

IDS 702: MODULE 6.5

STRATIFICATION AND MATCHING

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BALANCING COVARIATES: SMALL NUMBER OF COVARIATES

- When the number of covariates is small, the adjustment needed to get some balance can be achieved by **matching** or **stratification**.
- **Exact matching**: for each treated subject, get one control with the exact same value of the covariates (easier for categorical covariates).
- Exact matching ensures distributions of covariates in treatment and control groups are exactly the same, thus eliminating bias due to difference in X .
- After matching, compute treatment effect by using the matched data.
- However, exact matching is usually unfeasible, even with low dimensional covariates.

MATCHING

- Matching estimators impute the missing potential outcomes, using only the outcomes of **nearest neighbors** of the opposite treatment group.
- They have often (but not exclusively) been applied in settings where
 - the interest is in the ATT; and
 - there is a large reservoir of potential controls. This allows matching each treated unit to one or more distinct controls (nearest neighbors).
- More general settings: both treated and control units are (potentially) matched and matching is done with replacement.

MATCHING (FIXED NUMBER OF MATCHES)

- Let M_i be the set of the indices of M closest matches of unit i using a **distance metric** that depends on X .
- Let

$$\hat{Y}_i(0) = \sum_{j \in M_i} \frac{Y_j}{M} \quad \text{if } W_i = 1 \quad \text{and} \quad \hat{Y}_i(0) = Y_i^{\text{obs}} \quad \text{if } W_i = 0;$$

$$\hat{Y}_i(1) = Y_i^{\text{obs}} \quad \text{if } W_i = 1 \quad \text{and} \quad \hat{Y}_i(1) = \sum_{j \in M_i} \frac{Y_j}{M} \quad \text{if } W_i = 0.$$

- Then, the treatment effect within a pair is estimated as the difference in outcomes, and we can average these within-pair differences.
- That is,

$$\hat{\tau}^{\text{ATE}} = \sum_i \frac{\hat{Y}_i(1) - \hat{Y}_i(0)}{N};$$

$$\hat{\tau}^{\text{ATT}} = \sum_i \frac{(Y_i - \hat{Y}_i(0)) W_i}{N_i}.$$

MATCHING (FIXED NUMBER OF MATCHES)

- Pros: Matching estimators that ensure good balance in covariates between groups are generally robust.
- Cons: With fixed number of matches and matching with replacement, matching estimators can be biased.
- Matching estimators are generally not efficient.
- In fact, estimators combining matching and regression adjustment are usually more efficient.
- There can be residual imbalance in matching.
- Perform bias correction via regression on the matched sample.

MATCHING: TUNING

- Matching involves lots of tuning
 - distance metric
 - fixed or varying number of matches
 - for fixed M , number of matches
 - with or without replacement
- Tuning for matching is an art, with some theory and general guidelines available...

MATCHING: TUNING

- Distance metric: Mahalanobis distance, propensity score, tree-based.
- Fixed M or varying M ? For varying M :
 - Matching with caliper: define a caliper (say 0.1) and all units within that caliper are matches
 - M increases with sample size.
- For fixed M , the choice of M (number of matches per unit) has a bias-variance trade-off:
 - smaller $M \Rightarrow$ smaller bias but larger variance
 - larger $M \Rightarrow$, larger bias but smaller variance.
- Also depends on the proportion of treatment versus control: when there is a much larger control group, we can use one-to-many matching.

MATCHING: TUNING

- Matching with replacement:
 - Pros:
 1. computationally easier
 2. both controls and treated can be matched, but with high variances
 3. not order-dependent
 - Cons: some units (especially ones with extreme propensity scores) can be matched many times and thus heavily influence overall estimates.
- What about matching ties? What should we do about them?
- Matching is a vast topic and there are so many matching methods.
- Implementation in R: `Matchit`, `Matching`, and many more.

STRATIFICATION

- Another option is stratification.
- Suppose we have a single covariate X with k levels (e.g. race).
- We will continue to assume unconfoundedness and overlap holds.
- Suppose we want to estimate ATE.
- Let
 - n_k be the number of observations with $X_i = k$; and
 - $\bar{Y}_{k,w}$ be the sample average of all Y_i values among observations in cell $X_i = k$ and $W_i = w$.
- Once again, recall that ATE is $\tau = E[Y_i(1) - Y_i(0)]$.

STRATIFICATION

- Then we have

$$E[Y_i(1)] = \sum_k E[Y_i | X_i = k, W_i = 1] \cdot \Pr[X_i = k],$$

and

$$E[Y_i(0)] = \sum_k E[Y_i | X_i = k, W_i = 0] \cdot \Pr[X_i = k].$$

- We can estimate $E[Y_i(1)]$ using a consistent estimator $\sum_k \bar{Y}_{k,1} \frac{n_k}{N}$. We can use a similar estimand for $E[Y_i(0)]$.
- Therefore, the ATE τ can be estimated by

$$\hat{\tau} = \sum_k (\bar{Y}_{k,1} - \bar{Y}_{k,0}) \frac{n_k}{N}.$$

STRATIFICATION

- What if X is continuous?
- **Stratification (subclassification)**: split X into k classes.
- Then, for class k , define n_k and $\bar{Y}_{k,w}$ as before.
- An estimator of τ is then once again

$$\hat{\tau}^k = \sum_k (\bar{Y}_{k,1} - \bar{Y}_{k,0}) \frac{n_k}{N}.$$

- $\hat{\tau}^k$ is generally biased for τ , however, stratification of over 5 blocks can remove 90% of the bias!
- **Overall, the key idea with stratification is this:** even though we may not have balance across the entire sample, we likely can get balance by focusing on subgroups, one at a time.

BALANCING COVARIATES: LARGE NUMBER OF COVARIATES

- What if we have a large number of covariates?
- With just 20 binary covariates, there are 2^{20} or about a million covariate patterns!
- Direct matching (exact or nearest neighbors) or stratification is nearly impossible.
- Need dimensional reduction to a single score which we can then use to match or stratify.
- The most popular option is the **propensity score**:
 $e(x) = \Pr[W_i = 1 | X_i = x]$.
- We will focus on **propensity score methods** over the next few modules and use them to analyze the minimum wage data.

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WHAT'S NEXT?

MOVE ON TO THE READINGS FOR THE NEXT MODULE!