Matching and synthetic controls

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2021 ClimBEco course

Causal Inference from observational data

Synopsis: Today, we will be looking into methods that help us find (aka *match*) or simulate (aka *synthesize*) a control group for inferring causal effects from observational data, and its recent developments

In particular, we will develop an understanding of

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- matching approaches
- synthetic controls
- machine-based learning methods

Intuition

Consider a situation where the untreated are very different from the treated:

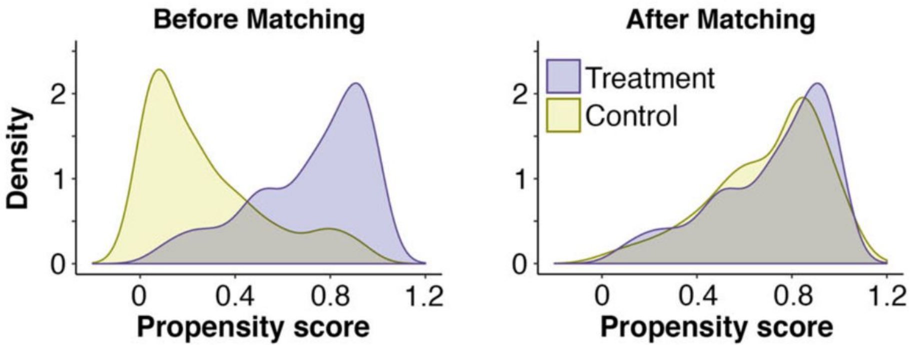

Image source: Schleicher et al. 2020

basic conditions

The classical overarching conditions for robust causal inference:

- stable unit treatment value assumption (SUTVA)
  - treating one individual unit does not affect another's (potential) outcome
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  - $(Y(1), Y(0)) \perp T$: treatment assignment is independent of the outcomes
  - i.e. no omitted variable bias (recall the storch example)
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$\rightarrow$ but should maybe not (King and Nielsen 2019), we will see alternatives

Overview

Here is a general overview of possible matching methods

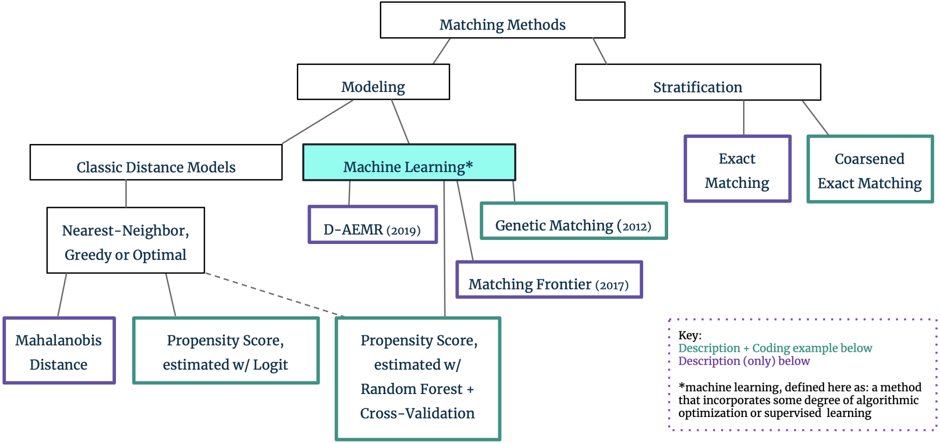

Image source: Sizemore and Alkurdi 2019

References I

King, Gary and Richard Nielsen (2019). 'Why Propensity Scores Should Not Be Used for Matching'. In: *Political Analysis* 27.4, pp. 435–454. ISSN: 14764989. DOI: 10.1017/pan.2019.11.

Schleicher, Judith et al. (2020). 'Statistical matching for conservation science'. In: *Conservation Biology* 34.3, pp. 538–549. ISSN: 15231739. DOI: 10.1111/cobi.13448.