Google

Advanced Digital Signal Processing

A digital marketing application

Umberto Poschi - Head of Search Sales, Data Science & Business Insights

Lara Tulipano - Analytical Consultant

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Some marketing basics and our use case

Objective

One of the most used methodology to measure the impact of an intervention relies on qualitatives and Pre-post analyses with several limitations.

The objective of this project is to find a more solid measurement solution to identify whether or not a specific intervention impacted client's performance and quantify this impact.

Marketing Problems

An important problem in marketing is to understand if a specific feature implementation, product adoption or optimization has an incremental effect on an outcome metric over time.

We would like to present a very common case in digital advertising.

But let's start with some basic definitions...

Marketing KPIs

- **Cost**
  How much an advertiser is spending on the Google properties

- **Clicks**
  How many user clicks an ad receives

- **Conversions**
  A specific action completed by the users relevant for the advertiser business (e.g. an online purchase for a retailer, a booking for a travel agency, ...)

Automated Bidding tools

All the new ways to connect online are giving marketers a wide range of opportunities to reach customers.

Considering all these new touchpoints, however, can be a nightmare if a marketer have to manually adjust its budget allocation and settings to match every single mix of signals (e.g. time, device, browser, language, ...)

The **Automated Bidding tools [AB]** use machine learning algorithms to quickly analyze millions of signals and proactively set real-time, granular adjustments.

Our use case

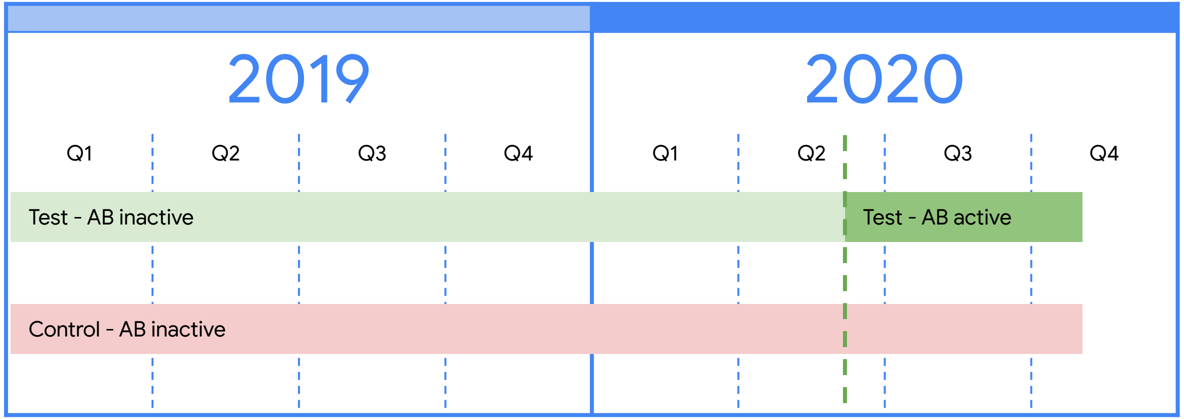
A retail company implemented the AB tool in a certain date (2020-06-03).

We would like to understand the impact of the AB implementation on digital performance KPIs like cost, clicks and conversions.

Design Ideas

Design:

- **Test group:** the KPI trend (time-series / signal) of the advertiser that implemented AB in a certain date (2020-06-03).
- **Control group:** the same KPI trends of other advertisers in the Retail market with no AB implementations for the full analysis time range
- **KPIs:** cost, conversions, clicks



Some notes on terminology

- **KPI Trend:** the KPI track, represented by $x_k(t)$ for the k^{th} company, where the number of tracks is $k = 0, 1, 2, \ldots, K$, and t is a discrete variable that denotes the time samples in working days.

Model I

The individual evolution of the KPI track for the kth company is represented by $x_k(t)$, and the number of tracks is $k = 0, 1, 2, ..., K$, where t is a discrete variable that denotes the time samples in working days. Each of the KPI track is affected by seasonal activity, e.g., summer or winter is more or less active. Furthermore, each trace can change its properties as consequence of marketing instances (e.g., product or brand promotion, etc) occurring at a set of times $T_{k,n}$, the behavour of $x_k(t)$ is a combination of these instances:

$$x_k(t) = \bar{x}_k(t) + \sum_n g_{k,n}(t - T_{k,n})$$

where $g_{k,n}(t)$ is a causal signature, dependent on the specific instance. Signatures are typically linearly growing as $g_{k,n}(t) \simeq \alpha_{k,n} t$ for a certain time interval after the instance in $T_{k,n}$.

Model II

$$x_k(t) = \bar{x}_k(t) + \sum_n g_n(t - T_{k,n})$$

The temporal values of the instances $T_{k,n}$ is known only to the kth company, and not known to the others. The asyncrony of these instances make each signature $x_k(t)$ non stationary random sequence. The tracks $x_0(t), x_1(t), \ldots, x_K(t)$ are mutually correlated as purposely selected to belong to same retail sectors. This means that, on the average, one can state that $E[x_k(t)x_\ell(\tau)] \neq 0$, and thus the tracks are predictable each other up to a certain degree.
Notice that the presence of instances makes the predictability be affected by the instances.

Model III

Exercises

Let $x_0(t)$ be the track of interest, and all the other tracks $(k \neq 0)$ are called control tracks. Goal is to estimate

$$\hat{x}_0(t) = f[x_1(t), x_2(t), ..., x_K(t)]$$

and it's uncertainty $\sigma_k(t)$ for $t \geq T_{0,\bar{n}}$ with the goal to estimate the unpredictable instance $\alpha_{0,\bar{n}}$

- Problem #1: use a Bayesian linear estimator for $f[.]$ and obtain the covariance of the predictions vs $t \geq T_{0,\bar{n}}$ assuming that all the control tracks $x_1(t), x_2(t), ..., x_K(t)$ are not affected by the respective instances (i.e., there is no instances on $x_1(t), x_2(t), ..., x_K(t)$);
- Problem #2: assume that the control tracks $x_1(t), x_2(t), ..., x_K(t)$ are themselves affected by respective asynchronous instances, propose a method to still design a Bayesian linear estimator for $f[.]$ and obtain the covariance of the predictions vs $t \geq T_{0,\bar{n}}$
- Problem #3: define a method to detect the instances times $\{T_{k,n}\}_{k=1}^{K}$ for the competing companies $k = 1, 2, ..., K$ of $k = 0$, and redesign the Bayesian linear estimator for $f[.]$ and obtain the covariance of the predictions vs $t \geq T_{0,\bar{n}}$

Our Model

How Causal Impact works

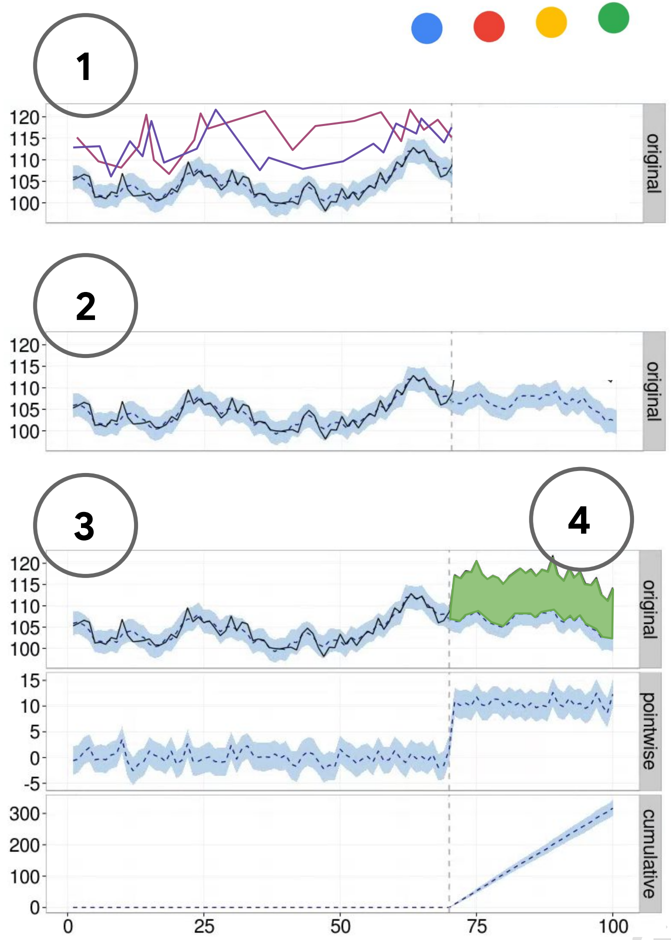
For any of the KPIs:

1. Based on a training period, the model identifies **which are the best predictors of the test time-series** in the control group

2. Using those predictors, it **forecasts the expected trend of the metric** for the test time-series

3. It then **calculates the difference between this estimate and the actual performance of the test time-series** (and the probability that this difference is given by chance)

4. The green shaded area (Test minus Prediction) and the **cumulative trend** is the impact of the intervention



Causal Impact Setup

We tested several settings in order to make sure results were consistent

Parameter	Test 1	Test 2	Test 3
PrePeriodStartDate	2020-01-01	2019-01-01	2019-01-01
PrePeriodEndDate	2020-04-15	2020-04-15	2020-04-15
PostPeriodStartDate	2020-06-04	2020-06-04	2020-06-04
PostPeriodEndDate	2020-10-15	2020-10-15	2020-09-01
Alpha	10%	10%	10%
NSeasons	7	7	7
SeasonDuration	1	1	1
NIter	1000	1000	1000

PrePeriodStartDate: the starting date of your data, both for test and control group.

PrePeriodEndDate: the date in which the impact happened.

PostPeriodStartDate: the starting date of the "forecasting" period, post impact.

PostPeriodEndDate: the ending date of the post impact period.

Alpha: α is the significance level. This means that for a significance level of α you obtain a confidence interval I1−α.

NSeasons: is the period of the seasonal components. 1 means no seasonal component is used. 7 a daily seasonal components, 365 a yearly seasonal components.

SeasonDuration: is the duration of each season.

NIter: number of MCMC samples to draw. Default to 1000.

Causal Impact Results

We tested several settings in order to make sure results were consistent

KPI	Test 1	Test 2	Test 3
Conversions	↑	↑	↑
Clicks	↓	↑	↑
Cost	↓	↑	↑

In every scenario, the model estimated a significant conversions increase for test versus the control group, therefore we can conclude they obtained an higher volume of conversions thanks to the implementation of AB.

PrePeriodStartDate: the starting date of your data, both for test and control group.

PrePeriodEndDate: the date in which the impact happened.

PostPeriodStartDate: the starting date of the "forecasting" period, post impact.

PostPeriodEndDate: the ending date of the post impact period.

Alpha: α is the significance level. This means that for a significance level of α you obtain a confidence interval $I1-\alpha$.

NSeasons: is the period of the seasonal components. 1 means no seasonal component is used. 7 a daily seasonal components, 365 a yearly seasonal components.

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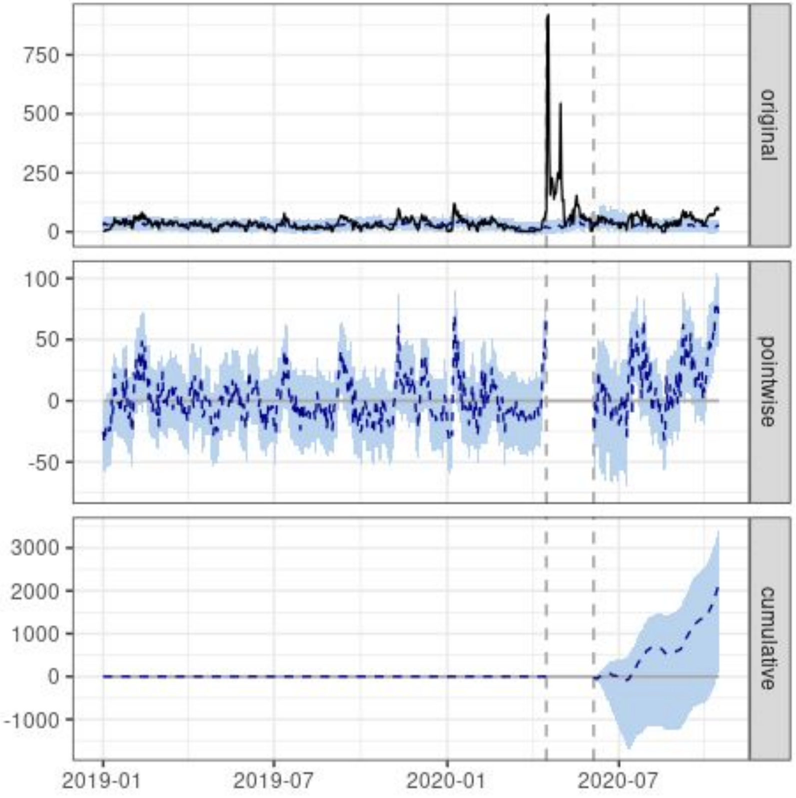
Results for Conversions



Those results show

a conversions increase of +37%

for test versus the control group with a high statistical confidence (minimum effect 27%, average effect 37%, max effect 51%).

During the post-intervention period, the response variable had an average value of approx. a. By contrast, in the absence of an intervention, we would have expected an average response of b<a.

The **probability of obtaining this effect by chance** is very small:

Posterior tail-area probability p (p-value): **4%**

Posterior probability of a causal effect: **96%**

This means the causal effect can be considered statistically significant.