optimize advertiser spend and increase performance. Although there are many studies on this subject in the literature, algorithms and models used are developing day by day. This literature review aims to provide a comprehensive overview of current research on creative selecting and bid optimization algorithms and highlight their key objectives.

The OECD Competition in Digital Advertising Markets article defines an AI system as a machine-based system capable of making decisions, recommendations and predictions that affect a real or virtual environment for a human-defined target set ,[10]. OECD included topics such as neural networks and deep learning among these artificial intelligences used. With these methods used, artificial intelligence can facilitate the personalization of advertisements. With the personalization of advertisements, point-and-shoot advertisements will be available to users. Many research have revealed various gains by combining artificial intelligence systems with various algorithms such as Thompson, multi-armed bandit. The most important point here is to ensure that the users meet the ads within milliseconds and that these algorithms should give an output within milliseconds. It is given to the potential visitor within milliseconds immediately after the necessary information exchange is provided in the website or application where the advertisement area is available. In the ad request made by SSP, that is, publisher-side platforms, there is a decision stage on the side of the advertiser platforms. an advertiser does not respond to every request for quotation [11]. After considering various parameters, it decides whether to bid or not. Zhang et all said that one of the main challenges for the demand-side platform is to automate this process based on all the information gathered in the past, the budget, and the campaign goal [12] .All this information collected in the past is vital for both algorithms mentioned [13]. Many platforms complete these two algorithms at once at various stages. If we examine both algorithms in themselves:

2.1 CREATIVE SELECTING ALGORITHM

The Real-Time Bidding with Multi-Agent Reinforcement Learning in Display Advertising article optimizes bidding using multi-agent reinforcement learning [14]. The results obtained show that it gives a much better result than the single-agent and bandit algorithms discussed in many articles and theses. Tabao display advertising system examines the process in 3 parts. The first stage is the matching stage, and ads that match user information are called. It is listed by relevance, and in the second stage, the real-time prediction engine, RTP, detects CTR and CVR for the resulting ads. In the third stage, bid x pCTR ranking of candidate ads, called eCPM (effective cost per thousand impressions), is made. Sorted ads are shown.

A stochastic learning-to-rank algorithm and its application to contextual advertising article proposes a framework in which contextual advertising Ranking models are both optimized using the same information retrieval metrics such as Normalized Reduced Cumulative Gain and Average Average Precision. Thus, it was aimed to minimize the definable loss functions. The method was observed to greatly improve its relevance [15].In the article RankViz: A visualization framework to assist interpretation of Learning to Rank algorithms, rankviz, which aims to fill the gap in how ad rank and selection is ranked in learning to rank, which is a machine learning approach, and to explain its different aspects, is proposed. Rankviz, on the other hand, analyzes the data properties related to this ranking after a certain ranking is provided, and supports comparative analysis [16].

2.2 BID OPTIMIZATION ALGORITHM

In the article Bid optimization using maximum entropy reinforcement learning, They used the stochastic reinforcement learning (RL) algorithm. First, they helped the bid price adapt to the RTB environment by taking advantage of linear bidding, and second, they used the maximum entropy RL algorithm to get rid of the convergence problem of the deterministic reinforcement learning algorithm and optimize the adjustment factor of impressions. When they compared the strategy, they had the most clicks in 9 out of 12 experiments.

The article Joint Optimization of Bid and Budget Allocation in Sponsored Search suggested an optimization to maximize ad rank and advertiser profit [17]. It has been shown that the optimization problem can be approximately solved by optimizing the advertiser's total budget and bid price range constraints. In addition, it was predicted that advertiser performance increased as a result of various evaluations.

The article about functional bid landscape forecasting for display advertising, presents a functional bidding environment estimation method without considering any assumptions. In this presented method, it aims to automatically learn the specific match of the function to the auction feature and market price distribution of each ad. Besides proposing a decision tree model, it aims to overcome the censored market price problem by including survival model in tree learning and prediction models. As a result of the experiments, it was predicted that the performance increased significantly, according to previous studies [18].

This literature review examined studies on creative selection and bid optimization on the advertiser platform in programmatic advertising. Research has developed many models for advertisers to select appropriate advertising content for the target audience and determine optimal bids. The developed models show that they can increase the performance of their campaigns. Future studies should aim to conduct further research in this area and to develop more advanced methods with the obtained data.

3. PROBLEM STATEMENT

Advertising can be bought and sold in many ways in a programmatic advertising environment. For example, an advertiser price is not known to advertisers. In addition, advertisers cannot be aware of each other's bid prices. For this reason, the advertiser determines a maximum budget and maximum bid prices from the platform interface. According to these determined prices, it can enter the auctions where it meets the base price. But dynamically optimizing algorithms determine whether it will win, and whether it will also get a chance to get impressions in the placement with a lower bid price. In addition, there are many parameters that need to be evaluated and kept in balance to select suitable ads and send them to the exchange platform, as well as to gain impressions in the advertising area with affordable prices. For example, the campaign can reach its target between the start and end dates, consume the total and daily budget, determine the advertising areas that can provide maximum benefit with the specified maximum bid price, evaluate the historical data and historical bid prices, score the different performance data of the campaign on a single line, seasonal or seasonal changes. One of the most important of these parameters is the clickthrough rate (CTR). Click-through rate is used by building models to predict click-through rates for undisplayed ads. It is then estimated based on the characteristics of the ads that have been created around this model. Many variables should be considered, such as the inclusion of campaigns with no performance data and poor performance data in the algorithm. In addition, If we examine the optimization created for performance by a large ad network, we can see that there are about 1 million decision variables and 0.5 million restrictions [19].

In this thesis, we will focus on auctions and creating a dynamic algorithm that will increase win rate and relevance while reducing the number of bids in those auctions.

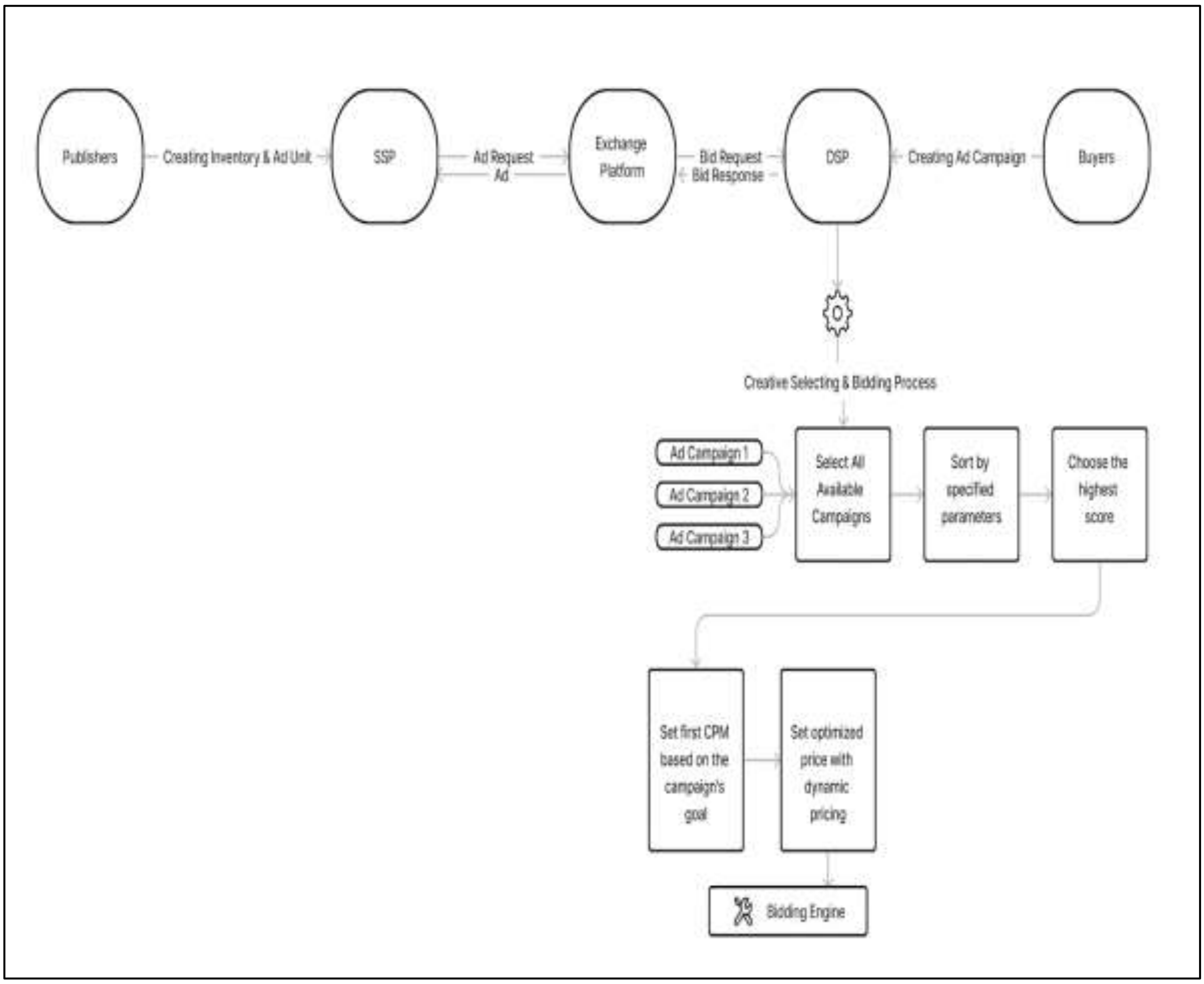

Figure 3.1: Programmatic Advertising Creative Selecting & Bidding Algorithm.

4. METHOD AND ALGORITHMS

4.1 A CREATIVE SELECTING ALGORITHM

The parameters considered when choosing advertisements may vary from platform to platform and according to needs. However, the main purpose is to keep the advertisement visible continuously according to the targeting and criteria determined by the publisher, to consume the budgets targeted by the advertisement campaigns in line with the criteria determined by the advertiser and to deliver them to the right users. The most basic purpose of the DSP platform is to compete the campaigns of all advertisers equally, to make the campaign visible in appropriate places without discriminating between good performance and bad performance. The main parameters to be used for this purpose are:

a. Shortest Campaign Duration

b. Performance value (All performances are converted to CTR type)

c. Ratio of spending to total budget

d. Ratio of spending to daily budget

e. The bid price (max bid)

f. Estimated Performance (Forecast)

These are the sample parameters determined for this thesis, and the parameters used vary from platform to platform.

4.1.1 Campaign Duration

The creatives of the campaigns that are suitable for the proposal request are listed first, and those that are not suitable are eliminated. The number of hours remaining is important in terms of dividing the remaining hours after the ratio of the expenditure to the budget and affecting the election decision. The closeness of these campaigns to the end dates are listed in descending order.

Table 4.1: Total Hours Table.

Creative Name	Total Hours
Creative 1	300
Creative 2	128
Creative 3	27

**Added sample hours data for each creative.*

As can be seen in table, the total hours are sorted from highest to lowest.

4.1.2 Performance

Creatives with performance value are listed by converting to CTR type.

(Ctr type is used in this thesis. Different performance parameters can be used.)

CTR Calculation: (clicks ÷ impressions) *100

Table 4.2: Performance Table.

Creative Name	Total Hours	Performance(CTR)
Creative 1	300	%0,13
Creative 2	128	%0,39
Creative 3	27	%0,56

**Added sample performance data for each creative.*

As can be seen in table, the total distance to the daily budget and the distance to the total budget are listed and ordered from largest to smallest.

4.1.3 Ratio of Spending To Total Budget

The ratio of spend to budget gives the amount spent so far in the progress of the campaign. The remaining budget is then divided by the number of hours remaining and the daily expenditure is found. We assign a spending and total budget value for each creative. Next, we divide our assigned spending sum by the total budget and multiply by 100.

Ratio of spending to budget: (spend/total budget)x100

a. We assume that Creative 1 is a 7-day campaign. Its total budget is $11200, its daily budget is $1600 and its spending so far is $300.

b. We assume that Creative 2 is an 8-day campaign. Its total budget is $21600, its daily budget is $2700 and his spending so far is $540.

c. We assume that Creative 3 is a 5-day campaign. Its total budget is $3750, its daily budget is $750 and its spending so far is $276.

Table 4.3: Ratio of Spending to Total Budget Table.

Creative Name	Total Hours	Performance (CTR)	Spending/Total Budget*100
Creative 1	168	%0,13	%2,67
Creative 2	192	%0,39	%2,5
Creative 3	120	%0,56	%7,36

**Added sample data for each creative.*

As can be seen in the table, they are listed according to their ratio of spending to total budget.

4.1.4 Ratio of Spending To Daily Budget

We apply the above process for the daily budget.

Ratio of spending to budget: (spend/daily budget)x100.

Table 4.4: Ratio of Spending to Daily Budget Table.

Creative Name	Total Hours	Performance (CTR)	Spending/Total Budget*100	Spending/Daily Budget*100
Creative 1	168	%0,13	%2,67	%18,75
Creative 2	192	%0,39	%2,5	%20
Creative 3	120	%0,56	%7,36	%36,8

**Added sample total budget data for each creative.*

As can be seen in the table, they are listed according to their distance from the total budget.

4.1.5 Max Bid Price

Table 4.5: Max Bid Price Table.

Creative Name	Total Hours	Performance (CTR)	Spending/Total Budget*100	Spending/Daily Budget*100	MaxBid Price(CPM)
Creative 1	168	%0,13	%2,67	%18,75	$ 10.00
Creative 2	192	%0,39	%2,5	%20	$ 3.00
Creative 3	120	%0,56	%7,36	%36,8	$ 7.00

**Added sample bid price data for each creative.*

As can be seen in the table, they are listed according to their max bid price.

(In this thesis, all ads are based on CPM[4] type campaigns.)

4.1.6 Performance Forecasting

One of the key points of advertising here is the importance of data in forecasting. Product sales may increase or decrease on certain days. Users' willingness to interact with an ad may

[4] Cost Per Mille

also change periodically. For this reason, we will use the weighted moving average method when estimating performance and only consider a specific period close to date. In this thesis, we consider the weight of the last 4 days of data in order to make the forecast more reliable. The forecasting is based on click type.

$$\text{Weighted MA} = \text{ P1 x(n)} + \text{ P2 x(n} - 1) + \text{ P3(n} - 2) + \cdots \text{ Pn} = 0$$

Weights

0,4, 0.3, 0.2, 0.1 weight will be used in this model.

(Weights were determined as 0.4, 0.3, 0.2 and 0.1, going backwards from the most recent day, since 4 days of data were used.)

Table 4.6: Weighted Moving Average Calculation Table For Creative 1.

Day	Performance (%)	WMA (%)
1	39	-
2	44	-
3	40	-
4	45	-
5	38	42.7
6	43	41.1

**Added sample performance data for each creative.*

For Creative 1:

F1= 0.4(45)+0.3(40)+0.2(44)+0.1(39)

=42.7

F2= 0.4(38)+0.3(45)+0.2(40)+0.1(44)

=41.1

F3= 0.4(43)+0.3(38)+0.2(45)+0.1(40)

=41.6

Table 4.7: Weighted Moving Average Calculation Table for Creative 2.

Day	Performance (%)	WMA (%)
1	27	-
2	35	-
3	42	-
4	48	-
5	36	41,5
6	41	32,7

**Added sample performance data for each creative.*

For creative 2:

F1= 0.4(48)+0.3(42)+0.2(35)+0.1(27)

=41,5

F2= 0.4(36)+0.3(48)+0.2(42)+0.1(35)

=32,7

F3= 0.4(41)+0.3(36)+0.2(48)+0.1(42)

=41

Table 4.8: Weighted Moving Average Calculation Table for Creative 3.

Day	Performance (%)	WMA (%)
1	23	-
2	19	-
3	25	-
4	29	-
5	32	25,2
6	37	28,4

**Added sample performance data for each creative.*

For creative 3:

F1= 0.4(29)+0.3(25)+0.2(19)+0.1(23)

=25,2

F2= 0.4(32)+0.3(29)+0.2(25)+0.1(19)

=28,4

F3= 0.4(37)+0.3(32)+0.2(29)+0.1(25)

=32,7

Table 4.9: Performance Table.

Creative Name	Total Hours	Performance (CTR)	Spending /Total Budget*100	Spending /Daily Budget*100	Max Bid Price (CPM)	Performance Forecasting (Click)
Creative 1	168	%0,13	%2,67	%18,75	$ 10.00	%42.7
Creative 2	192	%0,39	%2,5	%20	$ 3.00	%41.5
Creative 3	120	%0,56	%7,36	%36,8	$ 7.00	%25.2

**Added sample forecast data for each creative.*

We assume that the creatives are on day 5, and we get the estimated performance values accordingly.

Each of these listed creatives is listed with certain parameters in mind. Sorted from largest to smallest and by priority.

a. The closest campaign total time, the highest priority,

b. The highest priority with the best performance in CTR,

c. Ratio of spending to total budget

d. Ratio of spending to daily budget

e. The highest priority with the best performance forecast in click,

We give percentages to the determined parameters to vary in line with the purposes of the platform.

i. The closest campaign total time 20%
ii. Performance (CTR) 20%
iii. Ratio of spending to total budget 20%
iv. Ratio of spending to daily budget10%
v. Max bid 10%
vi. Forecasting (click) 20%

Creatives are listed and scored based on percentages. The ad with the highest score is selected. Also, the percentages stated here are determined according to the order of importance foreseen for this thesis. The importance ratio varies from platform to platform.)

Creatives without performance data (with at least 300 impressions) are not included in this algorithm. 70% of the algorithm is run, 30% is chosen randomly to test ads without performance data and collect performance data.

4.1.7 Scoring

Table 4.10: Scoring.

Creative Name	Total Hours (%20)	Performance (CTR) (%20)	Spending /Total Budget*100 (%20)	Spendin g /Daily Budget* 100 (%10)	Max Bid Price (CPM) (%10)	Performance Forecasting (Click) (%20)
Creative 1	2	1	2	1	3	3
Creative 2	3	2	1	2	1	2
Creative 3	1	3	3	3	2	1

Added score for each creative.

Creative1=0,4+0,2+0,4+0,1+0,3+0,6=2

Creative2=0,6+0,4+0,2+0,2+0,1+0,4=1,9

Creative 3=0,2+0,6+0,6+0,3+0,2+0,2=2,1

Creative 3 is selected as the most appropriate creative for the impression.

4.1.8 Sample Creative Selecting Algorithm Code

The algorithm mentioned below represents the entire ad selection algorithm written in python language.

Def creative selecting (line_item_total_time, performance_ctr, total_distance_daily_budget, total_distance_total_budget, max_bid, forecasting):

campaign_total_time_weight = 0.2

performance_ctr_weight = 0.2

Ratio_of_spending_to_total_budget = 0.2

Ratio_of_spending_to_daily_budget = 0.1

max_bid_weight = 0.1

forecasting_weight = 0.2

campaign_total_time_score = campaign_total_time * campaign_total_time_weight

performance_ctr_score = performance_ctr * performance_ctr_weight

Ratio_of_spending_to_total_budget_score=Ratio_of_spending_to_total_budget* Ratio_of_spending_to_total_budget_weight

Ratio_of_spending_to_daily_budget_score=Ratio_of_spending_to_daily_budget* Ratio_of_spending_to_daily_budget_weight

max_bid_score = max_bid * max_bid_weight

forecasting_score = forecasting * forecasting_weight

total_score = (

campaign_total_time_score +

performance_ctr_score +

Ratio_of_spending_to_total_budget_score +

Ratio_of_spending_to_daily_budget_score +

max_bid_score +

forecasting_score

```
)
print("parameter_scores:")
print("Campaign Total Time Score:", campaign_total_time_score)
print("Performance (CTR) Score:", performance_ctr_score)
print("Ratio Spending to Daily Budget Score:", Ratio_of_spending_to_daily_budget_score)
print("Ratio Spending to Total Budget Score:", Ratio_of_spending_to_total_budget_score)
print("Max Bid Score:", max_bid_score)
print("Forecasting Score:", forecasting_score)
print("Toplam Skor:", total_score)
if total_score > 0:
print("highest rated ad selected")
else:
print("No ads selected!")
```

4.2 BIDDING ALGORITHM

After choosing the right creative, the next step is to set the right bid price. In DSPs, the user can set goals, and in line with these goals, an auction can be tried to be won with higher bid prices or the lowest bid prices for the most accurate target audience. At this point, the user sets a maximum price, the platform determines the most accurate price by regularly optimizing before reaching the maximum price.

The platform optimizes it by performing a/b tests [5] over the price determined by the advertiser. The following parameters are used to optimize the price:

[5] Using two different methods

a. Campaign goal (we will use lowest cost per impression)

b. Whether an offer has been made before

A campaign goal is an advertiser's indicator of whether to buy impressions at low prices or to get a better impression. The higher the price, the higher the probability of winning at auctions. If a bid has been made before, the past bid price is known, which helps to find the bid that needs to be estimated. For this example, we'll consider an advertiser targeting a minimum price.

First, ‘has a bid price been placed and won before?’ question is asked. If Won, bids will optimize with the optimized last price won. Secondly, ‘was the bid price given and won for a different ad with similar ad sizes and similar ad types (video, audio, display) on the same platform?’ question is asked. If there is more than one winning bid in the past, the average is taken for the first bid. This average found becomes the initial bid price. If no bid has been made for the ad request specified on the platform, the bid is placed using the maximum bid price specified by the advertiser. For the sample campaign, we will go over the fact that the bid price has not been given before.

The steps in the table below will be applied based on the creative 1 that won the creative selecting selection. In the example, we will assume that no offer has been made by the platform and it will be the first time to bid.

Table 4.11: Win-Lost Auction Flow

<table>
<tr><th>Set</th><th>Set Result</th><th>Step 1</th><th>Result 1</th><th>Step 2</th><th>Result 2</th><th>Step 3</th></tr>
<tr><td rowspan="3">Set CPM</td><td rowspan="3">If CPM>winbid (WIN)</td><td rowspan="3">winning CPM price - (winning CPM price x 0.05)</td><td rowspan="2">If CPM>winbid (WIN)</td><td rowspan="2">CPM price - (CPM price x 0.05)</td><td>If CPM>winbid (WIN)</td><td>winning CPM price - (winning CPM price x 0.05)</td></tr>
<tr><td>If CPM<winbid (LOST)</td><td>lost CPM price + (lost CPM price x 0.025)</td></tr>
<tr><td>If CPM<winbid (LOST)</td><td>CPM price + (CPM price x 0.025)</td><td>If CPM>winbid (WIN)</td><td>winning CPM price - (winning CPM price x 0.05)</td></tr>
</table>

Table 4.11: Win-Lost Auction Flow ’’Table Continued’’.

					If CPM<winbid (LOST)	lost CPM price + (lost CPM price x 0.025)
	If cpm<winbid (LOST)	lost CPM price + (lost CPM price x 0.025)	Ifcpm>winbid (WIN)	CPM price - (CPM price x 0.05)	If CPM>winbid (WIN)	winning CPM price - (winning CPM price x 0.05)
					If CPM<winbid (LOST)	lost CPM price + (lost CPM price x 0.025)
			If CPM<winbid (LOST)	CPM price + (CPM price x 0.025)	If CPM>winbid (WIN)	winning CPM price - (winning CPM price x 0.05)
					If CPM<winbid (LOST)	lost CPM price + (lost CPM price x 0.025)

** If the status is the same as the previous result, the rate remains constant. If the status is different from the previous result, the rate is halved.

Table 4.12: Win-Lost Formulas.

Status	**Formulas**
winning	winning cpm price - (winning cpm price x a)
lost	lost cpm price + (lost cpm price x b)

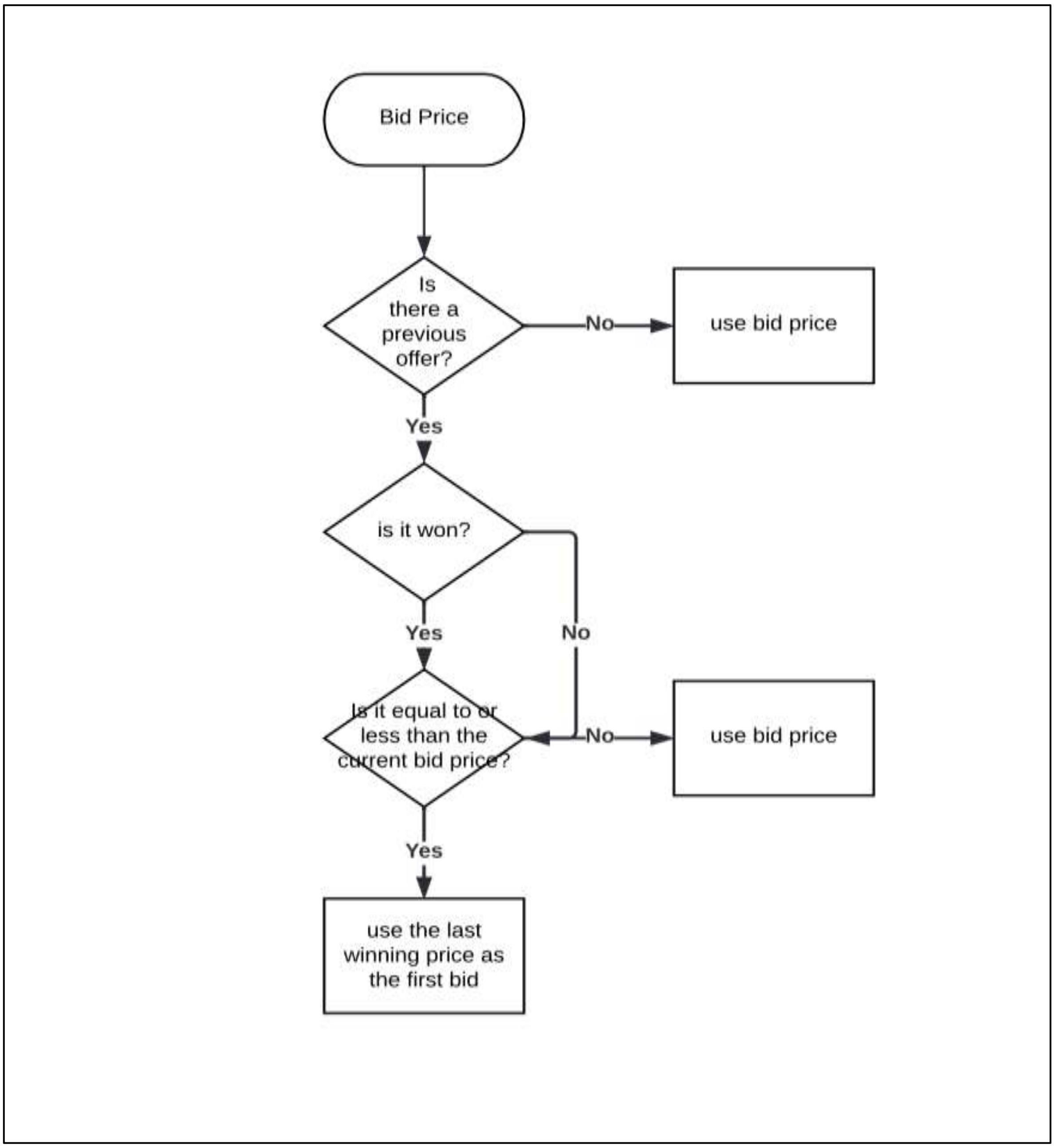

Figure 4.1 Bid Price Calculation.

Just optimizing isn't enough to win a bid. It directly affects the bids of other advertisers. For this reason, offers are in the testing phase up to a certain impression limit. However, after a certain period of time, it will become easier to predict the data. The flow above includes the necessary steps to simply optimize an ad price.

Based on the Creative 3 example, we cannot increase the bid in case of losing since we will use the maximum price, we will proceed according to the scenario we won here.

We won with \$7, we will bid for \$6.65 next. In the losing scenario, when we increase the bid as indicated in the formula, we will bid \$6. After each bid, the system will continue to run the algorithm within the specified cycle.

5. CONCLUSION

Programmatic advertising is now an indispensable fact of our lives. When used correctly, it is much more effective and much more memorable than any advertisement. Year-over-year reports cover the bulk of advertising revenue. When used correctly and analysed correctly, it should greatly support reaching the targeted audience, improving performance and advertising efficiency by analyzing, and increasing brand awareness. The fact that the number of publishers and advertisers is increasing day by day in this field, which is developing day by day and increasing its importance, has brought both positive and negative results. Although it increases diversity and efficiency and provides the opportunity to reach a much larger audience, in this ecosystem where there are so many publishers and advertisers, the auctions that take place in milliseconds have created confusion and need to be optimized. The ads that are circulating on every online platform are shown to different people based on their personality and the AI system decides which ad is for which sort of audience [16].

This thesis aimed to provide a simpler and more feasible solution by using important parameters without the need for a specific algorithm and modelling related to choosing the most suitable advertisement in three stages and optimizing the bid price. In the first stage, it is aimed to choose the right advertisement by using the most key parameters. Although the parameters used vary from platform to platform, the most important parameters have been chosen to determine an advertisement. It is aimed to help the consumption of the budget with the daily and total budget. With the total hour range, it is aimed to highlight the most recent and furthest advertisements to reach the total hour. Ads with the highest performance were determined by performance and received plus points. Using the Weighted moving average method, the system handled the data of the last 4 days and aimed to predict the advertisement that could have the highest performance. The campaign with the highest bid price and the highest bid has plus points. The ultimate goal is for the advertiser to deliver its advertisement to its audience within the specified time and to select the most appropriate advertisements for the offer within the platform in line with the target of the campaign. We aim to divide the newly added campaigns into two categories as performance and newly added campaigns to the platform, and to include the newly added campaigns in the system randomly until they reach a certain impression and achieve performance.

In the second stage, we aimed to ensure that the selected ad can reach the most appropriate bid price in order to win the bid. The ultimate goal is to ensure that the campaign can consume its budget within the specified budget and time, therefore, the end date has been taken as one of the most important parameters. While winning the auction is the top priority, being able to win at an optimized price is crucial. Although it varies from type to auction, multiple advertisers participate in auctions and advertisers do not know each other's bid prices. Within each optimization attempt, the bid price is increased or decreased according to the situation, so that the optimized price is obtained and stored for future use.

In the third stage, various suggestions are included in the conclusion to move the given algorithm to better points. Although targeting can be done using both DSP and SSP data management platforms for ad selection, compatibility parameter can be added in line with the information from the visitor while selecting the target ad. In this way, it can be made more efficient by choosing a more compatible and most suitable ad for the target audience. A more efficient ad can be selected by analyzing the size and ad type (audio, video, display, native) that has the highest performance in the offers previously given by the platform in the advertising area and adding it as a parameter. By providing the user with information about the common features of high-performing ads in the specified ad spaces, ads can be added accordingly. The important point about optimizing the bid is that a bid price can be determined by evaluating not only how many bids have been bid in the past for the specified bid price, but also bids placed on similar ad slots. The user can be offered a bid price suggestion based on similar bids created within the platform, and thus a more reasonable maximum bid price will be defined. Thus, advertisements are displayed more effectively. From time to time, the user can be given suggestions about increasing or decreasing the bid price according to the status of the auctions. A more advanced algorithm is obtained by including constraints that restrict users' access to advertisements such as day parting, frequency capping, closeness to the end date, the user's relevance, and exactly where in the daily and total budget are included in the optimization.

All these recommendations can be increased. However, the important point here is that the algorithm has milliseconds to make the most accurate advertising decision and determine the most accurate bid price. For this reason, it will always be more beneficial to proceed with as few focus parameters as possible. We tested the creative selecting and bid optimization algorithms that we mentioned in our thesis in real life, and we found that the results were satisfactory to the customer. There are many studies on the topics mentioned in the literature. With the hope that this approach will find its place in the literature, we believe that such studies will increasingly develop in the developing programmatic advertising sector.

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