Model-based matching for causal inference in observational studies

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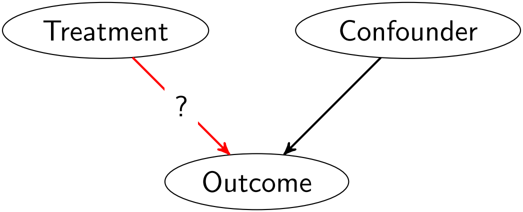
Observational Studies vs Experiments

- **Problem:** Estimate the causal effect of a treatment on outcome of interest
- In randomized experiments, treatment is assigned to individuals at random.
- In observational studies, the way individuals select into treatment groups is unknown.



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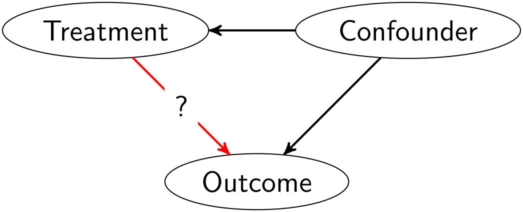
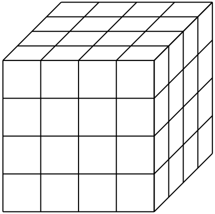


Matching

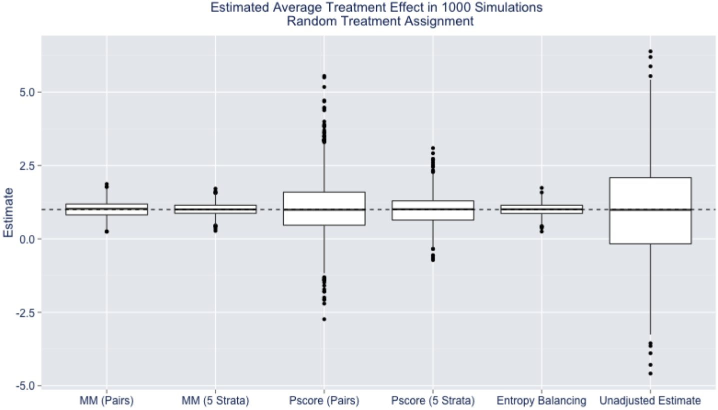
- **Ideal:** group individuals by important confounders to estimate subgroup treatment effects and then average over subgroups
- **Reality:** many covariates, perhaps continuous, make it difficult to stratify



- **Solution:** use a one-dimensional score to match or group individuals
- Stratify according to the "best" prediction of the response, $\hat{Y}$, based on all covariates except for the treatment

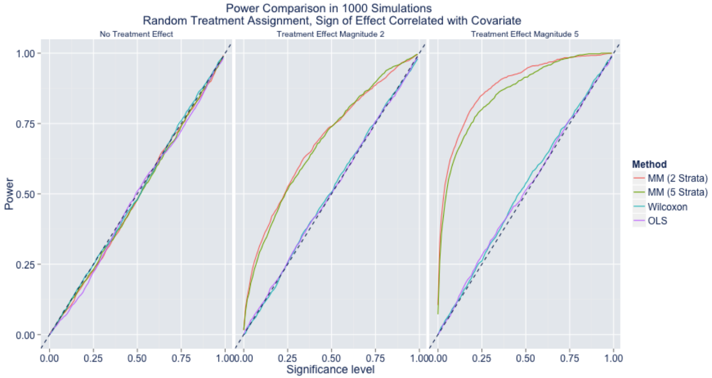
Model-based Matching

- Under standard assumptions (conditional independence of treatment and potential outcomes given X), the **average treatment effect** is nonparametrically identified
- Estimate it using the difference in average residuals, $Y - \hat{Y}$, between treated and controls



Model-based Matching

- Use stratified permutation test to test the **strong null hypothesis** of no treatment effect whatsoever
- Stratifying on $\hat{Y}$ allows us to detect non-constant and non-linear treatment effects



Future Directions

- Do different test statistics give greater power when the treatment effect is nonlinear?
- What is the optimal way to stratify?
- How to quantify uncertainty – standard errors and confidence intervals?