Causal Effect Identification by Adjustment under Confounding and Selection Biases

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Introduction

In data-driven fields, a usual goal is to compute the ***effect of interventions*** -- how an outcome $\boldsymbol{Y}$ react if we take an action $\boldsymbol{X}$, altering the natural state of the system, i.e., $P(\boldsymbol{y} \mid do(\boldsymbol{x}))$.

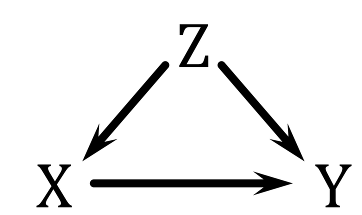
There are two types of *systematic biases* that pose obstacles to causal effect identification: ***confounding bias*** and ***selection bias***.

Structural Causal Models provide a formal and powerful language to model and reason about real world situations, including the identification and recoverability of causal effects in the presence of those biases.

Confounding Bias

The existence of a set of covariates ($\boldsymbol{Z}$) affecting both the action $\boldsymbol{X}$ and the outcome $\boldsymbol{Y}$ blurs the actual effect of the former on the latter.

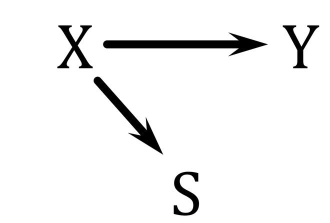
Graphically, each factor is represented with a node connected to both $\boldsymbol{X}$ and $\boldsymbol{Y}$ by paths emerging from $\boldsymbol{Z}$.



Sampling Selection Bias

Sampling selection bias occurs when the inclusion of units in the study is differentially affected by factors in the analysis, which means that the proportion of units in the sample and the target population is *distorted*.

Graphically, the sampling mechanism is represented by a special variable S. In the unbiased case, which is many times naively assumed, S is not differentially affected by any other variable.



Adjustment

Adjustment has been the most widely used procedure to control for **confounding bias** in data-driven fields, and is usually called *Backdoor Criterion*. If a set of variables $\boldsymbol{Z}$ is backdoor admissible, the causal effect can be computed using the *adjustment formula,* namely:

$$P(\boldsymbol{y} \mid do(\boldsymbol{x})) = \sum_{\boldsymbol{z}} P(\boldsymbol{y} \mid \boldsymbol{x}, \boldsymbol{z}) P(\boldsymbol{z})$$

Before this work, no complete criterion to control for **both** confounding and selection bias was known.

Our Contributions

We provide conditions to decide whether the causal effect of $\boldsymbol{X}$ on $\boldsymbol{Y}$ can be computed using an adjustment set $\boldsymbol{Z}$, when:

- **Only biased data is available** (***Theorem 1***). If identifiable, the expression is:

$$\underbrace{P(\boldsymbol{y} \mid do(\boldsymbol{x}))}_{\text{Unbiased causal effect}} = \sum_{\boldsymbol{z}} \underbrace{P(\boldsymbol{y} \mid \boldsymbol{x}, \boldsymbol{z}, S=1)}_{\text{Biased data}} \underbrace{P(\boldsymbol{z} \mid S=1)}_{\text{Biased data}}$$

- **There is biased data** + **external data** on $\boldsymbol{Z}$ (***Theorem 2***). If identifiable, the expression is:

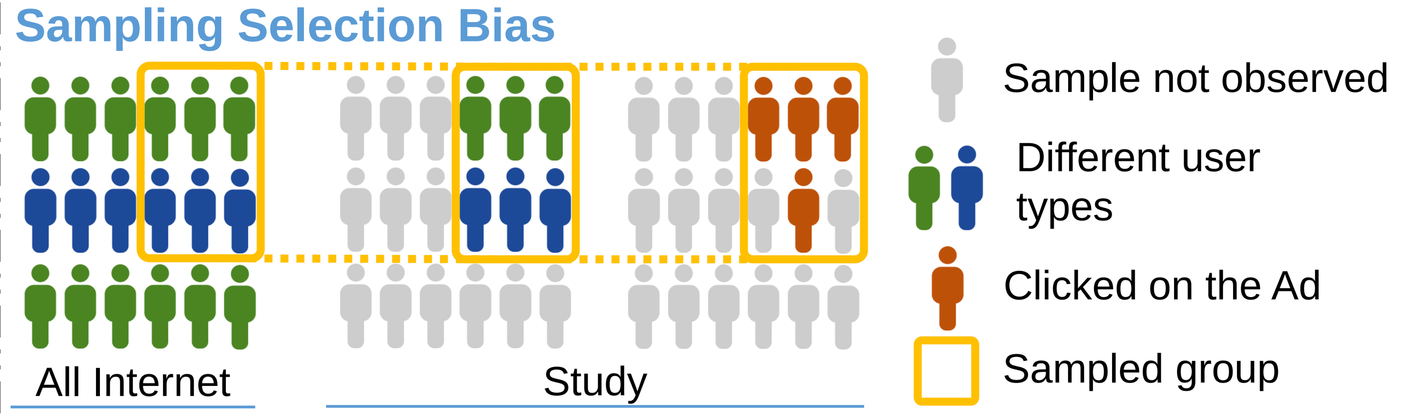
$$\underbrace{P(\boldsymbol{y} \mid do(\boldsymbol{x}))}_{\text{Unbiased causal effect}} = \sum_{\boldsymbol{z}} \underbrace{P(\boldsymbol{y} \mid \boldsymbol{x}, \boldsymbol{z}, S=1)}_{\text{Biased data}} \underbrace{P(\boldsymbol{z})}_{\text{External data}}$$

- We describe an algorithm to list all admissible sets $\boldsymbol{Z}$ when external data is available, with *polynomial delay* complexity (each result or failure is outputted by the algorithm in polynomial time since the last output).

Example – Online Advertisement Campaign

Question: *How will the click-through rate ($\boldsymbol{Y}$) change if the ad system varies the format ($\boldsymbol{X}$) of the ad displayed to the users*?

Sampling Selection Bias



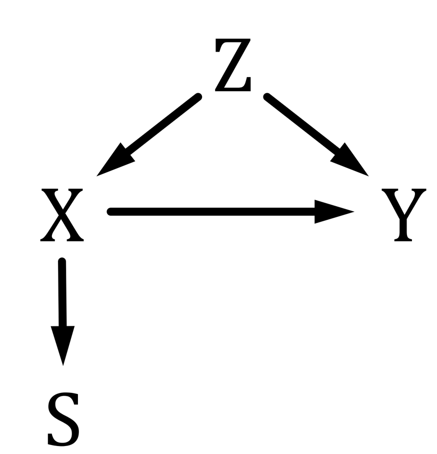
The problem:

The *user type* distribution differs between the sample (50%-50%) and the overall population (33.3%-66.6%). The inclusion of a sample is affected by the *format* since data was obtained from sources specialized in some formats more than others (i.e. video).

User type is relevant to the click through rate.

Will the conclusions from the sample be valid in general?

Graphical Model:



Confounding:

- User type ($\boldsymbol{Z}$) influences what ads (with a specific format) are more likely.
- User type ($\boldsymbol{Z}$) also affects the likelihood of the user clicking the ads (conversion).

Causal effect is identifiable and recoverable in this model using Adjustment with external data over $\boldsymbol{Z}$ (*using Theorem 2*)

Future Work

- Consider adjustment when a **subset** of covariates is measured without bias (external data).
- Use adjustment to remove selection bias from **experimental** data (e.g., randomized trials).
- Design **statistically efficient** methods to estimate the adjustment expressions from data.
- Move beyond adjustment to the problem of general identifiability/recoverability.

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