Online Display Ad shown to a user

User is exposed to multiple advertising channels in time

The user converts online

- The online display ad is shown to a user, which triggers 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 user 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 randomization 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].
- For all users visiting the Publisher Website

For users visiting the Publisher Website

- We condition the analysis to all the users visiting the publisher websites where the users can be 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 for 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.

\[
Y_t = F_t \Theta_t^{(s)} + F_t \Theta_t^{(c)} + \nu_t, \quad \nu_t \sim N(0,V)
\]

\[
\Theta_t = \Theta_t^{(s)} \Theta_t^{(c)}
\]

\[
Y_t = \left[ y_t^{(s)}, y_t^{(c)} \right], \quad \Theta_t = \left[ \Theta_t^{(s)}, \Theta_t^{(c)} \right]
\]

\[
F_t = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \times \begin{bmatrix} F_{t}^{(s)} & 0 \\ F_{t}^{(c)} & F_{t}^{(c)} \end{bmatrix}
\]

- \(F^{(s)}\) and \(F^{(c)}\) 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: \(Q(\Phi | y^{(i)}) = E_{\Theta^{(s)},\Theta^{(c)} | y_{1:T}} \log P(\Theta^{(s)}, \Theta^{(c)} | y_{1:T}, \Phi)\)

M-step: \(\Phi^{(i+1)} = \arg \max Q(\Phi | y^{(i)})\)

Kalman Filtering and Smoothing

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

Results

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

\[
CL = \frac{F^{(s)} - F^{(c)}}{F^{(s)}}
\]

- 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.

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 our 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.

References


Acknowledgements

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

<table>
<thead>
<tr>
<th>Method</th>
<th>Campaign 1</th>
<th>Campaign 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>MCL-Raw</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>MCL-Trend</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>MCL-Raw</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>MCL-Trend</td>
<td>Low</td>
<td>Low</td>
</tr>
</tbody>
</table>

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