Causal Inference

Tuesdays, Thursdays: 15:00-16:20

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Course directory for summaries of lectures and problem sets:

`http://biosun01.biostat.jhsph.edu/~cfrangak/biostat_causal`

Evaluation: four problem sets and a report.

The instructor acknowledges sharing of valuable ideas and material with Donald Rubin and Guido Imbens.

SYLLABUS

The course covers the topics outlined below. The articles listed comprise relevant reference material. Starred articles are included in a course packet.

1. Introduction and Framework.

   1 Introduction.

   2 Framework of potential outcomes and assignment mechanism.

   *Neyman (1923, pp. 465-468), *Rubin (1990), *Rubin (1974, pp. 688-695), *Holland (1986), *Cox (1992).

   3 Historical review.

   4 Notes and outline of the course.

2. The completely randomized assignment.

   1 Fisher's mode of inference on focusing on the null hypothesis.

   Fisher (1925), Fisher (1947), Cox *(1958).

   2 Neyman's mode of inference; covariates, efficiency considerations.

   *Neyman (1923, p. 468-472)

3. Treatment assignment with known and varying probabilities

   1 Assumption of assignment; studies that have this form.

   2 Fisher's mode of inference, limitations.

   3 Neyman's mode of inference, limitations.

   Horwitz and Thompson (1952).

4. Ignorable treatment assignment and propensity scores.

   1 Studies we can address with this template; assumption of ignorability.

   2 Role of models for the outcome.

      (1) Likelihood mode of inference; estimation under additivity of effects, nonadditivity.

      (2) Small number of important covariates, matching, subclassification, weighting, modeling; limitations with large number of covariates.

   *Rubin (1978), *Rubin (1977), Cochran (1968), *Rubin (1984)

   3 Role of propensity score.

      (1) Definition, main properties.

      Case study for:

      (2) fitting and diagnostics for the propensity score.

      (3) using the propensity score.

   *Rosenbaum and Rubin (1983a), *Rosenbaum and Rubin (1984), *Rubin (1997)

      (4) comparison of propensity score with other methods: a case study

   *Lalonde (1986), *Dehejia and Wahba (1999)

   4 Sensitivity analysis and other issues

   Cornfield (1959), *Rosenbaum and Rubin (1983b), *Manski et al (1992), Rosenbaum (1999), Scharfstein, Rotnitzky, and Robins (1999)

   5 Propensity scores for multiple groups *Imbens (2000), Huang et al. (2004)

   6 Bayesian inference (*Rubin, 1978)

5. Studies with treatments at mutliple times: case of sequentially ignorable assignment.

   1 Introduction: what studies we consider.

   2 Problems with standard methods.

   3 Estimating causal effects with full modelling.

   *Robins (1987), Pearl (1995), Robins, Greenland and Hu (1999).

   4 Estimating causal effects by limited modelling:
   marginal structural models and estimation.

   *Robins, Hernan, and Brumback (2000).

6. Studies with nonignorable noncompliance and instrumental variables

   1 Introduction: studies with treatment-noncompliance.

   2 Assumptions of instrumental variables with potential outcomes.

   3 Estimating causal effects of interest.

   *Sommer and Zeger (1991), *Card (1993), McClellan et al. (1994), Robins and Greenland (1994),

   *Angrist, Imbens and Rubin (1996), *Imbens and Rubin (1997), Balke and Pearl (1997)

   Hirano et al. (2000), Frangakis, Rubin, and Zhou (2002).

7. Studies with multiple partially controlled factors

   1 Partially controlled studies.

   (1) What causal effects are of interest.

   (2) Standard definitions.

   (3) The framework of principal stratification.

   *Frangakis and Rubin (2002)

   2 Studies with noncompliance to treatment and incomplete outcomes.

   (1) Invalidity of intention-to-treat analysis even for the intention-to-treat effect.

   (2) Estimation of causal effects.
   Case study: evaluating school choice on student performance

   *Frangakis and Rubin (1999), Baker (2000), *Barnard et al. (2003).

Case study: evaluating needle exchange programs

*Frangakis et al. (2004)

Case study: evaluating vaccine trials

*Gilbert et al. (2003).

Case study: estimating missing data related to death using interventional designs

Rubin (2000), *Zhang and Rubin (2003), *Frangakis, Rubin, An, and MacKenzie (2007).

References - articles with $*$ are available in a course packet

*Neyman, J. (1923). On the Application of Probability Theory to Agricultural Experiments. Essay on Principles. Section 9, translated in *Statistical Science*, (with discussion), Vol 5, No 4, 465–480, 1990.

*Rubin, D. B. (1990). Comment: Neyman (1923) and Causal Inference in Experiments and Observational Studies. *Statistical Science* 5, 472-480.

*Rubin, D. B. (1974). Estimating Causal Effects of Treatments in Randomized and Non-randomized Studies. *Journal of Educational Psychology*, 66, 688-701.

*Holland, P. (1986). Statistics and Causal Inference (with discussion). *Journal of the American Statistical Association*, 81, 945-970.

*Cox, D. R. (1992). Causality: Some Statistical Aspects. *Journal of the Royal Statistical Society*, Series A, 155, part 2, 291–301.

Fisher, R. A. (1925). *Statistical Methods for Research Workers*, 1st ed. Edinburgh: Oliver and Boyd.

Fisher, R. A. (1947). *The Design of Experiments*, 4th ed. New York: Hafner-Publishing.

*Cox, D. R. (1958). *Planning of Experiments*, New York: Wiley, chapters 1–3.

Horwitz, D. G., and Thompson, D. J. (1952). A Generalization of Sampling Without Replacement From a Finite Universe. *Journal of the American Statistical Association*, 47, 663-685.

*Rubin, D. B.(1978). Bayesian inference for causal effects: The Role of Randomization. *Annals of Statistics*, 6, 34–58.

*Rubin, D. B. (1977). Assignment to a Treatment Group on the Basis of a Covariate. *Journal of Educational Statistics*, 2, 1-26.

Cochran, W. G. (1968). The Effectiveness of Adjustment by Subclassification in Removing Bias in Observational Studies. *Biometrics*, 24, 295-313.

*Rubin, D. B. (1984). William G. Cochran's Contributions to the Design, Analysis and Evaluation of Observational Studies, in *W. G. Cochran's impact on statistics*, Podurl and Rao (eds).

*Rosenbaum, P., and Rubin, D. B. (1983a). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, 70, 1, 41–55.

*Rosenbaum, P., and Rubin, D. B. (1984). Reducing Bias in Observational Studies Using Subclassification on the Propensity Score," *Journal of the American Statistical Association*, Vol 79, 516–524.

*Lalonde, R. (1986). Evaluating the Econometric Evaluations of Training Programs. *American Economic Review*, Vol 76, 4, 605–620.

*Dehejia, H. R., and Wahba, S. (1999). Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs. *Journal of the American Statistical Association*, 94, 1053–

1062.

*Rosenbaum, P., and Rubin, D. B. (1983b). Assessing Sensitivity to an Unobserved Binary Covariate in an Observational Study with Binary Outcome. *Journal of the Royal Statistical Society, Series B*, 45, 212-218.

*Manski, C., Sandefur, G., McLanahan, S., and Powers, D. (1992). Alternative Estimates of the Effect of Family Structure During Adolescence on High School. *Journal of the American Statistical Association*, Vol 87, No. 417, 25–37.

*Imbens, GW. (2000). The role of the propensity score in estimating dose-response functions. *Biometrika* **87**, 706–710.

Huang, IC, Frangakis, CE, Dominici, F, Diette, GB, Wu, AW. (2005). Application of a propensity score approach for risk adjustment in profiling multiple physician groups on asthma care. *Health Services Research* **40**, 253–278.

*Robins, J. M. (1987). A Graphical Approach to the Identification and Estimation of Causal Parameters in Mortality Studies with Sustained exposure Periods. *Journal of Chronic Diseases*, 40, 1395–1615.

Pearl, J. (1995). Causal diagrams for empirical research (with discussion). *Biometrika*, 82, 669–710.

Robins, J. M., Greenland, S., and Hu. F.-C. (1999). Estimation of the Causal Effect of a Time-Varying Exposure on the Marginal Mean of a Repeated Binary Outcome. *Journal of the American Statistical Association*, 94, 687–712.

*Robins, J. M., Hernan, M. A., and Brumback, B. (2000). Marginal Structural Models and Causal Inference in Epidemiology. *Epidemiology*, 11, 550–560.

*Sommer, A. and Zeger, S. L. (1991). On Estimating Efficacy from Clinical Trials. *Statistics in Medicine*, 10, 45–52.

*Card, D. (1993). Using geographic variation in college proximity to estimate the return to schooling. NBER paper no. 4483.

McClellan M, McNeil BJ, Newhouse JP. (1994). Does more intensive treatment of acute myocardial infarction in the elderly reduce mortality? Analysis using instrumental variables. *Journal of the American Medical Association*, 272(11), 859–866.

Robins, J. M. and Greenland, S. (1994). Adjusting for differential rates of prophylaxis therapy for PCP in high-versus low-dose AZT treatment arms in an AIDS randomized trial. *Journal of the American Statistical Association*, 89, 737–749.

*Angrist, J., Imbens, G. W., and Rubin, D. B. (1996). Identification of Causal Effects Using Instrumental Variables (with discussion). *Journal of the American Statistical Association*, Vol 91, No.434, pp. 444-472.

*Imbens, G., and Rubin, D. B. (1997). Bayesian Inference for Causal Effects in Randomized Experiments with Noncompliance. *The Annals of Statistics*, Vol 25, 305–327.

Balke, A. and Pearl, J. (1997). Bounds on treatment effects from studies with imperfect compliance. *Journal of the American Statistical Associatin*, 93, 929–934.

Hirano, K., Imbens, G., Rubin, D., and Zhou, X. (2000). Causal Inference in Encouragement Designs with Covariates, *Biostatistics* **1**, 69–88.

Frangakis, CE, and Rubin, DB, and Zhou, X-H. (2002). Clustered encouragement designs with individual noncompliance: Bayesian inference with randomization and application to Advance Directive forms. *Biostatistics*, (with discussion) **3**, 147–164.

*Frangakis, CE, and Rubin, DB (2002). Principal stratification in causal inference, *Biometrics*, 58, 21–29.

*Frangakis, C. E. and Rubin, D. B. (1999). Addressing Complications of Intention-to-Treat Analysis in the Combined Presence of All-or-None Treatment-Noncompliance and Subsequent Missing Outcomes. *Biometrika*, 86, 365–379.

*Baker, S. G. (2000). Analyzing a Cancer Prevention Trial with a Missing Binary Outcome, an Auxilliary Variable, and All-or-None Compliance. *Journal of the American Statistical Association*, 95. 43–50.

*Barnard, J., Frangakis, C. E., Hill, J. L., and Rubin, D. B. (2002). School Choice in NY City: A Bayesian Analysis of an Imperfect Randomized Experiment. Forthcoming in *Case Studies in Bayesian Statistics*, New York: Springer-Verlag.

*Frangakis, CE, Brookmeyer, RS, Varadhan, R, Mahboobeh, S, Vlahov, D, and Strathdee, SA. (2004). Methodology for evaluating a partially controlled longitudinal treatment using principal stratification, with application to a Needle Exchange Program. *Journal of the American Statistical Association*, **99** 239–249.

Rubin, D. B. (2000). Comment on "Causal inference without counterfactuals", by AP Dawid, *Journal of the American Statistical Association* **95**, 435–437.

*Zhang JL and Rubin DB (2003). Estimation of causal effects via principal stratification when some outcomes are truncated by "death". *Journal of Educational and Behavioral Statistics* **28**, 353–368.

*Gilbert, P. B., Bosch, R. J., and M. G. Hudgens (2003). Sensitivity analysis for the assessment of causal vaccine effects on viral load in AIDS vaccine trials. *Biometrics* **59**, 531-541.

*Frangakis, CE, Rubin, DB, An, MW, MacKenzie, EA. (2007). Principal stratification designs to estimate input data missing due to death. To appear in *Biometrics*, (with discussion).