Dynamic Evaluation of Online Advertising with Randomized Experiments: An Aggregated Approach

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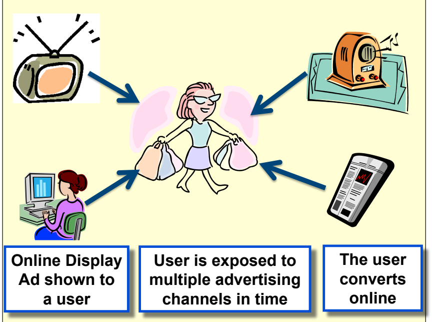
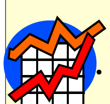
Introduction

- Online Marketing Campaign evaluation has received a great amount of attention by the research community and industry recently.
- The estimation of the incremental effects of advertising campaigns under the presence of other channels represents the attribution challenge.



- The use of randomized experiments, also known as A/B testing, has demonstrated to be effective to evaluate marketing campaigns without over-estimating their effects [4, 2].
- These methods require a time window where users are tracked and the measures of interest are collected. As a result, the estimation is aggregated for that time window.

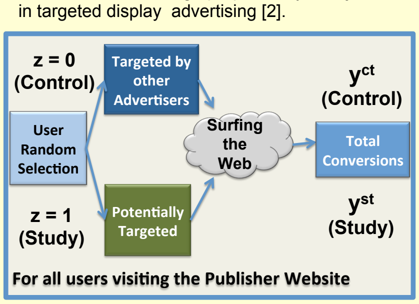
This aggregation is a limitation as often sales are affected by seasonal effects. Thus, detecting when the campaign is more effective provides more insight to understand and improve the campaign.



- We propose a time series approach to estimate the effects of marketing campaigns on the daily number of sales or conversions
- In previous work, we developed a method to estimate these effects without randomized experiments [1].
- In this approach, we incorporate an accurate baseline to draw causal conclusions from the randomized experiment.

Randomized Experiment Design

- We consider the design proposed by Barajas et al. in targeted display advertising [2].



- We condition the analysis to all the users visiting the publisher websites where the users can be potentially targeted
- We randomize the users before any decision has been made in the targeting process.
- As randomization rule, we use the last two digits of the birth timestamp of the user cookie.
- We aggregate the daily number of conversions over all the users and consider these sales time series for the control and the study groups.

Methodology

- We decompose the control and study conversion time series jointly into weekly and trend components using Dynamic Linear Models (DLM) [5].
- We infer the daily mean causal effect as the sales trend differences between both series.

$$\underbrace{\text{Sales Series (Control)}}_{} = \text{Background base model} + \text{Trend model (Control)}$$

$$y_t^{ct} = \overbrace{F'^{(0)}\theta_t^{(0)}} + \overbrace{F'^{(tr)}\theta_t^{ct(tr)}}$$

$$\text{Sales Series (Study)} = \text{Control Sales Series State} + \text{Trend Difference (Attribution)}$$

$$y_t^{st} = \overbrace{F'^{(0)}\theta_t^{(0)} + F'^{(tr)}\theta_t^{ct(tr)}} + \overbrace{F'^{(tr)}\theta_t^{st(tr)}}$$

y_t^{ct} = Number of Sales at Day t (Control)
y_t^{st} = Number of Sales at Day t (Study)
$F^{(0)}, F^{(tr)}$ = Base, Trend DLM Obs Matrix
θ_t^{0} = Any DLM State Background Model
$\theta_t^{ct(tr)}$ = State Trend Model (Control)
$\theta_t^{st(tr)}$ = State Trend Difference (Attribution)

- **This model can be written as a 2-D DLM:**

$$Y_t = F'\theta_t + \nu_t \qquad \nu_t \sim N(0, V)$$

$$\theta_t = G\theta_{t-1} + w_t \qquad w_t \sim N(0, W)$$

$$Y_t' = \left[y_t^{ct}, y_t^{st}\right] \quad \theta_t' = \left[\theta_t^{ct(tr)}, \theta_t^{st(tr)}, \theta_t^{(0)}\right]$$

$$F' = \begin{bmatrix} p(z=0) & 0 \\ 0 & p(z=1) \end{bmatrix} \times \begin{bmatrix} F'^{(tr)} & 0 & F'^{(0)} \\ F'^{(tr)} & F'^{(tr)} & F'^{(0)} \end{bmatrix}$$

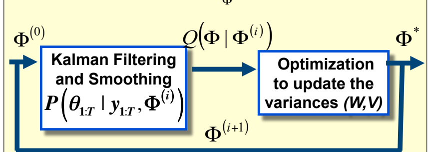
- ***F***$^{(tr)}$ and ***F***$^{(0)}$ are set to model a random walk trend and a weekly seasonal components.
- ***G*** is constructed as the superposition of these basic components.
- ***P(z)*** is known from the experimental design

Model Fitting

- We find the MLE of the variances $\Phi = (V, W)$ through the EM algorithm [3] and smooth the series to analyze the trend component.

E-step: $Q\left(\Phi \mid \Phi^{(i)}\right) = E_{\theta_{1:T}|y_{1:T},\Phi^{(i)}}\left[\log P\left(\theta_{1:T} \mid y_{1:T}, \Phi\right)\right]$

M-step: $\Phi^{(i+1)} = \arg\max_{\Phi} Q\left(\Phi \mid \Phi^{(i)}\right)$



- Given the ML estimates {V*,W* }, we smooth the time series to find the expected causal trend difference attributed to the campaign.

Results

- We find the causal lift (CL_t) as the percentage change in sales trends, due to the campaign:

$$CL_t = 100 \times \frac{F'^{(tr)}\theta_t^{st(tr)}}{F'^{(tr)}\theta_t^{ct(tr)}}$$

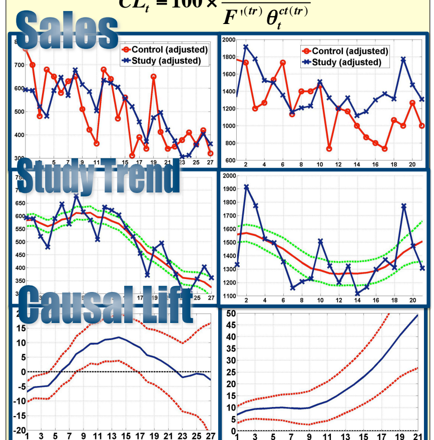


Figure: Dynamic Attribution for: campaign 1 (left), and campaign 2 (right)

- We observe positive and negative effects for campaign 1 at different times.
  - This campaign shows immediate effects. At the beginning of the experiment users wait to buy, probably to survey the competition. Then, campaign effects peak to gradually fade to the prior-campaign sales level.
- Positive effects are clear from the observed data towards the end of the series for campaign 2.
  - This campaign shows delayed effects after the campaign is finished.

Method	Campaign 1			Campaign 2		
	Low	Med	High	Low	Med	High
MCL - Trend	1.31	3.11	4.91	17.03	19.47	21.90
MCL - Raw	-5.03	1.31	7.65	8.29	14.50	20.71

Table: Mean attribution lift (%) estimated from the trend differences (MCL-Trend) and the raw data (MCL-Raw)

- **MCL-Raw** is noisier than **MCL-Trend** and does not provide any insight about the time when the campaign is more effective.

Discussion and Current Work

- We have presented a time series approach to attribute trend differences to marketing campaigns with causal estimates based on randomized experiments.
- The approach we have presented is an aggregated analysis over users.
- As on-going work, we will incorporate the series of the number of users exposed to the campaign.
- We will model these user visitations and exposures as time series in a joint distribution.

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References

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