Causal Inference Crash Course Part 4: Best Practices: Outliers, Class Imbalance, Feature Selection, and Bad Control

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Causal Inference Series

1) Foundations
2) Defining Some ATE/ATET Causal Models
3) ATE/ATET Inference, Asymptotic Theory, and Bootstrapping
4) **Best Practices: Outliers, Class Imbalance, Feature Selection, and Bad Control**
5) Heterogeneous Treatment Effect Models and Inference
6) Difference-in-Difference Models for Panel Data
7) Regression Discontinuity Models
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Overview

- This presentation will outline best practices for issues around causal inference which can be applied to other ML settings.

A. Outliers;
B. Class Imbalance in Propensity Scores;
C. Feature Selection; and
D. Bad Control

- For each issue, we will discuss what the problem is, why it's a problem, and a solution outline.

A. Outliers

Why are outliers problems?

- Generally, treatment effects estimates are about the average.
  - Average treatment effect
  - Average treatment effect on the treated
  - Conditional average treatment effect
- This is represented in their technical implementation by the statistical conditions for estimation.
- For example, the unconfoundedness assumption can be represented as $E[u_i|X_i, W_i] = 0$

Outliers skew the average

- Obviously, outlier values cause the average to take on extreme values
- From a strictly theoretical perspective, this is sometimes okay because we have already decided our metric of interest is the average. We may care about the median instead, then the average would be a bad proxy measure.
  - We'll return to the median later.
- Outliers can be a problem if the data is is meant to be representative, but we still have low sample size.

Two types of outliers

$$Y_i = \tau W_i + g(X_i) + u_i$$

- This means that outlier values in Y_i are potentially a problem. Outlier values in X_i (without any corresponding outlier values in $\mathrm{Y_i}$) can be addressed with feature generation.
- We will discuss two types of outliers with simulations:

1. Outliers in Y_i due to random noise, or large values of $\mathrm{u_i}$;
2. Outliers in Y_i due to outlier values in X_i.

Outlier Y_i values due to large values of u_i

- Generally, large values of u_i are not a concern for the estimate, but can be a concern with inference. This is because u_i will be identified as random noise.
- Simulation setup:

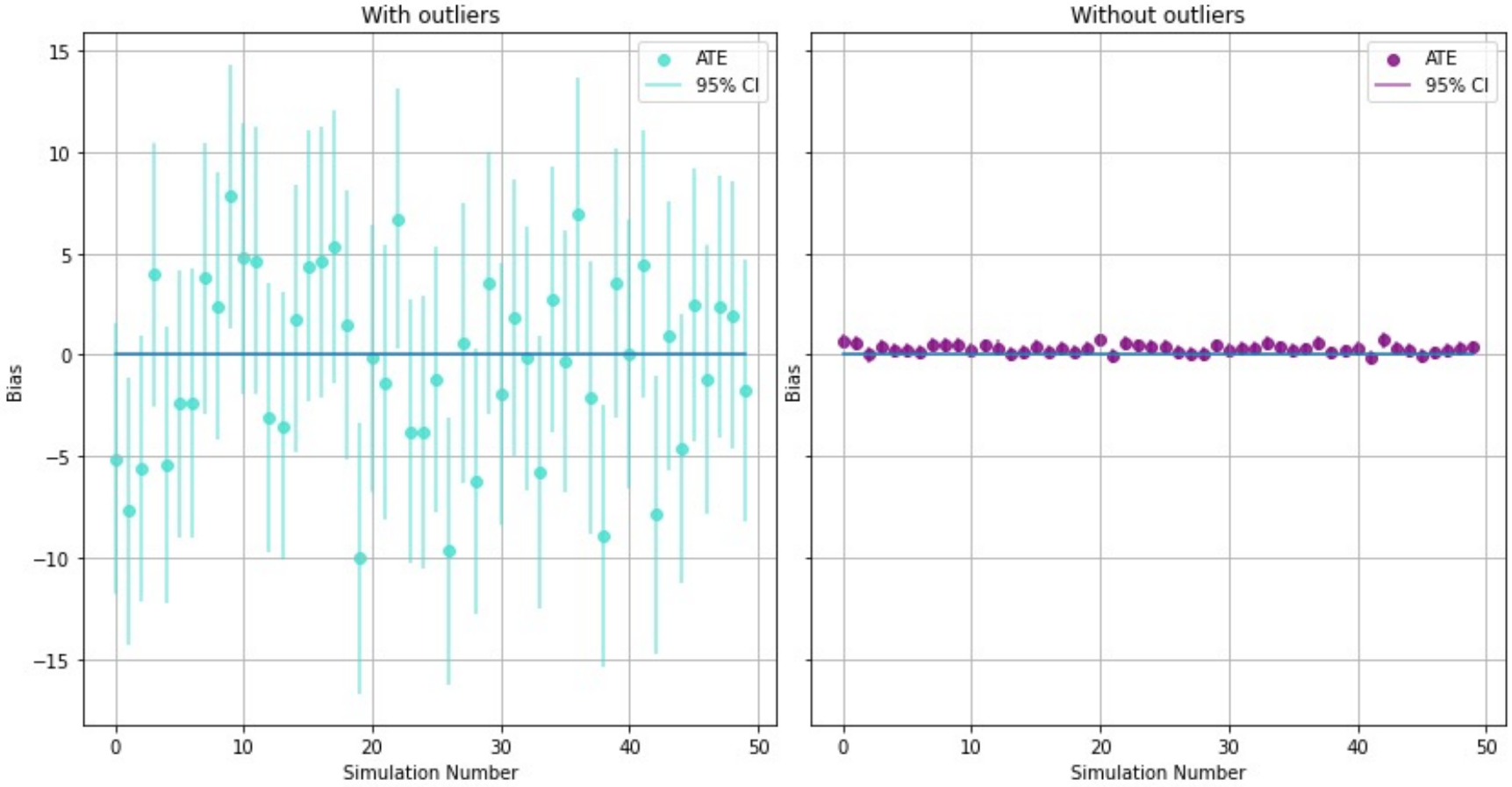
$$Y_i = \tau W_i + g(X_{1i}, X_{2i}) + u_i$$
$$W_i = h(X_{1i}, X_{2i}, \eta_i)$$

- Where u_i and η_i are random draws, and X_{1i} and X_{2i} are independent normally distributed features
- τ is the treatment effect, and the parameter of interest

Simulation evidence

- When the true value of τ is 50, create outlier values in Y_i with large values of u_i.
  - 10% of observations have large values of u_i.
- Compare the treatment estimate when those 10% do not have large values of u_i.

Simulation results on the bias



- With and without outliers, the estimate $\hat{\tau}$ has small bias.
- However, with outliers, the confidence intervals are much larger due the additional statistical noise.

Outlier Y_i values due to large values of $\mathbf{X}_i$

- This is a much larger concern because large values of Y_i are not driven by random noise. This means that conditioning on X_i raises theoretical concerns.
- In a simulation similar to before, outlier values of X_{1i} and X_{2i} create outlier values of Y_i. The estimated ATE is **500% larger** than the true treatment effect.
- Discuss three approaches:
  1. Conditioning on generated features;
  2. Truncation;
  3. Winsorization

Condition on generated features of X_{1i} and X_{2i}

Indicator of whether X_i is an outlier	Indicator of whether X_i is an outlier interacted with X_i	Natural log of $X_i + 1$	Estimate (True Value is 50)	Standard Error
X			333.766	360.346
X	X		288.162	361.047
X		X	328.213	358.607
X	X	X	262.311	358.995

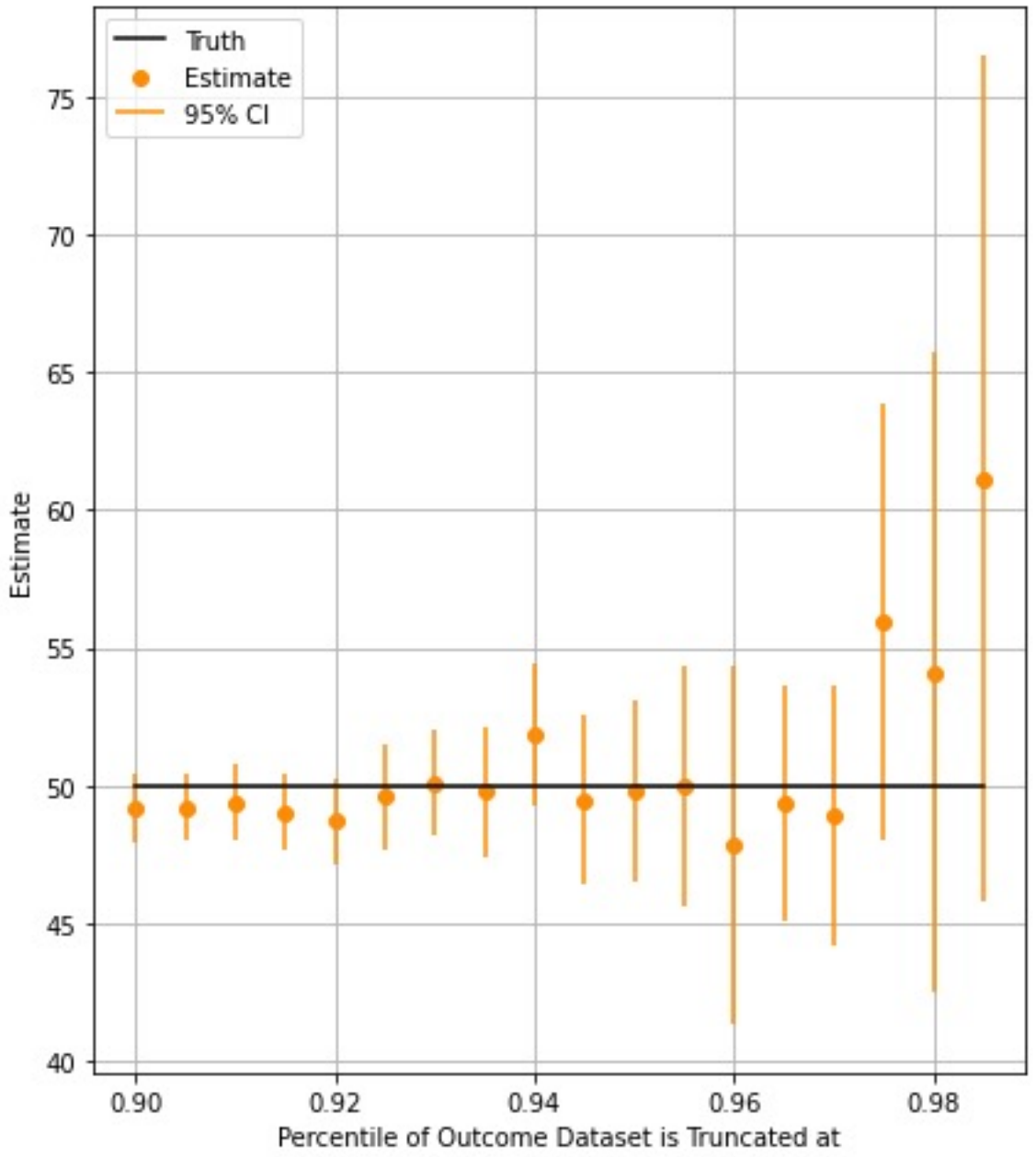
- Conditioning on additional features drives the estimate to be closer to the truth, but at best the estimate is more than 400% larger
- There is also no impact on the standard error

Truncating Values of Y_i

- Truncation is removing observations based on values of Y_i .
- However, it is unclear how much to truncate. The more data is truncated, the less natural variation in the data is removed.
- No principled way to determine the best truncation point.

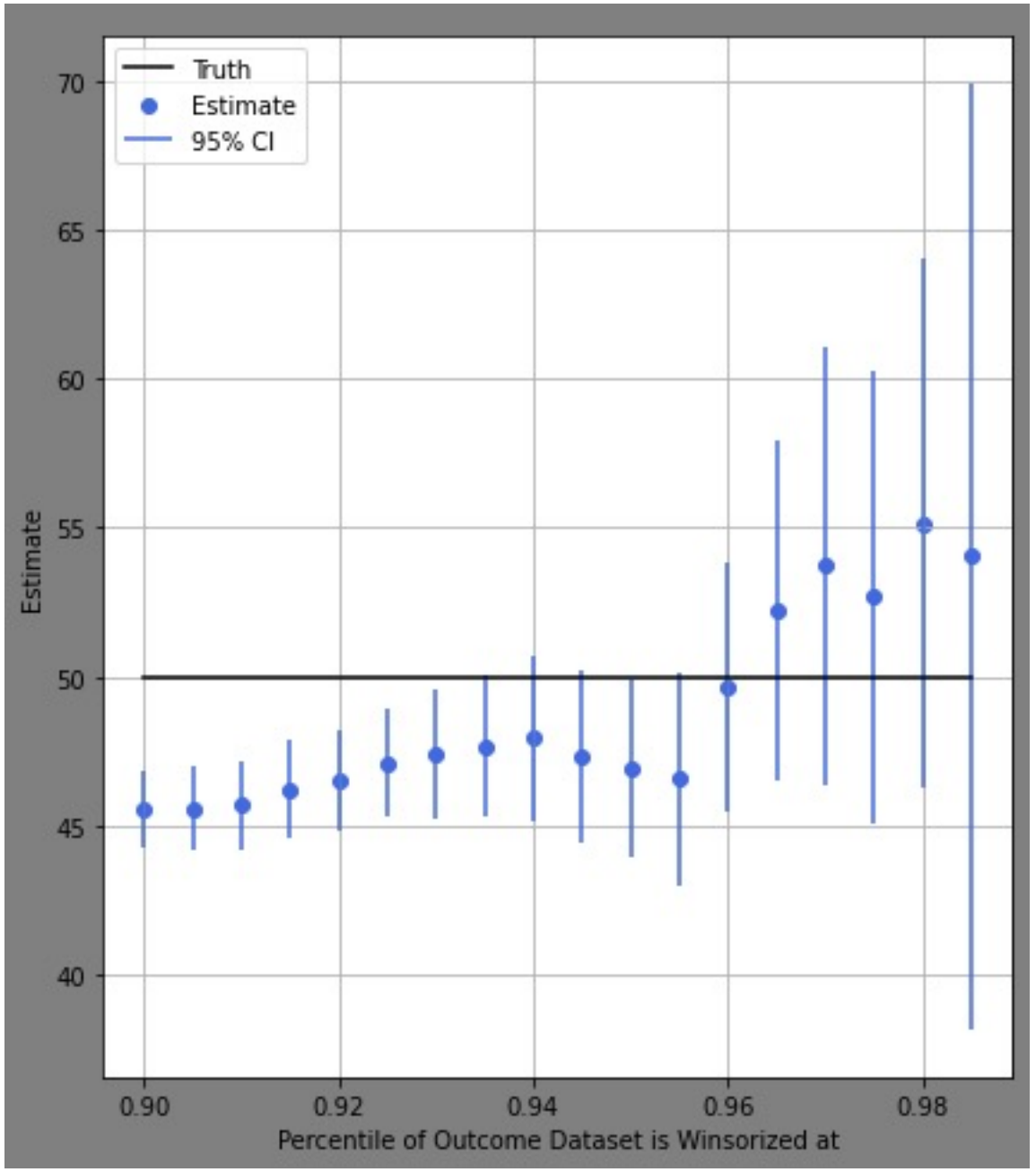
Truncation simulation evidence

- Truncated data based on the 90th , 91st, … 99th percentile in Y_i
- The less truncation, the more biased and less precise the estimate is.
- However, the idea of removing data is not palatable and will likely break down in more flexible data settings

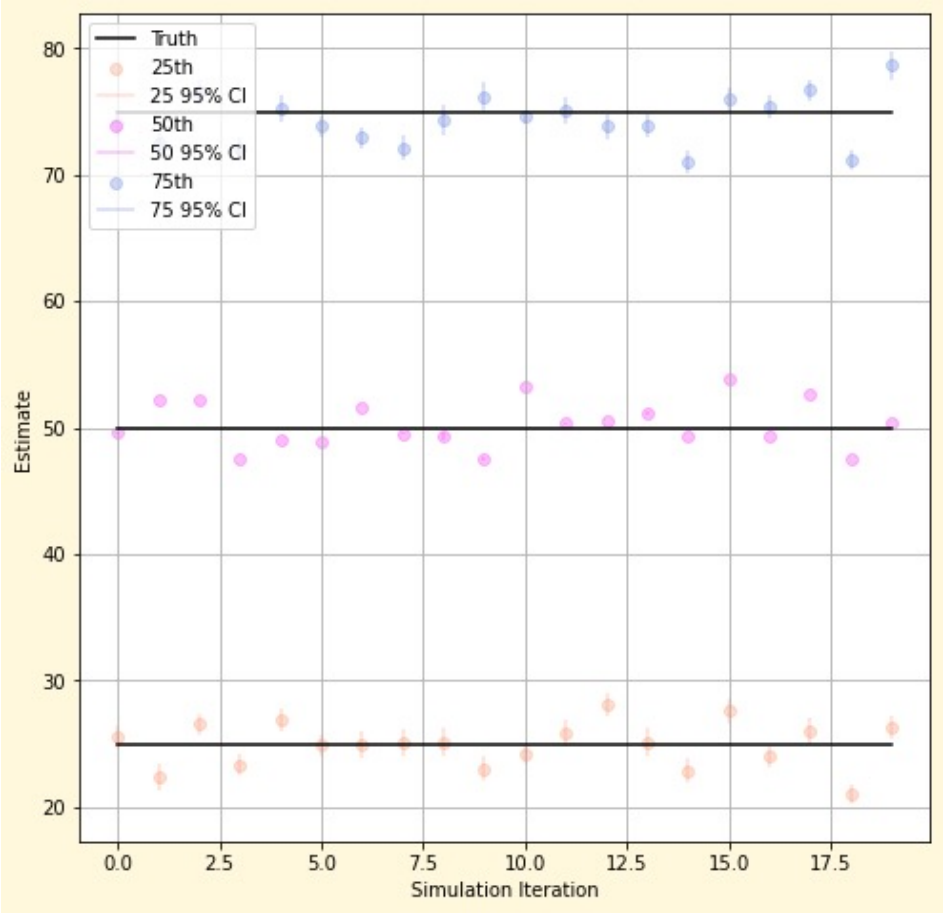


Winsorizing Values of Y_i

- Winsorizing is replacing values of Y_i with a top coded or bottom coded number
- Like truncation, it is unclear how much to winsorize.
- Simulation evidence shows that more winsorization leads to more biased estimates and more precision



WIP – Median and Quantile Treatment Effects



B. Class Imbalance in Propensity Scores

WIP

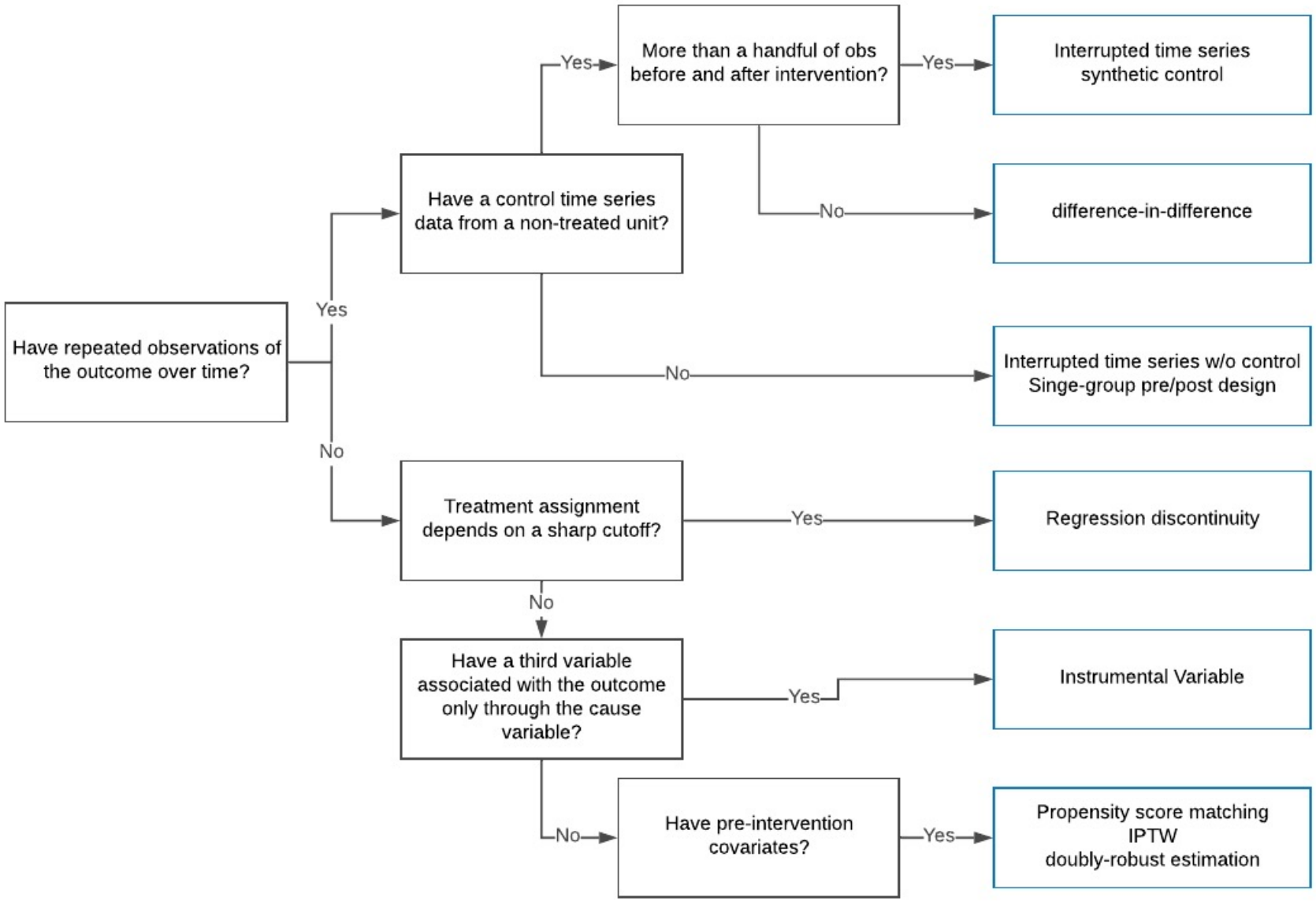
C. Feature Selection

WIP

D. Bad Control

WIP

Appendix



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