Propensity Score-Based Methods for Causal Inference

Module 7: Fitting the Outcomes Model



**I. Module Objectives**

After estimating each subjects’ propensity for treatment or exposure, and creating the pseudo population, an outcomes model can then be fit to that pseudo population.

The selection of the appropriate outcomes model depends on the method used to create the pseudo population. So, if data are matched or stratified on the propensity score (PS), the outcomes model should account for the matching (e.g. using a paired t-test or conditional logistic regression) or stratification (e.g. using Mantael-Haenzel odds ratio or other weighted estimate from stratified data). Similarly, if the pseudo population is formed through inverse probability weighting, the outcomes model should account for the weighting, which can be accomplished through standard statistical packages for analyzing probability samples. Finally, we may choose to simply adjust for the propensity score as a covariate (although doing so is generally considered a suboptimal approach; see Austin, et al., 2007a).

Doubly robust methods are another approach to estimating the exposure or treatment effect. The doubly robust approach fits separate models for the propensity score and the outcomes model within the exposed and within the unexposed groups. The subsequent model predictions are then used to estimate an effect that is unbiased if either the propensity score model or the outcomes model is correct.

Since the outcomes model is implicitly linked to the method used to create the pseudo population, the assignments in this module are, to an extent, overlapping with the previous module.

By the end of this module, you will be able to:

1. Describe the different approaches for fitting an outcomes model in propensity score-based methods
2. Describe how to calculate doubly robust estimates of the exposure or treatment effect

**II. Module Assignments**

**Required Assignments: (~63 pages to read)**

To describe approaches for estimating the final causal effect of treatment or exposure when using matching, and to be able to describe the differences between a few of the main approaches for matching, read the following review article: Stuart, E.A., 2010. Matching methods for causal inference: A review and a look forward. *Statistical science: a review journal of the Institute of Mathematical Statistics*, *25*(1), p.1-21.

To describe approaches for estimating the treatment effect when using weighting, and to be able to describe the differences between a few of the main approaches for matching, read the following review article: Austin, P.C. and Stuart, E.A., 2015. Moving towards best practice when using inverse probability of treatment weighting (IPTW) using the propensity score to estimate causal treatment effects in observational studies. *Statistics in medicine*, *34*(28), pp.3661-3679.

For a description of estimating the treatment effect when using stratification (or sub-classification), and a further review of all methods, read the following article: d'Agostino, R.B., 1998. Propensity score methods for bias reduction in the comparison of a treatment to a non‐randomized control group. *Statistics in medicine*, *17*(19), pp.2265-2281.

For a description of doubly robust estimation, read the following article: Funk, M.J., Westreich, D., Wiesen, C., Stürmer, T., Brookhart, M.A. and Davidian, M., 2011. Doubly robust estimation of causal effects. *American journal of epidemiology*, *173*(7), pp.761-767.

**Optional Assignments: (~33 pages to read)**

To further study matching methods, read the following article: Dehejia, R.H. and Wahba, S., 2002. Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and statistics*, *84*(1), pp.151-161.

To explore other approaches for matching, and compare approaches between caliber and nearest neighbor methods, read the following article: Austin, P.C., 2017. Double propensity-score adjustment: a solution to design bias or bias due to incomplete matching. *Statistical methods in medical research*, *26*(1), pp.201-222.

**III. Project Exercises**

Create a copy of this Google Doc or download the Module onto your computer and review the material offered above under Module Assignments before beginning these workbook exercises.

Thinking about what you learned in this module so far, begin developing the analysis plan for your project by answering the following questions:

1. What is the distribution of your outcome measure and the effect of interest?

Common choices for the distribution are binary outcomes (with a fixed follow-up time), survival or time-to-event (including censoring), counts of an event (with potentially differential follow-up time), and continuous measures.

Common choices for the effect of interest (that need to correspond to an applicable outcome distribution) are odds ratios or relative risk for binary outcomes, hazard ratios for survival outcomes, rate ratios for event counts, and linear coefficients for continuous outcomes.

Note that the choice of effect measure also depends on the sampling strategy. For instance, one cannot estimate a relative risk without representative sampling of cases and controls.

1. Based on your response to question #1, which outcome model is most appropriate for your research question?

Common choices are logistic regression for binary outcomes and odds ratios or relative risk, proportional hazards regression for survival outcomes and hazard ratios, Poisson or negative binomial models for event counts and rate ratios, and linear models for continuous outcomes and linear coefficients.

Once you select the outcomes model, also describe the assumptions being made in using that model.

1. Based on your responses to the exercises in the previous module, will you be creating the pseudo population using matching, weighting and/or stratification? Using multiple approaches may be more optimal since no one approach is necessarily best.

If you are using matching, describe how you will adjust for the matching in the outcomes model. For instance, that might include using conditional logistic regression for a binary outcome, using paired differences as the outcome in a linear model, or specifying a cluster using random intercepts in other settings.

If are using weighting, there are survey weighting functions that account for the inverse probability of treatment weighting in the outcomes model.

If you are using stratification, the overall estimate needs to account for weighting across strata, which can also be accomplished within most statistical software packages.

[Link to go back to the Course Overview Document](https://docs.google.com/document/d/1UDTkp3rbhqdun7jvSvktaZmTtoUWOz_VUDQw3HIsElg/edit?usp=sharing)