Matching for Adjustment and Causal Inference
Escuela de Invierno en Métodos y Análisis de Datos UCU-DCSP

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Overview

This class is an introduction to statistical adjustment using matching and propensity scores in the style pioneered by Rubin and Rosenbaum and currently in rapid development by many other methodologists across the social science and statistical disciplines. An important motivation for matching is to approximate an experimental design. And, since such a motivation arises from a desire to make transparent and defensible statements about causal relations, we will introduce the counterfactual conception of causal inference and the potential outcome formalization of these ideas. We will also spend some time on statistical inference (hypothesis testing, confidence interval creation) after the creation of a matched design. Finally, we will grapple with some of the questions that are current research topics in this area: When and how one can claim to have adjusted "enough"? How can we engage with concerns about unobserved confounds even if we have adjusted for what we observe?

Since methods of matching are rapidly developing in the methodology literature, we will here focus on the simplest and oldest form: post-stratification. The general concepts and work-flow should be transportable to more sophisticated methods of matched adjustment.

Goals and Expectations

This course aims to help you think about statistical adjustment using stratification and matching as compared to statistical adjustment using the linear model directly (adjustment by "residualization").

The course ought to give you opportunities to practice producing matched designs for your data and to ask questions that puzzle you as you do this work.

The point of the course is to position you to do the future learning that is at the core of your work as an academic analyzing data.

This course does not delve deeply into the theories of causal inference, statistical inference, or algorithms at the heart of these methods of statistical adjustment. Rather, through practice using tools, I hope that your curiosity is awakened and you begin to read more broadly and understand more deeply on your own.

Expectations   I assume some previous engagement with high school mathematics, probability and statistical computing in the R statistical computing environment. If you have not used R, you are welcome to take the class, but I encourage you to get a little experience with R before the first class session. Feel free to email me to ask for advice about how to practice with R before the class begins.

Participation   We will be doing hands-on work. I plan to lecture very little and instead will hope to pose problems of statistical theory, research design, and data for you to solve at your computers. I anticipate that you'll work in small groups, asking me and/or the group questions as you proceed. I will break away to draw on the board or demonstrate on my own computer now and then to clarify points or help you around particularly difficult tasks.

Computing   We will be using R in class so those of you with laptops available should bring them. Of course, I will not tolerate the use of computers for anything other than class related work during active class time. Please install R (http://www.r-project.org) on your computers before the first class session. You may prefer to use R in the context of the Rstudio IDE (http://www.rstudio.com/).

Computing is an essential part of modern statistical data analysis — both for turning data into information and for conveying that information persuasively (and thus transparently and reliably) to the scholarly community. In this course we will pay attention to computing, with special emphasis on understanding what is going on behind the scenes. You will be writing your own routines for a few simple and common procedures.

Books We will use the Rosenbaum book as our primary source. The other books are useful for further study.

Required: Rosenbaum, P. R. (2010). *Design of Observational Studies*. Springer (pdf free to download from some university ip addresses or via university library springerlink subscriptions: `http://www.springerlink.com/content/978-1-4419-1212-1/contents/`)

Recommended: Becker, H. S. (1986). *Writing for Social Scientists: How to Start and Finish Your Thesis, Book, or Article*. University of Chicago Press

Berk, R. (2004). *Regression Analysis: A Constructive Critique*. Sage

Gelman, A. and Hill, J. (2007). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge University Press (particularly chapters 9,10 and 23 see `http://www.stat.columbia.edu/~gelman/arm/`).

Morgan, S. L. and Winship, C. (2007). *Counterfactuals and Causal Inference: Methods and Principles for Social Research (Analytical Methods for Social Research)*. Cambridge University Press See `http://www.wjh.harvard.edu/~cwinship/cfa.html` for some links and background reading)

Rosenbaum, P. R. (2002b). *Observational Studies*. Springer-Verlag, second edition (see `http://www-stat.wharton.upenn.edu/~rosenbap/index.html` for lots of papers and presentations).

Rubin, D. B. (2006). *Matched sampling for causal effects*. Cambridge University Press, Cambridge; New York

Schedule

Note: This schedule is preliminary and subject to change. We will spend roughly 4 hours together for three of the days and 3 hours on one of the days. I anticipate mixing group discussions of your questions from the readings with in-class work using your own laptops to get practice creating, analyzing, and assessing matched designs.

Right now, we have too much reading assigned. Some of it will be moved to "recommended" sections soon.

1—July 14—Potential Outcomes, Confounding, and Linear Models

How does the linear model "control for" or "adjust for" potentially confounding variables when assessing a relationship between some outcome and some explanatory or causal variable? How can we know whether we have "controlled for" enough? How worried should we be about the influence of functional form on our causal inferences? How does a randomized experiment do the same task using design?

Reading: Rosenbaum (2010, Chap 1, 3, 7)

Gelman and Hill (2007, Chap 9 and 10) especially on (a) adjusting for post-treatment variables and (b) discussion of issues of interpolation, extrapolation, and covariance adjustment depending on functional form.

Gerber and Green, 2012, Chap 1 and 2

Holland, 1986

2—July 15—Adjustment by Simple and Complex, Algorithmic Stratification

Given the problems that arise from the use of the linear model, how can we use research design to approximate the randomized experiment? How would we assess whether a matched design adjusted enough or not? What does it mean to adjust enough? What actual steps do we take in order to flexibly express our ideas about what it means for "like to be compared with like."

Reading: Rosenbaum (2010, Chap 8–9,13)

Hansen (2004)

Hansen (2011) for an example walk-through of a matched analysis including a discussion of missing data on covariates.

Ho et al. (2007) [esp. their discussion of model sensitivity, for example their Fig 2]

Three different ideas about balance testing: (1) Imai et al. (2008); (2) Sekhon (2007a)[1]; (3) Hansen and Bowers (2008) Hansen (2008) or for a less mathematical version of the same argument (Bowers, 2011, §3).

3—July 16—Statistical Inference for Matched/Post-stratified Designs

What does it mean to do statistical inference for a matched design? To what unobserved quantities might we want to infer? What might justify the idea that what we observed might have been different? Here we focus on Neyman's ideas, but we will also talk briefly about Fisher's sharp null hypothesis of no effects.

Reading: Imbens and Rubin (2009, Chap 6,7,17)

Berk (2004, Chap 4) on general requirements for statistical inference

Rosenbaum (2010, Chap 2)

Imbens and Rubin (2009, Chap 17)

(Freedman et al., 2007, Appendix A-32 and 33) which summarizes Neyman (1990)

Freedman (2008b,a, 2007, 2006) Suggesting that even the large sample statistical inference from using linear regression in randomized experiments is biased. Also arguing that the Huber-White standard errors are not a good idea.

Rosenbaum (2002a) and Bowers and Panagopoulos (2011) showing how covariance adjustment is compatible with Fisher's randomization inference (and thus can be unproblematic after matching).

Schochet (2009); Green (2009) Suggesting that in large samples these biases worried about by Freedman ought not to worry us. Lin (2011) provides some useful proofs supporting the idea that linear regression with "robust" standard errors provides a useful large-sample way to do statistical inference about average treatment effects.

Imbens and Rubin (2009, Chap 6–8) Suggesting, similarly to Green and Schochet, that regression is fine for statistical inference in experiments (and further suggesting the use of the Huber-White robust standard errors).

Abadie and Imbens (2004) suggesting that the bootstrap is not a good approach with matched designs.

For advanced reading on the latest in statistical theory for statistical inference for "matching estimators" (which include but are not restricted to post-stratified studies) see:

Hansen (2009) for theory using randomization-inference.

Abadie and Imbens (2009) for a large-sample, Normal theory approach.

Hosman et al. (2010)

Rosenbaum (2010, Chap 14)

Rosenbaum (2002b, Chap 4)

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[1] http://sekhon.berkeley.edu/papers/SekhonBalanceMetrics.pdf

Imbens (2003)

4—July 17— Sensitivity Analysis

An observational study is not a randomized experiment, regardless of the research design and balance achieved. How can we address arguments that we did not adjust for variables that create confounding but which we do not observe?

Reading: Cornfield et al. (1959)

Hosman et al. (2010)

Rosenbaum (2010, Chap 14)

Rosenbaum (2002b, Chap 4)

Imbens (2003)

Other Topics

If we move quickly, or if the class has some organized preferences, we could change the syllabus to discussion some of these ideas.

Non-bipartite matching – Advances in Multivariate Matching: Beyond Binary Treatment *Recommended:* Rosenbaum 11; Lu et al. (2011);Imai and van Dyk (2004)

Longitudinal Matching – Advances in Multivariate Matching: Matching with Longitudinal Data *Recommended:* Rosenbaum 12

Stuff that was painfully left out but which is important

Here are just a few extra citations to launch self-study of aspects of matching which we did not cover in our class.

The class elected to focus on matching for longitudinal problems for the last class. We thus are unable to cover other approaches to matching that have been developed by political methodologists such as Genetic Matching (Diamond and Sekhon, 2006; Sekhon, 2007b) or Coarsened Exact Matching (Iacus et al., 2009, 2011) or Balance Optimization Subset Selection (Nikolaev et al., 2012) or more fine-tuned versions of the optimal post-stratification that we consider in this class (for example, (Zubizarreta, 2012)). Nor did we have time to engage with many other applied and theoretical topics in causal inference for observational studies such as the work establishing causal interpretation of the propensity score (cited in the Rosenbaum textbook), or the alternative approaches to causal inference based on weighting by functions of the propensity score such as those arising from work by Jamie Robins (Glynn and Quinn, 2010), let alone alternative conceptualizations of causal relations such at those developed by Judea Pearl (Pearl, 2000) or the work on estimation by Heckman or bounding causal inferences by Manski.

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