Estimating Marketing Uplifts as Heterogeneous Treatment Effects with Meta-learners

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1 Context

Marketing can be defined as a set of techniques to study a company's business strategy with regard to the market. Among these techniques, Mix Marketing Modeling (MMM) is used to optimize the commercial strategy maximizing the sales volume. MMM consists in modeling the contributions, called uplifts, of each marketing activity to the sales revenue. The goal is to estimate the Return On Investment (ROI) of the numerous marketing campaigns to decide on the next marketing plan.

As illustrated by Diemert et al. [3], uplift modeling can be formalized as an Individual Treatment Effect (ITE) estimation. In practice, directly computing an ITE is impossible because one individual can only be treated or non-treated and not both at the same time. Hence, the Conditional Average Treatment Effect (CATE) is considered.

In marketing, treatment variables can be binary (e.g., availability product indicator), categorical (e.g., products under promotion), or even continuous (e.g., media investment). Hence, considering non-binary treatments, also called Heterogeneous Treatment Effects, is necessary. Estimating such effects is still an active research topic.

2 Problem

Numerous methods and algorithms have recently been developed [2] to estimate CATEs. Meta-learners seem to be interesting estimator candidates as they constitute a non-parametric and model-agnostic family of methods. However, they are complicated to implement in the case of non-binary treatments.

Acharki et al. [1] already compared the different meta-learners from a theoretical perspective. They also carried out experiments on a semi-simulated dataset inspired by a drilling use-case. We are interested in investigating the generalization of these experimental results to other applications, particularly marketing.

Questions: Are Acharki et al. [1] results applicable on the provided marketing data? How can the differences observed be explained?

3 Challenge

3.1 Data

A semi-simulated dataset in accordance with hypotheses taken in Acharki et al. work [1] has been created. The dataset is composed of five variables:

- *Nb_stores*: the number of stores, integer positive variable
- *Price*: the average price of the studied products, real positive variable
- *Covid-19*: the Covid-19 regulation intensity measure, ordered categorical variable
- *Seasonality_trend*: the average week seasonality trend with regards to the sales, ordered categorical variable
- *Revenues*: the revenue generated by the sales of the studies products in all the stores during one week given the Covid-19 context, real positive variable. Ignoring the noise, the revenues are defined as following:

$$\textit{Revenues} \propto \frac{\textit{Nb\_store} * \textit{Price} * \textit{Seasonality\_trend}}{\textit{Covid-19}}$$

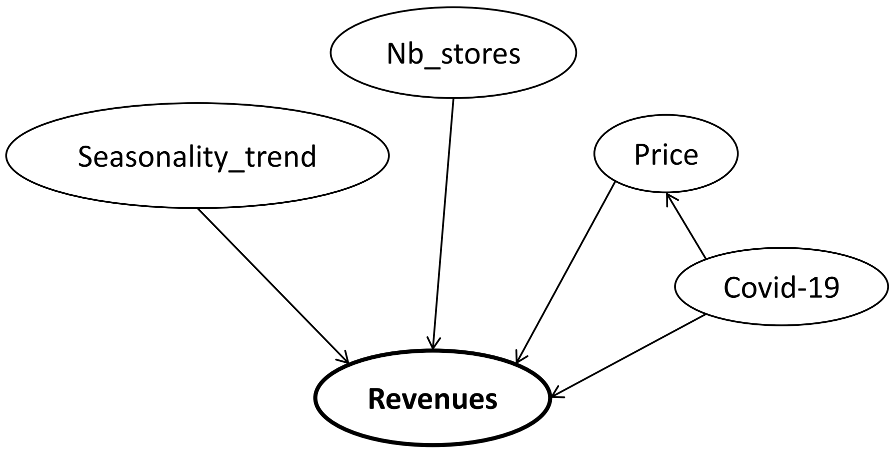

Figure 1: Causal graph

The causal dependencies linking the variables are described by the causal graph in Figure 3.1. Based on the data generation process that has been used, causal sufficiency (i.e., there is no hidden confounder) and no selection bias assumptions can be made.

3.2 Methods

As mentioned in Section 2, we suggest to focus on meta-learners: S-learner, T-learner, X-learner, DR-learner, R-learner, Domain Adaptation learner (also known as M-learner or PW-learner).

All these methods are available in *Python* in the EconML[1] library and in *R* using Acharki et al. [1] code[2].

[1] https://econml.azurewebsites.net/spec/estimation/metalearners.html
[2] https://github.com/nacharki/multipleT-MetaLearners/tree/main

3.3 Expected results

Deliverables: one presentation anwsering the questions presented in Section 2 + the developed code

The presentation should contain a brief description of the context and objective, a detailed presentation of the comparison of the new results to Acharki et al. [1] ones, and, a study of possible explanations for the differences observed. In this last section, any analysis is welcome, whether theoretical, experimental (e.g., running further tests on simulated data) or through the literature.

The work will be evaluated from a research perspective. More specifically, particular importance will be given to scientific reasoning, interpretation of the results, and reproducibility and repeatability of the experiments carried out.

The code is expected to be well-documented.

References

[1] Naoufal Acharki, Josselin Garnier, Antoine Bertoncello, and Ramiro Lugo. Comparison of meta-learners for estimating multi-valued treatment heterogeneous effects, 2023.

[2] Alberto Caron, Gianluca Baio, and Ioanna Manolopoulou. Estimating Individual Treatment Effects using Non-Parametric Regression Models: a Review. *Journal of the Royal Statistical Society Series A: Statistics in Society*, 185(3):1115–1149, 2022.

[3] Eustache Diemert, Artem Betlei, Christophe Renaudin, and Massih-Reza Amini. A Large Scale Benchmark for Uplift Modeling. In *KDD*, 2018.