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A Comprehensive Framework for Assessing the Immediate Effects of Television Advertisements

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Abstract: Precisely quantifying the direct influence of television commercials on online traffic is a complex endeavors. An exhaustive analysis is essential for a comprehensive understanding of consumer reactions to television advertisements. Nevertheless, this phenomenon has not undergone thorough investigation thus far. Prior research has employed either basic statistical tests or case studies to examine the responses of certain demographic groups, such as toddlers or a particular age range, to advertisements, or simple regression models to evaluate the effects of advertising. This paper presents TV-Impact, a comprehensive framework that utilizes the Bayesian structural time-series model called CausalImpact, together with unique supplementary approaches. TV-Impact incorporates a sophisticated algorithm that effectively identifies control variables, specifically targeting data sources that are not influenced by TV advertising. In addition, the idea of Group Ads was suggested to merge overlapping advertisements into a unified framework. In order to isolate the combined influence into discrete advertising affects, a Random Forest Regressor, which is a type of supervised learning technique, was utilized.
The TV-Impact framework was utilized to analyze data from iLab, a Turkish venture firm responsible for managing advertising strategy for its linked businesses. The findings indicated that the TV-Impact model had a favourable impact on organizations' allocation of TV advertising budgets and led to an increase in website traffic. It effectively functioned as a decision support system.

Keywords - Television advertising, causal inference, counterfactual analysis, online session traffic, supervised learning, machine learning.

Introduction

Mass media outlets have aided as significant venues for marketers to attract client attention and advertise their products and services. Television advertising has been a favoured method for effectively reaching extensive audiences. Statista's projections for 2023 indicate that worldwide spending on TV and video advertising is expected to reach $325.2 billion, representing more than 30% of overall advertising expenditure across different platforms. Given that digital advertising growth in Turkey is somewhat slower, yet still accounts for approximately 50% of the market, it is particularly relevant to analyze the influence of television advertisements on online traffic.
Consumer impressions of television advertisements have changed as a result of changes in how people consume media, developments in technology, and variations in advertising methods. Therefore, it is essential for companies to comprehend the influence of television advertising campaigns in order to optimize their return on investment (ROI) and make well-informed decisions based on facts. Precisely evaluating the efficacy of television advertisements enables advertisers to determine which advertising effectively reach their intended audiences, improve brand responsiveness, generate sales, and achieve a positive return on investment. Measuring the impact of advertising is challenging due to the influence of other non-advertising factors, including everyday living dynamics, social and humanitarian events, seasonality, and other aspects. Notwithstanding these obstacles, data analysis techniques can offer useful insights into the efficacy of television commercials.

Motivation

The primary difficulty in assessing the influence of TV advertising is from television's status as an offline platform, yet the intended outcome is frequently evaluated using online traffic measures. In addition, there are various non-advertising elements that can impact web traffic patterns. The objective of our research is to isolate the precise influence of television advertising campaigns on the amount of traffic generated on a company's website. Our focus is on distinguishing the effects of different individual advertisement creatives while reducing any potential biases. In addition, our examination of the immediate, temporary impacts of advertisements may be affected by macroeconomic variables in unstable markets or other broader environmental indicators that can have comparable effects over shorter time frames.

The TV-Impact framework is a new way that we have developed to examine the cause-and-effect relationship between a company's television advertising campaigns and its internet traffic performance. It has gained significant recognition for its strong influence on the country's digital environment.
The objective of our research is to precisely measure the distinct influence of television advertisements by each organization, while differentiating them from the impacts of other advertising endeavors. The TV-Impact framework employs the Causal Impact model, which was initially created by Google. Causal Impact use Bayesian structural time series (BSTS) methods to forecast the impacts of actions, such as advertising campaigns, by creating several scenarios using control variables. BSTS models have been widely used in various domains, such as examining the connections between Bitcoin prices and economic indicators, exploring changes in COVID-19 vaccine effectiveness due to demographic shifts, investigating the consequences of long-lasting conflicts like the Taliban insurgency, and measuring the cannibalization effects caused by individual promotional activities.

Contributions
Prior research focused on assessing the influence of television advertising has primarily addressed the issue from social science viewpoints. Although these research included quantitative analysis, their main foundation was simple statistical tests applied to data collected from human surveys. Our research presents a substantial contribution to the field by introducing a thorough methodology for evaluating the specific effects of TV advertising campaigns on online platforms. This technique is innovative and has not been previously explored in this area. Additional significant contributions of our work encompass:

The document includes various essential elements:
1. Development of a Flexible and Comprehensive Framework: This framework is created to be easily used by all television advertisers. It includes thorough explanations of crucial data definitions, information flows, algorithm pseudocodes, and measurement methods for evaluating the immediate impact of television advertisements.
2. Application of the Causal Impact Model: This model is used to examine real-world TV advertising data, offering a reliable approach for assessing the influence.
3. Comparison of Measurement Methods: The research introduces and evaluates three different methodologies for quantifying the impact of television advertisements within the suggested framework.
4. Introduction of a New Procedure: This paper presents a new approach for selecting dynamic control variables in the Causal Impact model, which improves the accuracy of effect assessments.
5. Differentiating Group Ads from Individual Ads: This study examines the distinction between the combined effects of grouped advertisements ("Group Ads") and individual ads, clarifying their distinctive implications.

The subsequent segments are structured as follows:
Section 2: Presents a comprehensive analysis of the current body of literature on the influence of television advertising.
Section 3: Provides an elaborate account and examination of the dataset included in the study, elucidating essential terminology and concepts employed throughout the work.
Section 4: Provides a concise summary of the fundamental method and the suggested framework for assessing the effectiveness of TV advertisements.
Section 5: Provides a comprehensive account of the tests carried out and the data gathered throughout the investigation.
Section 6: Provides a concise summary of the research, highlighting the main findings and discussing the implications derived from the study.
This methodical technique guarantees a thorough examination and assessment of the direct effects of television commercials within a rigorous analytical framework.

Related Work
Prior studies on the impact of television advertising have employed diverse methodologies. The investigation conducted by Lodish et al. about the success of traditional advertisements revealed that increased budgets do not necessarily result in more sales. However, they discovered that making adjustments to brand messaging, creative execution, and media

strategies could prove advantageous. A separate study conducted a targeted analysis of infomercial advertisements, with 876 participants, to evaluate the impact of various elements such as product endorsements, celebrity endorsements, and product comparisons on consumer purchase behavior, with a specific focus on the influence of consumer age. However, it should be noted that this study was restricted to examining only this particular style of advertisement. Ansari and Joloudar conducted a study on the effectiveness of TV advertising in capturing attention, generating interest, creating desire, and motivating purchase behavior. They demonstrated this effectiveness by using control groups. However, they did not investigate the effects of these ads on digital platforms. In 2011-2012, Vaver and Kohler were the first to use geographic control groups to measure the impact of advertisements. They emphasized the importance of regularly re-evaluating the effects of ads.

Kitts et al. examined the delayed impact of TV advertisements on site traffic and keyword searches, demonstrating their rapid digital influence, which is a primary area of interest in our research. In addition, they coined the phrase "group advertisements" to refer to advertisements that are broadcast simultaneously across multiple TV channels, making it easier to analyze their combined effects.

Joo et al. discovered that user digital behaviors had the ability to influence TV ad campaigns, even with the rise of integrated marketing. They also examined click-through rates in addition to search frequency. Lewis and Rao examined the difficulties in evaluating the performance of advertising campaigns using controlled experiments, mostly because of the high expenses involved and the need to consider personalized sales data.

A study conducted by Liaukonyte et al. has established a strong correlation between television advertising and a rise in online buying. The research specifically investigates the influence of aspects such as advertisement content and location on this connection. Additional research examined the effects of television advertisements on online conversations and the role of exposure time on purchasing decisions, taking into account demographic factors.

Sinha et al. provided significant contributions by accurately predicting treatment effects using different control groups. However, they did not use feature extraction during non-ad periods or address the impact of group commercials.

Our study expands upon these discoveries by presenting a thorough "TV-Impact" framework that outlines the specific ways in which TV advertisements affect digital traffic and the combined effects of group advertisements. This enhances our comprehension of how traditional and digital advertising interact with each other.

Dataset

The datasets used in our investigation were provided by iLab. The data includes information from 11 distinct organizations, each operating in different areas and implementing distinctive advertising tactics. Two main data sources were used for each company:

i. Online traffic data, obtained straight from the website analytics of the respective company.

ii. TV commercial data, acquired from the advertising agency tasked with overseeing the company's television advertising campaigns.

iii. By merging these two crucial data streams from the varied group of 11 iLab organizations, we conducted a thorough research to investigate the correlation between TV advertising efforts and the subsequent web traffic patterns for each organization.

Internet-based information regarding the flow of vehicles and users on digital platforms.

Google Analytics is used to collect online traffic statistics for each company, with the data being accessed on January 18, 2024. This platform logs comprehensive session data for visitors to the organization's website and/or mobile application. Typically, every firm logs around 60,000 user sessions every day, combining data from both desktop and mobile platforms.

Sessions are classified according to their originating channel:

- Desktop Sessions: Categorized based on direct, organic, paid, and referral traffic sources.
- Direct Sessions: Visitors access the website directly by manually entering the URL or using a saved bookmark.
- Organic Sessions: Users discover the website by accessing unpaid search engine results.
- Sponsored Traffic: Visitors are sent to a website through sponsored adverts.
- Referral Sessions: These sessions are triggered when visitors interact with links on external sources such as blogs, news items, social media platforms, or partner websites. These sessions may arise from collaborative endeavors to share content.

- Mobile Sessions: Categorized based on the Android and iOS platforms to identify the origin of traffic coming from mobile devices.
Our methodology gives priority to analyzing these four primary types of desktop sessions because they are very common, but it may also be adapted to include other categories of traffic sources if necessary. Table 1 presents a sample depiction of the online traffic log data.

Table 1. Sample of online traffic logs collected from a company website. Logs are collected as number of sessions in four categories: direct, paid, organic, and referral.

Time	Direct Sessions	Paid Sessions	Organic Sessions	Referral Sessions
2 September 2023 00:00:07 UTC	0.0	1.0	1.0	0.0
2 September 2023 00:00:10 UTC	2.0	1.0	0.0	0.0
2 September 2023 00:00:26 UTC	1.0	0.0	1.0	0.0

We create a specialized dataset for each organization by employing the web traffic log data. The data preparation process encompasses the subsequent stages:
• Sessions are divided into 10-second intervals to reduce the presence of extraneous zeros in the raw session data. Statistical indicators, including the mean, median, and quartile values, are calculated based on traffic data collected over the previous 7, 15, 30, and 60 days. This method guarantees thorough research by catching instantaneous trends from shorter time periods and probable seasonal patterns from longer time spans. Utilizing these calculated metrics rather than unprocessed time-series data is essential for minimizing the influence of anomalies and precisely detecting patterns.
• Time intervals coinciding to the airing of the company's TV advertising are eliminated before doing statistical computations. This step guarantees that the obtained statistics accurately represent time periods that are not influenced by television commercials. The dataset designates these advertisement times as -1.
By employing these techniques, we acquire datasets that have been statistically improved for every organization that is assessed. Data preparation is performed daily on newly obtained data, and no imputation is required as there are no null values present. An external data team is responsible for overseeing the process of anomaly management in order to preserve the integrity of the raw traffic data, ensuring that it remains free from any abnormalities or inconsistencies. Each dataset consists of 63 attributes for every 10-second time interval.
The suggested architecture integrates web traffic information from external organizations as additional inputs for analyzing a particular company. Stringent verification procedures are employed to guarantee the precision and dependability of this supplementary company information, obtained from periods unaffected by promotional pressures. From now on, the term "online traffic data" will be used to describe the dataset that includes enhanced statistical information from all businesses.
TV-Ad Data
The secondary data source comprises advertising data that is methodically collected on a daily basis from the collaborative advertising agency that works with the companies. Due to the diversity in advertising techniques and varying durations of campaigns across different organizations, the average number of advertisements per company each day varies.
The dataset is especially cantered on television advertising and comprises 11 essential attributes for each aired advertisement, including the date, time, duration, TV channel, and the program in which the ad was shown. The TV ad data consists of 11 features.
By accurately aligning the additional TV advertising data with the related internet traffic, we can do thorough studies that establish a connection between the companies' television marketing campaigns and the observed patterns of online user behavior. Although online traffic data serves as the main input, this supplemental TV advertising data is crucial for conducting full analyses
It is worth mentioning that consecutive television advertisements may be aired one after another, which could result in lingering impacts from the previous advertisements. The temporal overlap of TV advertising within the same or a

relatively near time frame makes it challenging to distinguish their individual effects. In order to resolve this problem, our framework categorizes these ads that overlap with one other and considers them as a unified, elongated ad unit referred to as a "Group Ad." Conversely, commercials that do not share any time period with other advertisements are categorized as independent "Individual Ads."
The process of categorizing ads is made easier by establishing a measure called "advertising impact duration," represented as t. We conduct an analysis of each individual advertisement by examining the time period that starts at the commencement of the commercial and extends t minutes beyond its end time. When analyzing these specific time intervals for advertisements, if the intervals overlap, the related ads are combined into a Group Ad. Figure 1 presents a demonstrative instance in which the value of t is established as 4 minutes, and four consecutive advertisements are aired. An ad that is not followed by another ad within 4 minutes after it ends is classified as an Individual Ad. However, because to their overlapping 4-minute effect windows, the following three spots are combined into a single Group Ad unit.

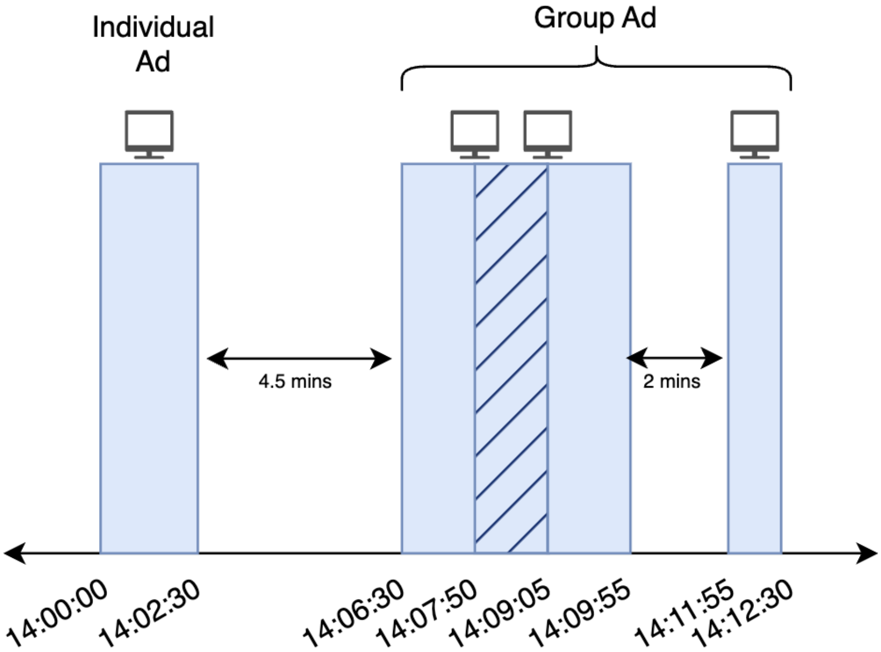


Figure 1 illustrates the representation of an individual advertisement and a group advertisement, each having a predetermined impact length of 4 minutes.

Methodology

a. *Analysis of Causal Inference*

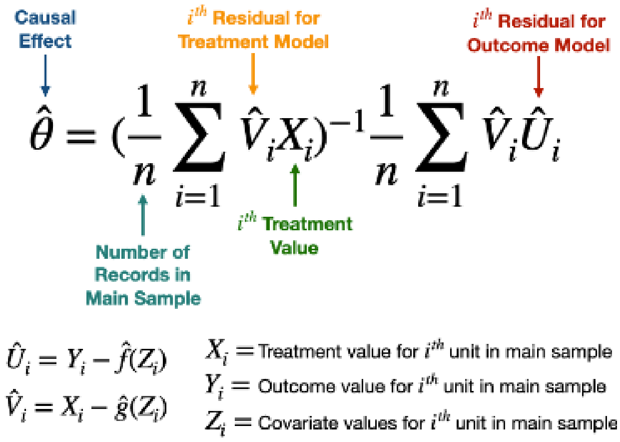
This part explores the examination of causal inference, providing a thorough explanation of the methodology and parameters used in the proposed framework.

Analysis of Causal Inference

This study utilizes causal inference methods to investigate the causal relationship between an intervention (event) and its future results. The evaluation of the impact of an intervention involves projecting a hypothetical scenario and then comparing it to the observed outcome. A counterfactual scenario refers to a hypothetical situation that depicts what would have happened if the intervention had not been put into effect. The chronology is partitioned into two discrete phases: pre-intervention and post-intervention. Pre-intervention data is utilized to construct a model that predicts the post-intervention period, establishing a reference point for comparison. Afterwards, the counterfactual scenario is compared to actual post-intervention data in order to assess the impact of the intervention.

The Causal Impact model

Causal Impact, created by Google, is a famous model for inferring causality. Bayesian structural time-series models are represented as state-space models that are governed by the following equations:



The model utilizes Markov Chain Monte Carlo (MCMC) sampling techniques to calculate the posterior distribution of states. Control variables are employed to assess the counterfactual situation in the absence of the treatment. The variables should exhibit a strong correlation with the target variable while remaining unaffected by the intervention. Prior to the intervention phase, the model acquires knowledge of the connections between control variables and the target variable, allowing it to make predictions about the predicted consequences after the intervention.

Purpose and Extent

Prior research, exemplified by the study conducted by Brodersen et al., has conceptualized advertising campaigns as treatments, assessing their efficacy by analyzing organic and paid clicks before and after the campaigns over a span of multiple weeks. Our study specifically examines the immediate effects of television commercials within shorter durations, such as minutes. This approach is crucial for reducing environmental biases that may arise over long periods and for accurately measuring the impact of advertising influenced by factors such as time of day, channel, and program content. In addition, doing short-term research allows for precise calculation of counterfactuals that are not influenced by television advertisements, hence preventing any overlap in the observed impacts of advertising across longer periods of time.

b. Determining the Immediate Impact of TV Advertisements

The TV-Impact framework consists of four separate stages, as depicted in Figure 2:

1. Data Preparation: Improves the quality and usefulness of online session data by using statistical calculations and removing periods that are influenced by advertisements, therefore ensuring the accuracy and relevancy of the data. Advertisements are categorized into two types: Individual Ads and Group Ads, as explained in Section 3.

The initial phase is vital as it establishes the basis for obtaining high-quality data inputs that are essential for following analytical phases within the framework. Effective data preparation enhances the accuracy and dependability of impact measurements generated during the whole TV-Impact process.

Figure 2 illustrates the process of the TV-Impact architecture.

The subsequent sections will examine two crucial domains: firstly, the procedure of choosing control variables for causal inference modelling; and secondly, the computation of TV advertisement effects, with a specific emphasis on the influence of TV advertising inside Group advertising.

Selection of dynamic control variables

The proposed method for selecting dynamic control variables involves computing the counterfactual, often using the pre-period data from a single company's advertising source. Depending exclusively on a single data source can pose problems if there are anomalies or external factors that influence the data. These factors can directly impact the counterfactual and lead to skewed assessments of the efficacy of the advertisement. Hence, it is crucial to integrate diverse data sources in order to mitigate these biases.

Our technique involves using data sources that are directly relevant to the advertisements, as well as incorporating external sanity checks on the advertisements. These sanity tests are based on proxy variables that should not be influenced by the advertisements themselves. These proxy variables offer broad and accurate samples of how consumers interact with and respond to advertisements on the internet, but they are not influenced by the specific commercials being studied. By adding these proxies, we guarantee that any biases associated with the advertising themselves do not overly impact the assessment of ad effectiveness.

More precisely, we provide proxies that are connected to how particular market segments might respond in distinct ways depending on demographic, socioeconomic, and geographic characteristics. We include proxies that are associated with how specific technologies/platforms can generate distinct user inclinations and clickstream patterns. In addition, we include temporal proxies that capture the evolving patterns of user responses to adverts.

Our proxy variables allow us to obtain a more fair and cautious assessment of the success of commercials, while reducing the influence of basic factors and trends in advertisement effectiveness. Our system offers the ability to easily include various proxy variables.

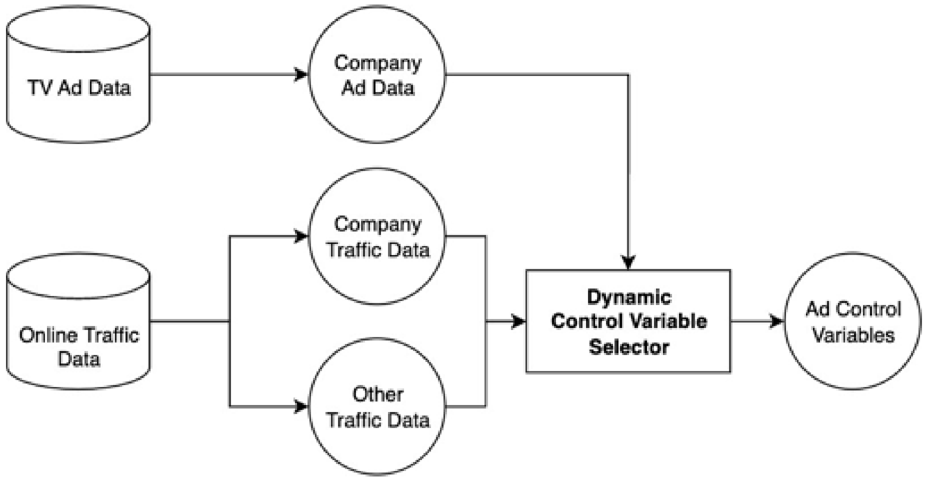


Figure 3. Selection of control variables for a specific company advertisement.

Dataset T is utilized to extract traffic data from the broadcasting corporation (target) as well as the remaining traffic data (ot) by utilizing the start and end periods of a TV ad obtained from dataset A. The correlation between each individual traffic data point (t) in the dataset (ot) and the target variable is computed. If the correlation is equal to or exceeds a predefined threshold (thr), t is included in the list of potential candidates. This operation is iterated for every occurrence of t. Afterwards, a predetermined number of variables with the highest correlation scores from the list of candidates are chosen as control variables.

Quantifying the Influence of Television Advertisements

Within this part, we will examine three separate methodologies for quantifying the impact of television commercials (Figure 4). One key approach entails computing the precise disparity between the real and hypothetical values. Nevertheless, this direct method has intrinsic difficulties within our analytical framework. If the projected counterfactual value is substantially greater than the actual value, it may erroneously imply a detrimental impact. TV commercials do not have a detrimental effect on online traffic. Additionally, the counterfactual takes into account small variations in session counts caused by intrinsic uncertainty, which can lead to misleading results by incorrectly attributing ineffectual increases to advertising.

In order to overcome the limits of this rudimentary method, we suggest three novel alternative expansions: pos_impact, cum_impact, and upper_impact.

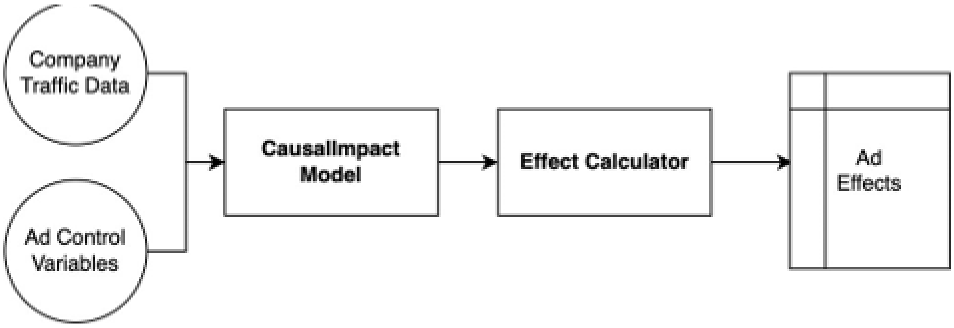


Figure 4. The flow of causal impact calculation of TV ads.

Group Ad Impacts Segregation

Group Ads are commonly seen as a unified and coherent advertisement when evaluating its influence. Nevertheless, given our particular circumstance, it is imperative to assess the distinct impact of every television advertisement. Hence, it is imperative to examine and isolate the consequences of Group Ads into distinct influences. In order to tackle this problem, we utilize a methodology that relies on artificial intelligence (AI), as depicted in Figure 5. During the initial step, a training set consisting of a dataset that includes the attributes and impacts of each unique advertisement is utilized. Within this framework, the affects are regarded as the outcome variable, while the qualities function as the predictor variables in the AI model. Table 3 illustrates these characteristics. Currently, a Random Forest Regressor (RFR) is being trained to forecast the impact of each particular advertisement.

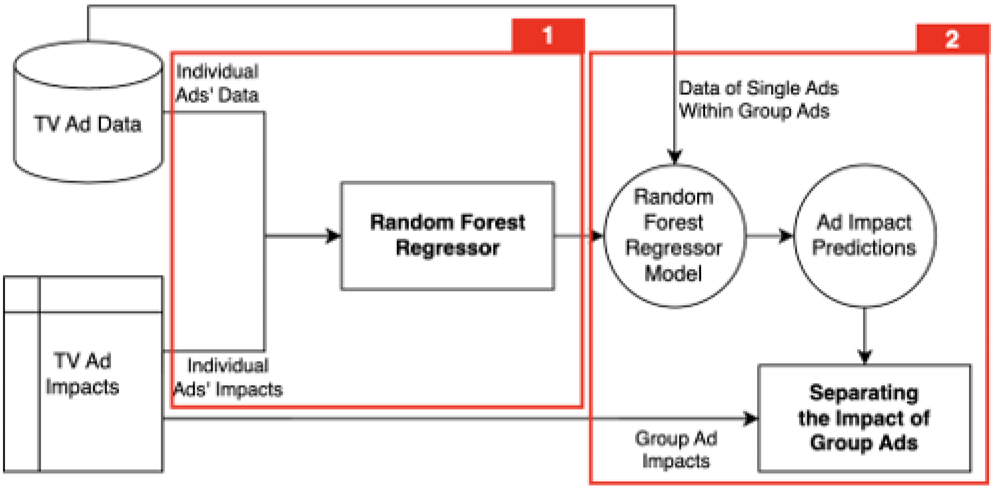


Figure 5. The flow of separating Group Ad impacts for the single ads within Group Ads.

In the second phase, the model generated in the initial step is employed to predict the impact of each individual advertisement comprising a Group Advertisement. The anticipated effect values function as coefficients to allocate overlapping impacts among the individual adverts.
Take, for instance, a Group Ad comprising of two separate commercials, as depicted in Figure 6. The advertisement impact is programmed to last for a length of 4 minutes. The impact is measured by the total number of unique sessions generated by a television commercial.
In Areas 1 and 3, where there is no overlap in influence within Group Ad, the effects assessed in these places are solely attributable to the individual ads themselves. More precisely, 30 sessions in Area 1 can be directly attributed to individual advertisement A, while 45 sessions in Area 3 can be linked back to individual advertisement B.
On the other hand, Area 2 has a noticeable overlap in effects. By employing the previously taught Random Forest Regressor (RFR), we can predict the influence of particular advertisements and allocate it in a proportional manner. Based on the predictions, advertisement A is expected to have an impact of 40, while advertisement B is expected to

have an impact of 60. However, the actual impacts of these commercials in the overlapping area are 20 for advertisement A and 30 for advertisement B. Therefore, the combined impact of the Group Ad, amounting to 125 sessions, is distributed as 50 sessions from individual ad A and 75 sessions from ad B.

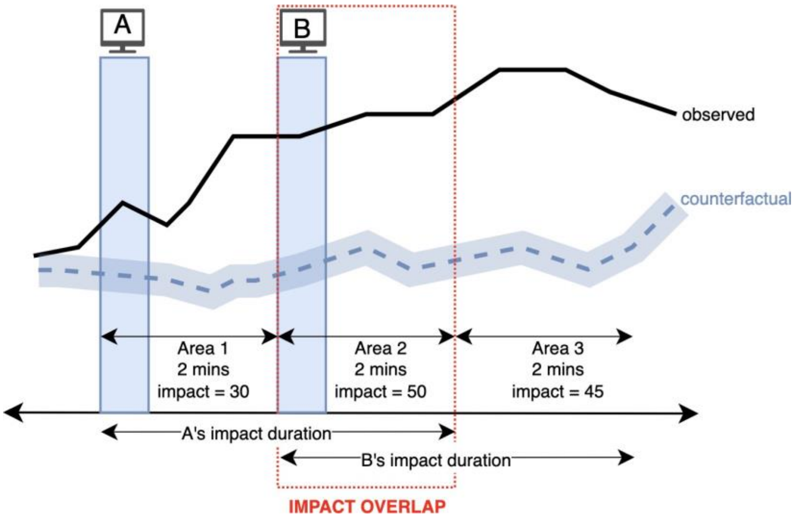


Figure 6 depicts the overlapping influence of two separate advertisements within a Group Advertisement.

Experimental Procedures and Findings

Data containing fictional advertising information.

Assessing the efficacy of the TV-Impact paradigm is difficult since there is a lack of dependable empirical evidence regarding the influence of TV commercials on online user sessions. Nevertheless, it is possible to evaluate time-series forecasting models that make predictions about hypothetical scenarios. As suggested in reference [4], the CausalImpact model can be assessed by modelling possible interventions. These interventions entail the collection of data from the target dataset without any external interference for a specified duration. For every hypothetical action, a counterfactual prediction is generated to simulate the result that would have occurred if the intervention had been implemented. The goal is to closely mimic the real outcome that would have occurred without the intervention. This approach enables meticulous fine-tuning of the parameters of the Causal Impact model in order to minimize error rates in the simulated intervention data.

Within our defined framework, we have isolated a subset of data from online sessions that excludes any impact from TV advertisements. This subset is referred to as Imaginary Ad Data. The data was derived from the comprehensive online traffic statistics of 11 partnering companies. This study specifically examines the Imaginary Ad data obtained from three carefully selected organizations, chosen based on the quality and quantity of their data. This research specifically analyses the data from these three companies, although there were similarities in the outcomes across all companies. The companies' identities are obscured and designated as Company 1, Company 2, and Company 3. The dataset being analyzed spans a period of 15 days and consists of a combined total of 472, 660, and 507 Imaginary Ads from the different companies. It is crucial to recognize that the insights and interpretations provided in this context are pertinent and applicable to all firms concerned.

Evaluation Metrics for Parameter Tuning

The ideal values for the framework parameters, \(t \) (limit) and \(\text{thr} \), are established by evaluating two fundamental error measures: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) values are computed using the following equations, where \(y \) denotes the actual values, \(\hat{y} \) denotes the hypothetical values, and \(n \) denotes the number of data points in the post-period.

Root Mean Squared Error (RMSE) is a mathematical measure used to evaluate the accuracy of a prediction model. It is calculated by taking the square root of the average of the squared differences between the predicted values and the actual values. The formula for RMSE is given by: \[\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i -

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\hat{y}_i)^2} \] where \(n\) The expression is the square of the difference between the actual value y_i and the predicted value $\hat{y}i$.

The Mean Absolute Error (MAE) is a metric used to measure the average absolute difference between predicted and actual values.The Mean Absolute Error (MAE) is calculated by taking the average of the absolute differences between the actual values (y) and the predicted values ($\hat{y}$) for a given dataset of size n.

Within our framework, the root mean square error (RMSE) number is 8, whereas the mean absolute error (MAE) value is 9. These metrics are employed to assess the precision of the counterfactual predictions and optimize the parameters \(t \) and \(\text{thr} \) in order to reduce prediction errors.

Root Mean Square Error:

The expression $\sqrt{(\Sigma(y - \hat{y})^2 / n)}$ can be simplified as 8.

Mean Absolute Error (MAE):

The formula \(\frac{\sum |y - \hat{y}|}{n} \times 9 \) computes the mean absolute deviation between the observed values \(y \) and the estimated values \(\hat{y} \), multiplied by 9 for scaling.

These error metrics evaluate the model's precision in depicting crucial data characteristics in the post-period. The framework settings were selected based on the objective of decreasing the error scores seen during the studies.

5.3. Parameters of the model

This section offers an elaborate elucidation of the parameters employed in the framework. The CausalImpact model was evaluated with multiple parameter values, and it was determined that the default values yielded the optimal outcomes. Thus, we adhered to the predetermined settings outlined in the library. The parameters pre_period and post_period were aligned with the ad impact duration (t) determined through experiments.

The Random Forest Regressor was developed using the scikit-learn package. The Grid Search hyperparameter selection technique was used to alter the values of the parameters n_estimators and max_depth to 500 and 15, respectively. The remaining settings were maintained at their default values.

Furthermore, the crucial parameters of the framework, namely the correlation threshold (thr) and the constraint on control variables (limit), were determined through a series of experimental assessments.

Duration of Advertising Impact (t)

When seeking the optimal value of the t parameter, one can explore multiple t values. However, when the value of the parameter "t" is increased, there is a higher overlap between the durations of subsequent ad hits, resulting in an increased frequency of Group Ads. Table 4 illustrates a negative correlation between higher t values and the average number of individual advertising made. Additionally, it shows a positive correlation between higher t values and the frequency of ads inside Group advertising.

Table 4. Average TV Ad distribution statistics for different *t* values.

t	Avg. Individual Ad Count	Avg. Group Ad Count	Avg. Number of Ads per Group Ad
2	86.07	70.02	3.15
3	54.87	66.60	3.76
4	38.20	56.13	4.77
6	22.33	42.00	6.82

The current scenario adversely affects the system as the reduction in the number of individual advertisements has a detrimental effect on the performance of the model employed to discern the influence of group advertisements. Hence, our research focused on analyzing t values of 2, 3, 4, and 6, while disregarding values that were higher.

Individualized advertisements were generated for each company in the Imaginary Ad Data, utilizing various t values. Subsequently, forecasts were established for the post-period. Considering the fact that these advertising are fraudulent, it was expected that the model's predictions would closely align with the actual results. The RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) scores were used to quantify the model's prediction error. Table 5 indicates that the t values corresponding to 4 and 6 minutes had the lowest error rates. After analyzing the ratio of individual and group ads displayed in Table 4, we have concluded that a 4-minute duration is the optimal length for our framework to exert an impact on commercials.

Table 5. RMSE and MAE scores of Imaginary Ad post-period predictions for different *t* Values.

Metric / *t*	Company 1		Company 2		Company 3	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
2	8.91	7.04	10.09	8.69	7.79	6.16
3	12.00	9.79	8.89	7.10	7.77	6.01
4	8.84	7.02	11.87	7.62	6.95	5.55
6	9.41	7.78	7.82	6.20	6.32	5.09

The correlation threshold (thr) and control variable limit (limit)

As elucidated in Section 4.2.1, control variables employed for counterfactual prediction must have a connection with the target variable and be constrained in quantity. An inquiry was conducted on the Imaginary Ad Data to ascertain the optimal values for the thr and limit parameters. The trials examined various thresholds and limit levels across three distinct companies.

Given that the prediction errors obtained from both the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) techniques yielded similar outcomes, we will focus on the RMSE scores for a more comprehensive evaluation of post-period forecasts. For more specific information, please consult Table 6. Company 1 and 2 attained the most advantageous results with a thr value of 0.5, whilst Company 3 achieved optimal outcomes with a thr value of 0.6. By specifying a limit parameter of 5, the performance of Companies 1 and 3 was enhanced, whereas a limit of 3 was deemed optimal for Company 2.

Based on these findings, the framework was modified to include a minimum parameter value of 0.5 and a maximum limit of 5. This update enhanced the model's capacity to precisely predict outcomes for the evaluated companies.

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Table 6. RMSE scores of Imaginary Ad post-period predictions for different *thr* and *limit* values.

thr / *limit*	Company 1			Company 2			Company 3		
	0.4	0.5	0.6	0.4	0.5	0.6	0.4	0.5	0.6
3	6.45	6.32	6.59	7.45	7.36	7.67	7.87	7.47	5.76
5	6.54	6.19	6.56	8.08	7.64	7.82	8.32	7.53	5.71
10	7.57	6.28	6.58	8.65	7.73	7.78	9.00	7.61	5.83
15	8.61	6.51	7.26	9.67	7.79	7.78	9.28	7.54	6.21

Overall Evaluation

After establishing the parameters, we proceed to utilize our TV-Impact framework to uncover the connections between advertising qualities (such as channel, program, time, etc.) and their corresponding consequences. It is crucial to recognize that the optimization of marketing campaigns and negotiation of transactions are ongoing and ever-changing processes. Potential overlaps between consecutive adverts from the same company may occur due to newly established agreements made throughout an advertising campaign. The Group Ad technique we employ tackles the issue of brief intervals between successive advertisements from different organizations. Evaluating the precise effects of advertising decisions becomes challenging when commercials from the same company are presented on the screen for varying durations.

Furthermore, the selection of evaluation criteria, such as the quantification of online sessions, presents its own distinct challenges. The choice of an evaluation metric depends on specific factors that go beyond the scope of advertising. Therefore, conducting this evaluation involves a distinct endeavor that surpasses the construction of the structure. While we do not provide an extensive evaluation technique in this study, we suggest assessing the efficacy of the TV-Impact framework by comparing the monthly session count of the current year with that of the previous year, while considering any seasonal variations. Company 1 saw an average increase of 41.5% in online session numbers compared to the previous year, while also experiencing an average decrease of 42.5% in advertising expenses per advertisement. Although the other two companies also saw a decrease in advertising spending, their web session numbers also decreased. It is important to note that a significant earthquake disaster occurred in Turkey during the study period, which likely had significant effects on the marketing and advertising businesses. Therefore, the greater decrease in spending compared to the decrease in session numbers could be seen as a positive sign. As mentioned earlier, determining the impact of advertisements on individuals can be quite challenging due to the multifaceted influence of various life events on people's behavior. Thus, in accordance with the recommendations of the advertising department, we give priority to the indicator of "Spending per Ad." All three firms experienced a decrease in this statistic, which suggests that the TV-Impact approach was successful.

Furthermore, the absence of a comparable standardized framework in the existing corpus of research hinders the ability to make direct comparisons with other studies. Our proposed TV-Impact technique accurately quantifies the direct influence of TV commercials on web traffic. This success is noteworthy, given the absence of a clear and measurable connection between television broadcasts and the volume of internet traffic on company websites. Moreover, any changes in an individual's life circumstances might significantly influence their behavior, therefore making it extremely challenging to differentiate the effects of advertisements on them. Therefore, our system is an innovative undertaking in quantifying the immediate impact of television commercials, supported by comprehensive experimental verification.

Table 7. Yearly change in number of sessions and spending per ad for three companies.

Company	Change in Number of Session	Change in Spending per Ad
Company 1	+41.45%	−42.59%
Company 2	−11.10%	−69.74%
Company 3	−23.03%	−46.21%

Conclusion

Traditionally, while evaluating the efficiency of advertisements in the social sciences, researchers have focused on analyzing marketing dynamics and customer behavior. Multiple prominent studies have thoroughly investigated the influence of television commercials on various factors, such as alcohol use patterns, dietary choices in early childhood, eating behaviors, brand establishment, and audience perspectives. The study introduces TV-Impact, a novel methodology that use machine learning methods to precisely quantify the immediate impact of TV commercials on concurrent internet traffic for the promoted brand. This framework accurately examines the internet traffic of the advertising company immediately following the display of the advertisement.

Quantifying such an impact is challenging due to the multitude of factors that shape individuals' behavior, including prevailing trends and contemporary circumstances. To address this challenge, we employ the Causal Impact methodology, which was initially created by Google and relies on Bayesian time-series analysis. This approach analyses the behavior of particular variables that are anticipated to remain constant due to the advertisement and then compares them to the actual outcomes following the advertisement. The approach demonstrates the effect of the advertisement by analyzing statistical disparities between the control variables and the real-time series signal following the occurrence of the event. The efficacy of the model is heavily reliant on the selection of appropriate control variables. Our TV-Impact framework streamlines the selection of optimal control variables through the use of a dynamic algorithm. This program employs data derived from adverts and website visits of external businesses. TV-Impact underwent testing utilizing data provided by iLab, a Turkish investment company with 11 subsidiary companies. Throughout the testing process, it effectively determined and measured the influence of every company's advertisement.

A further issue came when adverts from many companies were simultaneously broadcasted, leading to interference with our data. To tackle this problem, we introduced the concept of 'Group Ad,' which involves the rapid succession of multiple adverts, each with subtle and delayed effects. We adopted a supervised learning approach utilizing the Random Forest algorithm to distinguish between the impacts of Group Ads and individual ads. This method effectively differentiated the effects of individual and overlapping adverts within our TV-Impact framework.

Evaluating the efficacy of TV-Impact was hindered by the absence of a preexisting frame of reference for comparison. Moreover, the prolonged duration of advertising campaigns results in the amalgamation of one advertisement's impact with that of another. Hence, our primary goal was to develop a framework that could precisely detect and measure the impacts of advertising. In order to evaluate the effectiveness, we performed a comparative analysis between the outcomes obtained utilizing TV-Impact and the results from the corresponding months of the previous year, when our framework was not in use. Furthermore, we assessed the cost-effectiveness of commercials by comparing the expenditure per online session before and after the introduction of TV-Impact, as recommended by the marketing department. The investigation demonstrated that TV-Impact resulted in a reduction in spending per session.

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