Chapter 11 Essays

Amy Attaway

In Chapter 11 of Rosenbaum, he describes several different propensity matching methods which can be used for observational studies that attempt to recreate the environment of a randomized control trial. One specific type of matching he discusses is the method known as risk set matching, where the moment one person receives treatment that person is paired with someone else who has not been treated whose observed covariate was similar up to that point, and therefore involves matching controls for the past (but not for the future). I believe this type of matching would be very helpful for comparing patients with COPD who undergo lung volume reduction surgery. This is a very specialized surgery that is only offered to patients with severe hyperinflation and upper lobe predominant emphysema in their lungs, and involves surgically removing the top portion of the lungs to reduce static hyperinflation and improve the respiratory mechanics of breathing particularly in the diaphragm. Many patients must wait to receive this surgery, which is similar to the waiting involved when receiving a lung transplant, and there are a number of patients with just as severe disease that are not able to receive this specialized surgery because they do not meet strict criteria (in particular having upper lobe predominant COPD). I am planning on studying this population in the future and believe this matching method would be the ideal method for my study.

Wyatt Bensken

For me there were two aspects of Chapter 11 on matching that were particularly interesting and compelling. First, was how the chapter succinctly explored the various methods of matching and how each of those methods makes certain assumptions around the unmeasured covariates. I found this particularly helpful in recognizing that matching techniques are not as arbitrary as they may seem at first. The main piece, though, that I found that I could best relate to was the section on Risk Set Matching. While I was previously familiar with the topic from my epidemiology courses, I found reading it in this context brought to me a renewed interest in this technique.

This is largely driven by the fact that it is quite plausible a technique like this is one I would want to consider using for my current class project. As it is a panel survey and the exposure is emergency general surgery it may be beneficial to think of this approach where controls are not selected overall but rather controls are selected at each time-point that a case occurs. This risk set matching approach seems appropriate for this type of study where the treatment may be given at various times, and matching at the given time, rather than based on all available information, may alleviate some bias and matching concerns. I think this risk-set matching approach would be something I could think about applying to my study, or future studies that explore similar questions.

Sofija Conic

Chapter 11 describes various matching techniques, their benefits, and situations in which they are useful. I found this breakdown helpful because it can be difficult to choose a strategy in a structured way rather than trying it and seeing the outcomes. One section I found particularly interesting was the discussion of matching to a variable number of controls.

Rather than matching each treated person to the same number of controls, you can create matches where 1 treated person is matched to 2 controls while another is matched to 4 controls, for example. This is useful in cases when the available number of controls changes with the observed covariates, x. To decide on how many controls we expect to be available at an observed covariate x, we can use Frank Yoon's "entire number" (1- λ) / λ, with λ being the propensity score. The advantages of this method include potentially reducing bias compared to using a fixed number of controls. However, one shortcoming of this strategy is that a single control in a 1-to-2 match counts twice as much as a control in a 1-to-4 matched set. The result would be that describing the control group will be more difficult than a strategy with a fixed number of matches.

I don't think that this strategy would greatly impact my project, simply because my sample size is not large enough to create a varied number of match sets. However I do think it is a strategy that I will consider in future projects.

Joshua Froess

A matching concept that was talked about in this chapter that we haven't talked about much in class is fine matching or near-fine matching. I think the idea of completely matching one variable makes a lot of sense for certain studies. Some health outcomes have important relationships that are known and might want to be matched on completely.

When studying depression it is known that individuals in certain age categories are more likely to get depression than individuals in other age categories. Since this is well known as a researcher you might want to do fine matching on a categorical age variable. This would make sure that people who have experienced depression would have a similar age to those who have not. The propensity score can then just be matched for the other covariates in the study. This type of matching is interesting because it helps the researcher isolate one, or more, variables that are known to confound the outcome of interest.

Jesús Gutierrez

This most important lesson that I learned after reading this chapter is that there are many different modern matching techniques that are used to achieve slightly different and specific objectives. For example, fine balance matching improves adjustments for observed covariates. Paring aimed at reducing heterogeneity of outcomes attempts to reduce sensitivity to unmeasured covariates. Risk set matching address problems that often arise when the investigator does not control the timing of treatment. At the moment that one person receives the treatment, that person is paired with someone else who has not yet been treated whose observed covariates were similar up to that moment. In other words, the matching controls for the past, not the future. Template matching is a tool used to compare many treatments to one

another. This tool shares some of the strengths and limitations of matching with multiple controls. Given this overview of the different techniques available for matching, I will be more cognizant of the fact that not all matching techniques are created equal and that there are concrete advantages and disadvantages associated with each.

Morgan McGrath

My biggest takeaway from this chapter was a better understanding of the potential limitations of greedy matching, and why optimal distance matching techniques may be preferable. This seems pretty obvious in hindsight (greedy matching can back itself into a corner with the last few matches to be made), but the example laid out in Table 11.1 made the point much more concrete for me.

The other concept this chapter clarified was the benefits of matching with > 1 control. Previously, I thought I understood that the more controls you could match with, the better, limited by your sample size of course. Chapter 11 explained *why* exactly 1:2 matching is beneficial (decreases variance of the estimated average treatment effect), by exactly how much it is beneficial, and why 1:50 matching is really never worth it.

I probably won't have the numbers to do much beyond 1:1 matching in my project (although I could potentially swing 1:2 matching with a few tweaks to my sample). I do intend on looking into the possibility of using optimal distance matching as a way to come up with my final matches, whereas I was previously intending to go with a greedy matching technique. I'll try both and look at the results.

One final point, though this may have come from chapter 10, is that the discussion of separating the processes of matching and pairing really resonated with me. It makes a lot of sense to use matching to create a sample with balanced covariates, *then* pair individuals within that large sample based on a few variables thought to be highly predictive of the outcome. This effectively balances covariates and reduces the heterogeneity in paired differences in the outcome, thus improving your design sensitivity.