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Decision Trees for Optimization Display Campaigns for Conversion

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Dissertation

presented as partial requirement for obtaining the Master Degree Program in Data-Driven Marketing

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
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Decision Trees for Optimization Display Campaigns for Conversion

by

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Master Thesis presented as partial requirement for obtaining the Master’s degree in Data-Driven Marketing, with a specialization in Marketing Intelligence.

Supervised by/Orientada por:

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisboa, 14/07/2023

DEDICATION

The first acknowledgment goes to my mother and grandmother who have been my two rocks throughout my life, without their education and their support, I would not be the man I am today.

Secondly, I want to thank my lovely girlfriend, who has supported me daily these past couple of months. And, also my cousin that has been my professional mentor.

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ABSTRACT

Digital technology's evolution has impacted the marketing landscape and brought both opportunities and challenges for advertisers. Traditional marketing strategies have been shown to be supported by, and in some cases replaced by digital marketing techniques. Even though there are many different channels and forms for online advertising today, programmatic advertising has shown a lot of potential, particularly in terms of automation and algorithm development for buying ad space in real-time.

This study aims to explore the application of Decision Tree Algorithms in optimizing display campaigns for conversion and the competitive benefits they provide over traditional optimization methods, on the programmatic exchange.

In order to evaluate the effectiveness of the Decision Tree Algorithm, the research will be divided into three phases: phases 1, 2 and 3. Where phases 1 and 2 will focus on testing different bid modifier ranges to reach the best outcome. And, in phase 3 the two campaigns, utilizing the Decision Tree Algorithm and the Standard Optimization, will be directly compared with relevant KPIs, in an A/B test environment.

The results obtained showed that after the systematic testing process of multiple bid modifier ranges, it was possible to determine that the best-performing one has a range of 0,1 to 1,5, which, in phase 3, outperformed the standard optimization and generated more 21% clicks, 54% conversions and a 28% higher conversion rate.

KEYWORDS

Digital Marketing; Marketing Optimization; Programmatic Advertising; Traditional Advertising; Brand Awareness; Demand-Side Platforms (DSP's); Real-Time Bidding (RTB); Display Campaigns; DTA; Machine Learning; Supervised Conversion; Bid Modifiers; Online Advertising Tools; Campaign Performance Metrics; Marketing Effectiveness; Data-Driven Marketing; Algorithm Development.

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LIST OF ABBREVIATIONS AND ACRONYMS

DTA	Decision Tree Algorithm
RTB	Real-Time Bidding (RTB)
CPC	Cost per Click
KPI	Key Performance Indicator
CTR	Click-Through Rate
CVR	Conversion Rate
Standard Campaign	Campaign using the standard optimization
Custom Campaign	Campaign using the custom optimization
DSP	Demand-Side Platform
V1	Version 1
V2	Version 2
V3	Version 3
LI	Line Item
CPA	Cost-per-acquisition

1. INTRODUCTION

The growth of digital technology has actually changed the landscape of advertising and marketing, bringing with it opportunities together with obstacles for companies around the globe. There is an opportunity for digital marketing strategies can take advantage to reach certain consumers. Digital advertising approaches can benefit from the power of the internet together with digital technology to connect with customers have supported as well as in many cases changed, traditional advertising and marketing methods (Kotler et al. 2016).

The development of programmatic advertising which automates the decision-making procedure of media buying by concentrating on specific audiences as well as demographics is just one of the most important advancements in digital marketing. Programmatic advertising has essentially affected exactly how companies promote online due to their ability to directly target a certain target audience, accelerating the buying procedure by combining a large ammount of inventory across publishers with a high demand from advertisers (Gonzalvez-Cabañas & Mochón, 2016).

New academic opportunities in the field of data machine learning, data mining, and other related fields are presented by the recent growth of computational advertising. Real-Time Bidding (RTB), in particular, continues to evade the research community together with the programmatic advertising's exponential rise (Wang et al., 2017).

Display campaigns are becoming a crucial part of digital marketing strategy in the context of programmatic advertising. According to Gonzalez-Cabaas and Mochón (2016), these campaigns make use of visual ads that may be tailored to particular user, demographics and behaviors, making them an effective tool for online product and service promotion.

The main goal of this research work revolves around investigating the efficacy of a decision tree algorithm (DTA) in enhancing the performance of display campaigns for conversion. Although the DTA was developed for this project, the main objective relies around testing different bid modifiers range, providing a solid campaign test environment and testing multiple optimizations.

The study methodology used is quantitative and makes use of a demand-side platform (DSP) for data extraction. In order to enhance the total outcomes of the campaign and determine areas that need improvement, the efficiency of the DTA will be assessed and directly compared with standard optimization strategies.

A number of academic studies have revealed that custom algorithms outperform standard optimization strategies especially when it applies to metrics like click-through rate (CTR) as well as cost per click (CPC) (Madera et al., 2016). Additionally, research on the prediction of click-through rate (CTR) has been conducted (MC Blanc & Faria, 2019). This study aims to highlight the use and capacity of DTA for campaign improvement, considering key performance indicators (KPIs) including clicks, conversions, and conversion rate (CVR), which are crucial in judging its effectiveness.

The purpose of this study is to significantly advance the use of DTA in programmatic display ads for conversion. The study's findings may have substantial implications for advertising approaches and strategies.

2. LITERATURE REVIEW

2.1. CONTEXT

The digital era has reshaped marketing in considerable ways, presenting new tools together with approaches that have transformed just how companies interact with their customers. This digital landscape not just permits companies to reach more individuals, but additionally provides more ways to target and determine their efforts, automate tasks and also make decisions based on information (Araujo et al. 2020). This step in the direction of algorithm-based marketing suggests that we take another look at traditional marketing and better comprehend this digital marketing world.

This literature review will examine the present state of digital marketing, with a specific focus on programmatic advertising and the use of custom algorithms. The objective is to offer a complete understanding of these topics as well as what they imply for businesses today.

Digital marketing, that consists of platforms such as search engines, social media, and mobile apps, has really come to be an essential part of a business's strategies. The capability to get in touch with a wide audience and tailor marketing messages to each individual has actually made digital marketing a necessary tool for businesses (Gharibshah & Zhu, 2021). On top of that, digital marketing platforms give a lot of information that can be made use of to forecast customer habits along with boosting marketing strategies, which makes them even more valuable to businesses.

Advertising, a crucial component of digital marketing, has likewise transformed with the surge of digital technology. Automated advertising, which includes the automated buying and selling of online ad space, has ended up being a significant trend in the advertising sector. This approach enables companies to target specific audiences and determine the success of their campaigns in real-time leading to more efficient and efficient marketing (Araujo et al., 2020).

Custom algorithms are key in automated advertising as they leverage the assess to data and make decisions based upon that, such as, which ads to show to a certain consumer. These algorithms can substantially boost the efficiency of ad campaigns by maximizing ad placements as well as enhancing consumer interaction (Gharibshah & Zhu, 2021). Nonetheless, the performance of these algorithms can be influenced by various factors including cultural differences and the specific characteristics of the target market (Mattison Thompson & Brouthers 2021).

2.2. DISPLAY ADS

2.2.1. Display ads and its role in Marketing and Advertising

Advertising is a big sector, and advertisers are increasingly more focused on buying well-targeted ads. Display advertising represents a big percentage of the market with both opportunities and problems for ad targeting. It is promising because of the abundance of data that can be used to target ads. It is difficult because the display advertising ecosystem is a very complex system in which collecting data and delivering ads might include dozens of different companies (Perlich et al., 2013).

By strategically deploying display campaigns, businesses can also leverage the power of retargeting, which involves re-engaging with customers who have previously interacted with the brand. This approach significantly increases the chances of conversion, as it reminds potential customers of their prior interest and encourages them to complete a desired action (Lambrecht & Tucker, 2013).

Over the past several years, display advertising has developed significantly. With the growth of RTB that auctions off website's placements for displaying online display ads, has produced an effective platform for advertisers to advertise to specific consumers. We refer to the showing of a display ad to a particular consumer as creating an "impression," as is customary in the sector. A particular "slot" or placement on a specific website at an exact moment with a specific customer viewing represents the auction good in each RTB. The auctions are conducted in real-time, starting instantly as a user visits the page and continuing as the page is being shown in the user's browser. All potential buyers are given bid requests that include information about the location of the possible ad and an identifying random number for the internet user at the time of the auction. Advertisers frequently add to this data with previously obtained or purchased information on the specific consumer and website. A potential advertiser must choose whether to bid on this impression, how much it's willing to pay, and what advertisement it wants to display if it wins the auction before the sale can begin. Each day, there are billions of these real-time auctions, and advertisers need highly efficient algorithms to make decisions in milliseconds (Perlich et al., 2013).

2.2.2. Types of media buying (traditional and programmatic)

The world of display campaigns comprises two primary categories: traditional and programmatic. Traditional media buying relies on a manual process of buying and selling ad space for fixed price. Advertiser would pay a certain amount for a specific placement within a given online format. This method involves personalized interactions, allowing businesses to tailor their agreements and strategies based on specific requirements. Advertisers would buy placements or print-runs (the number of times a creative execution would appear in each placement) directly from existing formats, known as publishers. This advertising space is known as "inventory" (Gonzalvez-Cabañas & Mochón, 2016).

Programmatic appeared with the need to automate this manual buying process. The growth and propagation of internet access increases the number of both publishers, as well as in the volume of content these publishers' release. To avoid not selling inventory, multiple agents were created to mediate this automatic process of media buying. First, ad networks appeared, performing as agents or brokers, buying unsold inventory from publishers, and collecting segment audiences, packaging, and selling advertising accordingly. This created a large supply of unsold inventory, leading to the online advertising space becoming a highly competitive market and the need for ad exchanges, which allows both advertisers and publishers to exploit audiences rather than print-runs. Ad exchanges can target audiences via publishers' platforms. Rather than being booked and purchased directly, audiences are bought using a system of RTB, in which the winner places the highest bid. The winning bidder prevails over the right to position their advertising with the right audience at the right time. The advent of this new business model did not necessitate the removal of the old one; advertisers and publishers were now able to choose between buying and selling inventory via Ad Networks or buying and selling audiences via Ad Exchanges. With these changes, new ways to enhance speed and make the buying and selling process better began to emerge. At the buying end, certain advertisers established their own trading agencies (called private agency trading desks), while others acquired Demand Side Platforms (DSPs). Real-time online sales enable it to be easy for advertisers or ad companies to work with Ad Exchanges in both situations (Gonzalvez-Cabañas & Mochón, 2016).

On the selling side, some companies can join directly with Ad Exchanges, while others use Supply Side Platforms (SSPs). This process is like using DSPs when buying ads because it helps publishers connect with Ad Exchanges in an efficient way and automatically boosts the performance of their own inventory (Gonzalvez-Cabañas & Mochón, 2016).

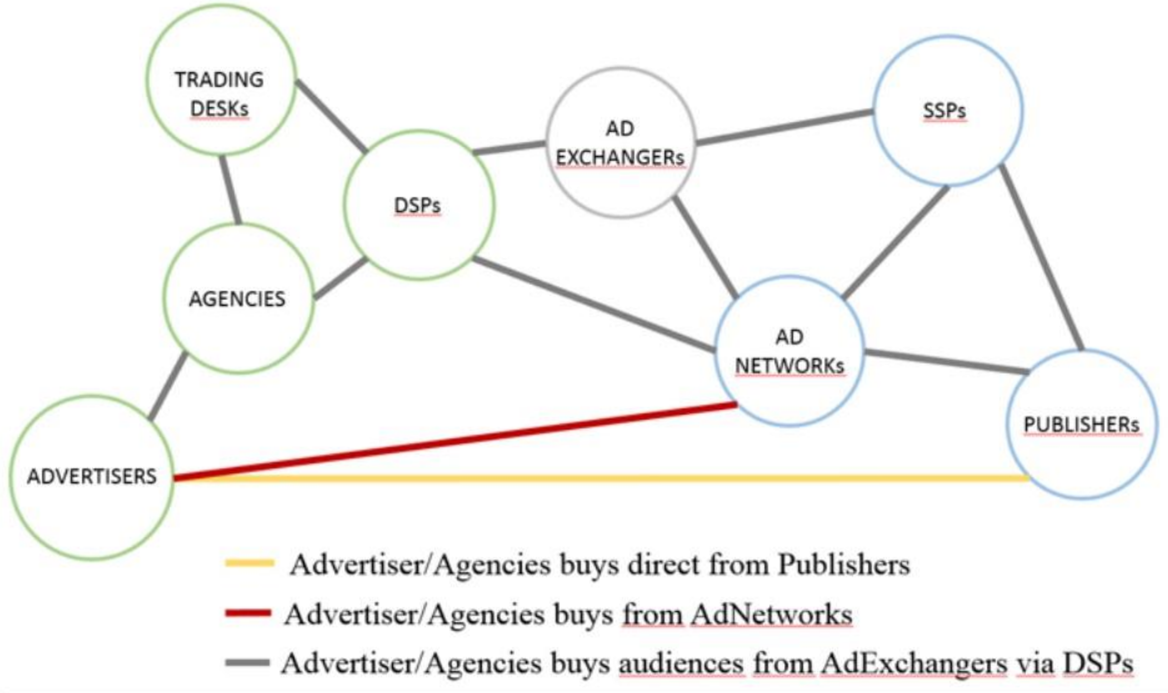

Figure 1: Online Advertising Business Models
Source: (Gonzalvez-Cabañas & Mochón, 2016)

2.2.3. Importance of display campaigns in creating brand awareness and customer conversion

Display campaigns play an important and irreplaceable role in the development of brand awareness and the assistance of customer conversion. With display campaigns brands can properly display their service or products to a huge and varied audience, therefore considerably enhancing their exposure and recognition. Developing a solid brand presence in the minds of customers is extremely important as it affects their decision-making process when buying any type of service or product (Fayvishenko et al. 2023). The capability of display campaigns to captivate and involve potential customers increases the chances of them remembering the brand and also considering it as a practical choice in their purchasing journey. Furthermore, display campaigns contribute in driving customer conversion by persuasively motivating possible clients to take the wanted action. By strategically crafting compelling ads, companies can influence as well as encourage their target audience to complete actions such as purchasing, submitting personal information, or registering for a service. Consequently display campaigns add to a boost in leads and sales and eventually, the overall income of the business (Fayvishenko et al., 2023). Therefore it appears that display campaigns are an essential tool in the advertising and marketing toolbox, making it possible for companies to properly get to and also involve their target audience while attaining their desired outcomes.

2.2.4. Role of Bid Modifiers in optimizing display campaigns

In the context of RTB, bid modifiers can be utilized to dynamically readjust bids and consequently manage KPIs such as the auction winning ratio and an effective CPC. This approach can lead to more cost-efficient bidding process as well as can cause substantial gains in campaign revenue (Ren et al. 2016). It's vital to keep in mind that learning from censored auction data where the proposal decision is made per impression and there are massive changes in campaign's KPIs can be tough. To resolve this, bid-aware gradient descents have been suggested which regulate both the value and also the direction of the gradient to achieve unbiased learning (Zhang et al. 2016).

Bid modifiers can considerably affect the efficiency of a display campaign by allowing dynamic adjustment of bids based on real-time data and market conditions. Nonetheless, their application needs careful consideration of various aspects, consisting of the bidding environment, KPI restrictions, and also the need for impartial learning from censored data.

2.2.5. A/B testing and user groups

A/B testing, also referred to as split testing, are an effective tool for online optimization implementations. A/B testing is used to test whether a version of a design or implementation produces better performance by presenting two versions to two different sets of consumers. A/B testing is frequently utilized to increase the performance of online advertisements due to the quick development of online advertising. In today's data-driven environment, the great majority of Internet businesses use A/B testing to evaluate the effectiveness of multiple variants. It’s fundamental to properly divide the selected subsets of user groups, by strictly defining the control group, allowing the testing framework to stay reliable (Ma et al. 2022).

To conclude, split tests and user groups are both important tools in the optimization of display campaigns. By using these techniques, advertisers can make data-driven choices and customize their campaigns to the specific needs and preferences of their audience resulting in improved performance and results (Ma et al. 2022).

2.3. DECISION TREE ALGORITHM

2.3.1. Overview of Decision Tree Algorithm

DTA are a kind of machine learning algorithm that is thoroughly utilized for both classification along with regression tasks. They are recognized for their simplicity and also interpretability, making them a popular option amongst data scientists and researchers (Rokach & Maimon 2008). DTA works by developing a model that can forecast the value of a target variable by finding out simple decision rules inferred from the data features. They are called decision trees since they take the form of a tree-like model of decisions, where each internal node represents a test on an attribute each branch stands for a result of the test, and each leaf node holds a class label (Kotsiantis 2013).

2.3.2. Types of Decision Tree Algorithm: classification and regression

There are 2 main types of DTA: classification trees and regression trees. Classification trees are utilized when the end result is a categorical variable, suggesting that it is utilized to identify the data right into particular categories. On the other hand, regression trees are utilized when the end result is a continuous variable implying that it is utilized to forecast an action (Kotsiantis 2013; Rokach & Maimon 2008). Regardless of their differences both kinds of DTA comply with the same fundamental procedure of dividing the data into distinct subsets based on criteria, and then making use of these subsets to make forecasts.

2.3.3. Importance of decision tree algorithm in supervised learning

DTA play a critical role in supervised learning, a type of machine learning where the model is trained using labeled data. They are specifically valuable in scenarios where interpretability is very important as they give clear rules that can be easily comprehended and interpreted, even by non-experts (Kotsiantis 2013). Additionally, DTA can manage both categorical and numerical data, and they can easily manage feature interactions making them a flexible tool in the field of machine learning (Rokach & Maimon, 2008).

2.4. DECISION TREE ALGORITHM AND DISPLAY CAMPAIGN OPTIMIZATION

2.4.1. Application of decision tree algorithm in display campaign optimization

Optimization algorithms have been increasingly applied in the realm of advertising. These algorithms can be used to make real-time decisions about which ads to display to a particular user (MC Blanc, Faria, 2019).

In advertising, CTR is a crucial KPI, which will determine if a user, after viewing an ad (impression), will click on it. In other words, the CTR predictability rate plays a big part and, in practical terms, it's a supervised machine learning problem, a binary classification problem. An impression that is based on past data characterized as a click (class 1) or as a non-click (class 0) is a dependent variable (MC Blanc, Faria, 2019). Although CTR plays an important role in advertising and there are several studies testing multiple algorithms in CTR prediction, such as logistic regression, decision trees, linear regressions, deep interest networks, and others (MC Blanc, Faria, 2019). No studies were found focusing on the usage of decision trees in display ads for conversion.

Moreover, DTA can be used to optimize the bidding process in programmatic advertising not just to predict the likelihood of a user clicking an ad but also completing a conversion. This way, it's possible to determine the optimal bid for each ad placement that will lead to a conversion, maximizing the number of conversions and CVR.

2.4.2. Challenges and Limitations in Applying Decision Tree Algorithms to Display Campaigns

Despite their benefits, the application of DTA to display campaigns also presents some challenges and limitations. Among the main challenges is the threat of overfitting, where the algorithm becomes too complex and starts to capture noise in the data as opposed to the underlying patterns. This can lead to poor performance when the algorithm is applied to new data (Dietterich, 1995).

DTA can also be sensitive to changes in the data. Small modifications in the data can lead to different decision trees, which can cause irregular forecasts. This can be a significant issue in the dynamic and rapidly changing environment of online advertising (Dietterich, 1995).

Despite these challenges, DTA remain a powerful tool for display campaign optimization. With careful implementation and ongoing monitoring, these algorithms can significantly enhance the effectiveness of display campaigns and deliver substantial benefits for advertisers.

2.5. Conclusion

The literature review has given important understandings into the role of display campaigns in advertising and marketing, the types of display campaigns and their relevance in creating brand awareness as well as conversions. It has been established that display campaigns are an effective tool for businesses to connect to their target audience as well as encourage them to take a particular action such as seeing a website, purchasing, or registering for an e-newsletter (Perlich et al., 2013; Lambrecht & Tucker 2013)

In terms of DTA, the literature has shed light on their overview, types, and importance in supervised learning. DTA have been found to be an effective tool for data classification and prediction, and they play a crucial role in supervised learning (Kotsiantis, 2013; Rokach & Maimon, 2008).

Furthermore, the application of DTA in display campaign optimization has been explored, highlighting the benefits and challenges of this approach. The literature suggests that DTA can enhance the efficiency and effectiveness of display campaigns by enabling more precise targeting and personalization (MC Blanc, Faria, 2019).

Despite the extensive research on display campaigns and DTA, there are still gaps in the literature. For instance, the application of DTA in display campaign optimization for conversion is a relatively new area of research, and more studies are needed to fully understand its potential and limitations. Moreover, most of the existing studies focus on specific types of display campaigns and DTA, leaving room for research on other types and their implications for marketing and advertising.

This study aims to fill these gaps by providing a comprehensive analysis of the use of DTA in optimizing display campaigns for conversion. It will certainly add to the existing body of knowledge by clarifying the useful effects of this approach for businesses and online marketers. In addition, the research will provide empirical proof on the effectiveness of DTA in boosting the efficiency of display campaigns thereby providing beneficial insights for future research and practice.

2.6. RESEARCH QUESTIONS

Based on the conclusion of the literature review, a few questions arise that are relevant to explore throughout this study to address some of the identified gaps in section 2.5 and explore the effectiveness of DTA in display campaign optimization for conversion.

Therefore, the following two RQ will be explored:

1. Are Clicks, Conversions and CVR the most relevant KPIs to consider when developing a DTA for display campaign optimization?
2. How do different bid modifier ranges impact the performance of DTA in display campaign optimization?

By formulating these research questions (RQ), the study aims to provide valuable insights and contribute to the existing body of knowledge in the field of advertising and machine learning.

3. HYPOTHESIS FORMULATION

In this section, will be provided the hypotheses that will serve as structure for the examination to bring into play the insights and findings discussed in the literature review.

In the previous section, it became clear that DTA and display ads play an important role in the growth and optimization of advertising and marketing techniques. (Perlich et al., 2013; Fayvishenko et al., 2023; MC Blanc & Faria, 2019). It was also clear that the application of DTA in advertising has been explored, highlighting the benefits and challenges of this approach. The literature suggests that DTA can enhance the efficiency and effectiveness of display campaigns by enabling more precise targeting and personalization (MC Blanc, Faria, 2019).

Although there has been some research conducted on display campaigns and DTA, there is possibility for further investigation, such as, understanding if the use of DTA can outperform a standard optimization when applied to display campaigns for conversion. Also, there is insufficient research regarding the testing of different bid modifiers to determine the optimal range to optimize display campaigns for conversion.

As we move on to discover the potential for DTA to boost the efficiency of display campaign for conversion it is necessary to develop hypotheses that direct the focus of this study. Therefore, the following hypothesis was formulated.

Hypothesis 1: DTA can significantly improve the performance of display campaigns compared to standard optimization methods.

Hypothesis 2: The optimal range of bid modifiers for a DTA can be determined through a systematic testing process.

4. METHODOLOGY

The purpose of this chapter is to describe the methodology used to evaluate the effectiveness of display campaign optimization for conversion using a DTA. Section 4.1 identifies the approach, the project's primary goal, and the framework for interpreting the results. Section 4.2 covers a more detailed overview of the structure, methods and procedures used for the data collection and analysis of the study. Section 4.3 showcases the framework for the setup and implementation of each campaign. Finally, section 4.4. briefly introduces the tools and technologies leveraged throughout the development of the custom algorithm using the decision tree.

In summary, this chapter will present the methodology used to study the hypotheses formulated in Chapter 3. In order to do this and to answer the RQ, the hypothesis will be tested using two separate campaigns, which will be explained in the following section, 4.1 Research Approach.

4.1. RESEARCH APPROACH

The project's primary goal focus on testing the efficacy of the DTA in enhancing the performance of display campaigns for conversion and, although the DTA was developed for this project, the main objective relies around testing different bid modifiers range, providing a solid campaign test environment and testing multiple optimizations.

Since the study will be more focused on gathering and analyzing numerical data to test hypothesis and quantify relationships between variables, the research approach chosen was quantitative design. Given the data available, only two campaigns will be tested and analyzed. The campaign that optimizes based on the standard optimization will be designated as "Standard Campaign", while the campaign that utilizes the CTA will be called "Custom Campaign".

With this research approach, data analysis will help the comparison between both campaigns, standard and custom, enabling the analysis in terms of pattern and trend identification and correlations between both campaigns and their KPIs. Furthermore, this will provide a detailed understanding of the effectiveness of the CTA on optimizing display campaigns for conversion, contributing to the current existing knowledge on the topic in hand.

4.2. RESEARCH DESIGN

The study was conducted in the programmatic exchange, utilizing Xandr, as a DSP, to set up, manage and collect data from advertising campaigns (Gonzalvez-Cabañas & Mochón, 2016). In addition to the focus on conversion, the campaign setup and optimization efforts also considered the bidding strategies. The Standard campaign was optimized using Xandr's conversion-based optimization. The Custom Campaign was optimized using the CTA with different bid modifiers in each phase, as explained in section 4.4. The goal was to optimize the campaigns to achieve the best possible results within the available budget and to continuously monitor and adjust the campaigns as needed to maintain optimal performance.

Two procedures were considered to ensure the test results' validity and precision. Maintaining a similar click volume across all campaigns in each phase and consistently applying user groups between campaigns when testing is essential (Ma et al. 2022). Because all the tested campaigns have the exact targeting, it is essential to create user groups to guarantee there is no bidding done in between campaigns. In addition, these approaches ensure that any observed differences in performance result from the optimization efforts and are not due to differences in budget or volume.

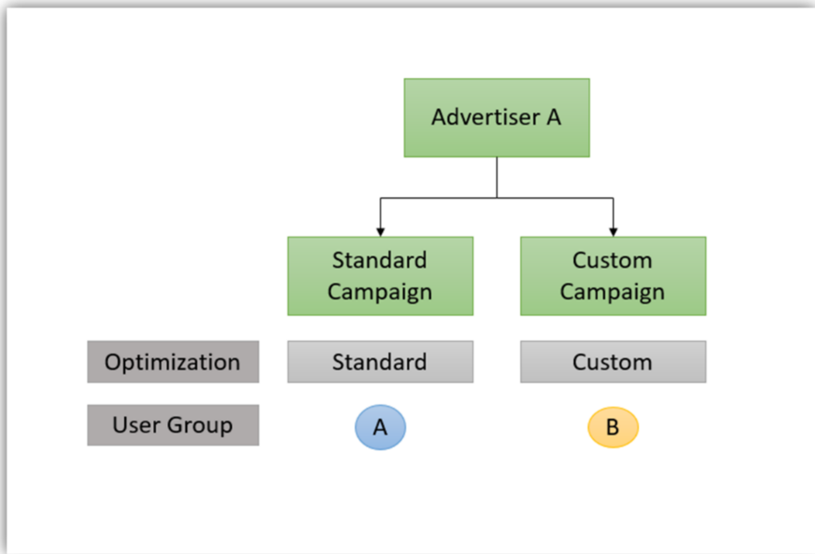

Figure 2: User Groups

In Section 4.3. Campaign Setup and Implementation, Xandr will be used as the platform to set up the campaign, define the main goals and manage its performance during the test. During this phase, Xandr will be utilized to collect campaign data, and at the end of the campaign, it will be possible to extract an Excel file containing all the data for analysis and to draw conclusions.

In Section 4.4. Decision Tree Development, Xandr, will serve only in data collecting. To train the decision tree, data was collected from Xandr with specific dimensions and timeframe. The dimensions mentioned later in section 4.4 have been selected to maximize the CVR in each campaign.

It is also worth mentioning the reason why display was chosen out of all the advertising formats to proceed with this test. As previously mentioned in the literature review, display campaigns are instrumental and indispensable in fostering brand awareness and facilitating customer conversion. By leveraging display campaigns, brands can efficiently present their products or services to a broad and varied audience, thereby substantially boosting their visibility and recognition (Fayvishenko et al., 2023).

Display campaigns' capacity to attract and engage potential customers enhances the probability of the brand being remembered and considered a feasible choice in their purchasing journey. Our goal is aligned with the ultimate objective of display campaign, which is to persuade the target audience to purchase the products and services offered but the companies and raise brand awareness through effective marketing strategies.

Regarding the data analysis, the relevant KPIs chosen to conduct this study were: Clicks, Conversions and CVR. The KPIs will be compared within both, Standard Campaign and Custom Campaign, in order to conclude which one performed better. Also, Excel was the selected data analysis tool for this study due to the following reasons:

- Objectivity: Quantitative research methods allow the collection of objective data sets that can be measured and analyzed correctly. This also can eliminate biases and subjectivity in the analysis process.
- Precision: Quantitative research methods allow for precise variable measurement and can help identify minor differences between groups. This can be used in identifying which algorithm is more effective at optimizing programmatic display campaigns for conversion.
- Flexibility: Excel provides excellent flexibility in terms of data organization and analysis. You can use various functions and formulas to manipulate your data and create custom visualizations or charts.

- Data Limitation: Excel is more suited for analysing data sets that are considered small with many variables. This way, it is possible to consider and compare multiple KPIs.

Moreover, the campaign lasted four months, from the 1st of February to the 31st of May of 2022 and was split into 3 phases. The two first phases, from the 1st of February to the 28th of February and from the 1st to the 31st of March, were conducted to test multiple bid modifiers and to reach the desired outcome, a higher conversion. The third phase, from the 1st of April to the 31st of May, was focused on setting up a fair comparison between the two campaigns, Standard Campaign and Custom Campaign, to compare results and reach a conclusion regarding the performance of both campaigns and their KPIs.

4.3. CAMPAIGN SETUP AND IMPLEMENTATION

Participants

One advertiser was considered to run the test for this study, advertiser A, which is company in the financial services industry, located in Portugal. This advertiser was used in the early-stage phase of the algorithm development, considered fundamental to define a well-founded basis to proceed with more tests and advertisers and used in the final test that brought the data and results that we will analyse later.

Advertiser's A campaigns are focused on a particular conversion, which is the final step in its website form request, for loan approvals. Because this advertiser has a significant investment in advertising, mainly in digital channels, the display campaigns provide assisted conversions to other channels. It is worth mentioning that most of the conversions used for the algorithm are post-view conversions.

Data Gathering

The data was collected from Xandr using the Analytics Report. The metrics exported from Xandr were: *Sum of Clicks, Sum of Conversions and CVR.* The time frame chosen to export the data was four months, from the 1st of February to the 31st of May 2022, the duration of the three phases of the project.
In total, 327 lines of Excel data were exported contemplating the mentioned KPIs, such as 59 487 clicks and 759 conversions.

Data Transformation

After exporting the data from Xandr, it was necessary to clean and reprocess it to ensure it was complete, accurate, and ready for analysis. This includes removing extra spaces. For example, some cells might contain these extra spaces at the beginning or end, which can be removed by using Excel's function "TRIM" and removing the data that contains errors, which can be done by using Excel's function "IFERROR" or Excel's "Find and Replace" feature to replace missing values.

Excel recognizes dates and times in different formats than Xandr. Therefore, it is essential to format dates and times using Excel's "Format Cells" option to avoid any issues when calculating or sorting data.

Measures

This sub-section will lay out the specific metrics that will be utilized to assess both campaigns' efficiency, the Standard Campaign and the Custom Campaign. These procedures will be used to analyze the impact of the algorithm on the campaign's performance and identify whether the algorithm has efficiently optimized the display campaign. By choosing these measures we can ensure that the data evaluation is robust and precise which the conclusions attracted from the study are well-supported. The measures chosen are based upon industry common KPIs as well as are meant to comprehend the campaign's performance comprehensively.

The measures that will be considered are:

- Clicks: number of times that users clicked the campaign's ads;
- Conversions: the number of times that users finished a desired activity on the website such as buying or filling in a form;
- CVR: ratio of conversions to clicks and also measures just how efficient the campaign is at converting clicks right into conversions;

Data analysis procedures

As formerly discussed, Excel will be utilized to carry out the comparisons and determine trends and patterns in the data. The analysis will be done by directly comparing each campaign's KPIs in the correspondent phase (1, 2 or 3) the campaign's performance and the previous phases.

Along with performing direct comparisons in between campaigns and phases the data evaluation will include using various Excel functions as well as formulas to adjust and organize the data. As an example, pivot tables will be utilized to group and summarize the data by various variables, such as amount of time, demographics, and creative elements. Charts and graphs will also be created to picture the data and determine any patterns that might arise.

Furthermore, Excel's conditional format feature will be utilized to highlight any type of outliers or abnormalities in the data. Generally, these data analysis procedures will allow us to get an extra thorough understanding of the influence of the DTA on campaign performance and determine any areas for additional optimization.

4.4. DECISION TREE ALGORITHM DEVELOPMENT

Data Gathering

For the DTA development, the same advertiser, advertiser A, was selected for the data gathering and analysis.

The data for the study was extracted from Xandr using the Network Device Analytics Report, which provided information on the KPIs such as Clicks, Conversions and CVR based on specific dimensions, such as *year, month, hour, day, device type, operating system family name, browser name, Line Item (LI) name, LI id, pixel id, size, campaign name, and campaign id*.

The timeframe for the data extraction was set for one year, from the 1st of January 2021 to the 31st of December 2021. This time frame was selected to ensure sufficient data was collected from past campaigns to train the model on the specific conversion successfully.

Data Transformation

The raw data from Xandr's report need to undergo specific data processing steps to ensure that it can be effectively utilized for the machine learning model. This data processing involves manipulating the raw data to extract the necessary variables and transforming it into a format suitable for the machine learning algorithm.

Here we define:

- Which is the column that is going to use to be used to sum the conversions of a given hour of the day (total conversion, post-click, post-view, etc)
- The pixels that are going to be optimized
- The target for the machine learning model (we are using "converted_or_not" as default because the model predicts which set of features have a higher likelihood of having conversions.

Combined with those definitions, it was also made some feature engineering to gather better insights from the data:

- Group hours of the day by periods
- Group device types
- Only consider the top-used browsers and operating systems

The final dataset is combined by a moment of the day, device type, operating system, browser, and creative size. The metrics are clicks, conversions, and CVR.

Train and evaluate the model

The data is split into two sets to train and evaluate the DTA: a training set and a testing set. This is done using the stratified shuffle split method with a ratio of 80:20 for the training and testing sets. Due to the unbalanced nature of the data set with a ratio of 1:12 conversions to non-conversions, an under-sampling method is applied to overcome the issue.

To classify the data, a Decision Tree Classifier model is created. Then, the hyperparameter optimization is carried out using the Grid Search method with a 5-fold cross-validation technique, considering the f1 score as the evaluation metric. This helps to select the best combination of hyperparameters that maximizes the f1 score and improves the model's performance.

Tree deployment

After developing and also assessing the decision tree model, the following step is to release the model. This includes transforming the decision tree into a bonsai tree as well as using the probability values of conversion generated by the model to produce bid modifiers. As discussed in section 2.2.4 Literature Review, bid modifiers are modifications made to the bid amount of an ad placement in order to boost or lower the possibility of that advertisement being shown to a particular audience. They allow advertisers to readjust their bids in real-time to maximize their campaign performance.

The range of bid modifiers is determined by conducting multiple tests and analysing the model's performance. These tests were divided into three phases. In phase 1, version 1 (V1) was created, using a bid modifier range of 0,1 to 1, against a bid modifier range of 0,1 to 2,5, for version 2 (V2). In phase 2, V1 was tested against version 3 (V3), a bid modifier ranging from 0,1 to 1,5. Therefore, three trees were deployed, V1, V2 and V3, with the same data and dimensions but different bid modifiers.

	Bid Modifier
V1	0,1 - 1
V2	0,1 - 2,5
V3	0,1 - 1,5

Figure 3: Bid Modifiers

Finally, the conversion process is carried out using a simple linear conversion. The three decision trees deployed are presented below.

```
if browser != 'Chrome (all versions)':
    if browser != 'Samsung Browser':
      if browser != 'HuaweiBrowser':
        if browser != 'Edge':
          if device_type != 'phone':
             0.0006369426751592356
          else:  # if device_type_phone > 0.5
             0.005714285714285714
        else:  # if browser_Edge > 0.5
          if os_family != 'Microsoft Windows':
             0.0
          else:  # if os_family_Microsoft Windows > 0.5
             0.037037037037037035
      else:  # if browser_HuaweiBrowser > 0.5
        if device_type != 'phone':
           0.0
        else:  # if device_type_phone > 0.5
          if size != '300x250':
             0.04878048780487805
          else:  # if size_300x250 > 0.5
             0.15
    else:  # if browser_Samsung Browser > 0.5
      if device_type != 'phone':
         0.0
      else:  # if device_type_phone > 0.5
        if size != '320x50':
          if size != '300x250':
             0.08695652173913043
          else:  # if size_300x250 > 0.5
             0.36363636363636365
        else:  # if size_320x50 > 0.5
           0.4782608695652174
else:  # if browser_Chrome (all versions) > 0.5
    if device_type != 'phone':
      if os_family != 'Microsoft Windows':
        if not user_hour range (13, 18):
          if not user_hour range (7, 12):
             0.0
          else:  # if user_hour_(7, 8, 9, 10, 11, 12) > 0.5
             0.03125
        else:  # if user_hour_(13, 14, 15, 16, 17, 18) > 0.5
          if os_family != 'Android':
             0.031914893617021274
          else:  # if os_family_Android > 0.5
             0.15384615384615385
      else:  # if os_family_Microsoft Windows > 0.5
        if not user_hour range (0, 6):
          if size != '160x600':
             0.6741573033707865
          else:  # if size_160x600 > 0.5
             0.9137931034482759
        else:  # if user_hour_(0, 1, 2, 3, 4, 5, 6) > 0.5
           0.24
    else:  # if device_type_phone > 0.5
      if os_family != 'Android':
         0.0
      else:  # if os_family_Android > 0.5
        if size != '160x600':
          if not user_hour range (0, 6):
             0.9086294416243654
          else:  # if user_hour_(0, 1, 2, 3, 4, 5, 6) > 0.5
             0.6206896551724138
        else:  # if size_160x600 > 0.5
           0.2
```

Figure 4: Decision Tree v1

```
if browser != 'Chrome (all versions)':
    if browser != 'Samsung Browser':
      if browser != 'HuaweiBrowser':
        if browser != 'Edge':
          if device_type != 'phone':
             0.10155440414507773
          else:  # if device_type_phone > 0.5
             0.11306715063520871
        else:  # if browser_Edge > 0.5
          if os_family != 'Microsoft Windows':
             0.1
          else:  # if os_family_Microsoft Windows > 0.5
             0.19411764705882353
      else:  # if browser_HuaweiBrowser > 0.5
         0.2111111111111111
    else:  # if browser_Samsung Browser > 0.5
      if device_type != 'phone':
         0.1
      else:  # if device_type_phone > 0.5
         0.6872340425531914
else:  # if browser_Chrome (all versions) > 0.5
    if device_type != 'phone':
      if os_family != 'Microsoft Windows':
        if not user_hour range (13, 18):
          if not user_hour range (7, 12):
             0.1
          else:  # if user_hour_(7, 8, 9, 10, 11, 12) > 0.5
             0.16923076923076924
        else:  # if user_hour_(13, 14, 15, 16, 17, 18) > 0.5
           0.25555555555555554
      else:  # if os_family_Microsoft Windows > 0.5
        if size != '160x600':
           1.7087912087912087
        else:  # if size_160x600 > 0.5
           2.275
    else:  # if device_type_phone > 0.5
      if os_family != 'Android':
         0.1
      else:  # if os_family_Android > 0.5
        if size != '320x50':
          if size != '300x250':
             1.5454545454545456
          else:  # if size_300x250 > 0.5
             2.34
        else:  # if size_320x50 > 0.5
           2.3285714285714287
```

Figure 5: Decision Tree v2

```
if browser != 'Chrome (all versions)':
    if browser != 'Samsung Browser':
      if browser != 'HuaweiBrowser':
        if browser != 'Edge':
          if device_type != 'phone':
             0.10089171974522293
          else:  # if device_type_phone > 0.5
             0.10800000000000001
        else:  # if browser_Edge > 0.5
          if os_family != 'Microsoft Windows':
             0.1
          else:  # if os_family_Microsoft Windows > 0.5
             0.15185185185185185
      else:  # if browser_HuaweiBrowser > 0.5
        if device_type != 'phone':
           0.1
        else:  # if device_type_phone > 0.5
          if size != '300x250':
             0.16829268292682925
          else:  # if size_300x250 > 0.5
             0.31
    else:  # if browser_Samsung Browser > 0.5
      if device_type != 'phone':
         0.1
      else:  # if device_type_phone > 0.5
        if size != '320x50':
          if size != '300x250':
             0.2217391304347826
          else:  # if size_300x250 > 0.5
             0.609090909090909
        else:  # if size_320x50 > 0.5
           0.7695652173913043
else:  # if browser_Chrome (all versions) > 0.5
    if device_type != 'phone':
      if os_family != 'Microsoft Windows':
        if not user_hour range (13, 18):
          if not user_hour range (7, 12):
             0.1
          else:  # if user_hour_(7, 8, 9, 10, 11, 12) > 0.5
             0.14375
        else:  # if user_hour_(13, 14, 15, 16, 17, 18) > 0.5
          if os_family != 'Android':
             0.14468085106382977
          else:  # if os_family_Android > 0.5
             0.3153846153846154
      else:  # if os_family_Microsoft Windows > 0.5
        if not user_hour range (0, 6):
          if size != '160x600':
             1.043820224719101
          else:  # if size_160x600 > 0.5
             1.3793103448275863
        else:  # if user_hour_(0, 1, 2, 3, 4, 5, 6) > 0.5
           0.43599999999999994
    else:  # if device_type_phone > 0.5
      if os_family != 'Android':
         0.1
      else:  # if os_family_Android > 0.5
        if size != '160x600':
          if not user_hour range (0, 6):
             1.3720812182741116
          else:  # if user_hour_(0, 1, 2, 3, 4, 5, 6) > 0.5
             0.9689655172413792
        else:  # if size_160x600 > 0.5
           0.38
```

Figure 6: Decision Tree v3

5. RESULTS

In this section, both campaign's, custom campaign and standard campaign, performance will be evaluated, including additional findings and insights that can be useful for future work. As previously stated, the study was divided into phase 1, phase 2 and phase 3, therefore, the following sub-topics will follow this structure.

5.1. PHASE 1

Phase 1 was live from the 1st of February 2022 to the 28th of February 2022 and its objective was to evaluate multiple bid modifiers and assess their impact on the efficiency of the DTA. The results of this phase offer understanding into the bid modifier range that is ideal for the DTA and aid us to determine the most effective optimization approach for the display campaign.

The bid modifiers tested were V1 ranging from 0,1 to 1 and V2, ranging from 0,1 to 2,5. As shown in Figure 7 both campaigns delivered a similar quantity of clicks with V1 delivering around 7% more clicks than V2 and also exceeding the conversion quantity by roughly 92%, totalling 46 conversions out of the 2 431 clicks.

Although it is clear to see that the bid modifier V1, ranging from 0,1 to 1 brought better results when compared to the bid modifier V2 ranging from 0,1 to 25, it would certainly be interesting to examine a bid modifier in between these values, the V3 ranging from 0,1 to 1,5.

Results

User groups		Clicks	Conversions	Conversion Rate
A	**V1**	2431	30	1,23%
B	**V2**	2278	24	1,05%

	Bid Modifier
V1	0,1 - 1
V2	0,1 - 2,5
V3	0,1 - 1,5

Figure 7: Phase 1 Results

5.2. PHASE 2

In Phase 2 we continued to evaluate various bid modifier ranges to establish the ideal range to utilize when enhancing a display campaign. It was taken into consideration V1 and also V3, with bid modifiers ranging from 0,1 to 1 as well as 0,1 to 1,5, respectively. This phase was online from the 1st of March 2022 to the 31st of March 2022.

Although the CVR of V1 slightly increased when compared to the previous phase, phase 1, it is clear that V3 stood for the bid modifier with the highest CVR. For that reason, although V1 had more 3,4% clicks than V3, this distinction was considered residual as well as did not had a significant change in the outcome of the test due to the fact that the absolute number of conversions is also inferior to V3.

Results

User groups		Clicks	Conversions	Conversion Rate
A	**V1**	2609	34	1,30%
B	**V3**	2523	41	1,63%

	Bid Modifier
V1	0,1 - 1
V2	0,1 - 2,5
V3	0,1 - 1,5

Figure 8: Phase 2 results

5.3. PHASE 3

Finally, phase 3 is focused on comparing the performance of the Standard Campaign and the best performance Custom Campaign, the V3. This phase was live for two months, from the 1st of April 2022 to the 31st of May 2022 and aimed to establish a fair comparison between the two campaigns and evaluate the effective ness of the DTA in optimizing the display campaign. The results of this phase provided valuable and reliable insights to conclude the viability of using a DTA when optimizing display campaigns.

As previously stated in section 4.2, Research Design, the volume of clicks must be within an acceptable range when comparing campaigns to ensure consistency. In this case, we can register a discrepancy of nearly 21% when comparing the clicks of V3 and the Standard Optimization. Therefore, although efforts were made to manage and optimize the Campaign to have a similar volume of clicks, the Standard Campaign needed to meet the target, and the V3 could meet the criteria. Therefore, we came to our first conclusion: The V3 had a more significant capability of delivering clicks and achieving the KPIs.

Analysing the volume of conversions and CVR, it is notable that V3 also outperformed the standard optimization by 134 conversions, equalling an increase of 54% in terms of conversions. Also, the CVR was 28% higher than the standard optimization.

Results

User groups		Clicks	Conversions	Conversion Rate
A	**V3**	27178	382	1,41%
B	**Standard Optimization**	22468	248	1,10%

	Bid Modifier
V1	0,1 - 1
V2	0,1 - 2,5
V3	0,1 - 1,5

Figure 9: Phase 3 Results

6. CONCLUSIONS AND DISCUSSION

The main goal of the study was to assess how well a DTA would perform when optimizing display advertising. The study was laid out in three phases: 1,2 and 3. This first two phases, 1 and 2, were mainly focused on trying new bid modifiers and other variables to improve its performance. In the final phase, phase 3, it was destined for the “real” test, the CTA was compared with standard optimization.

One of the research’s main findings was the impact of different bid modifiers on the campaign’s performance. The bid modifier V3, which has a range between 0.1 to 1.5, came out on top in terms of CVR performance when compared to the other ranges: 0,1 to 1 and 0,1 to 2. This helps to solidify the fact that picking the right bid modifier range is mandatory when building a DTA for optimizing display ads and should be taken into consideration for future campaign strategies. Additionally, it was possible to verify hypothesis 2 – “The optimal range of bid modifiers for a DTA can be determined through a systematic testing process”.

As previously mentioned in section 5.3, the DTA and the standard optimization were directly compared in the study's final phase, V3. The custom campaign, which used DTA for optimization, generated a higher number of clicks and conversions, as well as an improved CVR, 21%, 54% and 28%, respectively, proving that the DTA was more effective in captivating customers into converting, or, in other words, purchasing advertiser’s A services. Therefore, confirming hypothesis 1 – “DTA can significantly improve the performance of display campaigns compared to standard optimization methods”.

Finally, the research revealed that the DTA can enhance the efficiency of display advertising. It offered convincing proof that a well-designed and successfully implemented DTA might outperform standard optimization, resulting in more effective marketing campaigns. The results of this study could have a positive impact on how digital marketers operate, especially in the display advertising space.

7. LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORKS

This research study, as any type of various other, has a couple of constraints which are necessary to point out. The major one is the truth that the research was performed just making use of one advertiser's data, Advertiser A, for both information gathering and performance analysis. Although this offered a solid basis to develop the DTA and examine its efficiency, it also indicated that the findings for may not apply to various other advertisers or sectors. It is essential to highlight that the DTA might differ depending upon details project attributes and with advertisers' goals.

An additional restriction is the collection of KPIs utilized to examine the project efficiency: Clicks, Conversions and CVR... Although these metrics are transversal to any type of programmatic campaign, they too meet the needs for this campaign and advertiser. There are various other metrics that can offer an extra understanding such as: CPC, Return on ad spend, Viewability Rate, Bounce Rate, Average Frequency, along with others.

It's also important to mention that this research study was also centered on a specific type of campaign, display advertising. Although this reveals several constraints regarding replicability to other types of projects, such as search, video, or social media, it also gives a strong base for future studies that wish to check DTA's performance in these channels.

Regarding future work recommendations, to better test the efficiency of DTA, more studies can be carried out on various advertisers, industries as well as channels, helping to provide a much more extensive understanding of the algorithm's versatility and applicability.

Also, future work could explore the usage of other metrics when evaluating the performance of the campaign. This would provide a comprehensive view of the campaign's performance and other benefits of using a DTA.

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