IDS 702: Module 6.5

Stratification and matching

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IDS 702

Balancing covariates: small number of covariates

- When the number of covariates is small, the adjustment need 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 $\mathcal{M}_i$ be the set of the indices of M closest matches of unit i using a distance metric that depends on X.

- Let

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

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

- That is,

$$\hat{\tau}^{\text{ATE}} = \sum_i \frac{\hat{Y}_i(1) - \hat{Y}_i(0)}{N};$$
$$\hat{\tau}^{\text{ATT}} = \sum_i \frac{\left(Y_i - \hat{Y}_i(0)\right) W_i}{N_i}.$$

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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 $\tau = \mathbb{E}[Y_i(1) - Y_i(0)]$.

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Stratification

- Then we have

$$\mathbb{E}[Y_i(1)] = \sum_k \mathbb{E}[Y_i|X_i = k, W_i = 1] \cdot \mathbb{P}\mathrm{r}[X_i = k],$$

and

$$\mathbb{E}[Y_i(0)] = \sum_k \mathbb{E}[Y_i|X_i = k, W_i = 0] \cdot \mathbb{P}\mathrm{r}[X_i = k].$$

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

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

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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

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

- $\hat{\tau}^k$ 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 of 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: $e(x) = \mathbb{P}\mathrm{r}[W_i = 1 | X_i = x]$.
- 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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Acknowledgements

These slides contain materials adapted from courses taught by Dr. Fan Li.

What's next?

Move on to the readings for the next module!

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