March 2019 **Bremen**

Causal Inference and Machine Learning

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Course Description

The course will cover topics in causal inference with a particular emphasis on methods related to machine learning.

Lectures

There will be four lectures, on Tuesday, March 26th, 2019, 10-11.15am, 11.45am-1.00pm, 2.00- 3.15pm, 3.45-5.00pm.

Background Reading

We strongly recommend that participants read these articles in preparation for the course.

- Athey, Susan, and Guido W. Imbens. ”The state of applied econometrics: Causality and policy evaluation.” Journal of Economic Perspectives 31.2 (2017): 3-32.
- Athey, Susan, and Guido W. Imbens. “Machine Learning Methods Economists Should Know About.”

Course Outline

The course will cover recent topics in causal inference with a particular emphasis on using modern maching learning methods. The first lecture will cover recent advances in experimental design, focusing particularly on multi-armed bandits and Thompson sampling, that are widely used in experimentation in online settings. The second lecture will discuss estimation of average treatment effects under unconfoundedness with many covariates. The third lecture will consider estimation of average treatment effects conditional on covariates, as well as estimation of optimal assignment policies exploiting heterogeneity in treatment effects. The fourth lecture will focus on synthetic control methods.

1. Causal Inference and Randomized Experiments
   (a) S. Scott (2010), “A modern Bayesian look at the multi-armed bandit,” *Applied Stochastic Models in Business and Industry*, vol 26(6):639–658.
   (b) M. Dimakopoulou, S. Athey, and G. Imbens (2017). “Estimation Considerations in Contextual Bandits.” http://arXiv.org/abs/1711.07077.
2. Estimating Average Treatment Effects Under Unconfoundedness
   (a) Imbens, Guido W., and Jeffrey M. Wooldridge. ”Recent developments in the econometrics of program evaluation.” Journal of Economic Literature 47.1 (2009): 5-86.

(b) Athey, Susan, Guido W. Imbens, and Stefan Wager. ”Approximate residual balancing: debiased inference of average treatment effects in high dimensions.” Journal of the Royal Statistical Society: Series B (Statistical Methodology) 80.4 (2018): 597-623.

(c) V. Chernozhukov, D. Chetverikov, M. Demirer, E. Duflo, C. Hansen, W. Newey, and J. Robins (2017, December) “Double/Debiased Machine Learning for Treatment and Causal Parameters.” https://arxiv.org/abs/1608.00060.

3. Causal Inference: Heterogeneous Treatment Effects

(a) S. Athey and G. Imbens (2016) “Recursive Partitioning for Heterogeneous Causal Effects,” *Proceedings of the National Academy of Sciences*.

(b) S. Wager and S. Athey (2017) “Estimation and inference of heterogeneous treatment effects using random forests.” *Journal of the American Statistical Association* http://arxiv.org/abs/1510.04342

(c) S. Athey, Tibshirani, J., and S. Wager (2017, July) “Generalized Random Forests” http://arxiv.org/abs/1610.01271

4. Synthetic Control Methods and Matrix Completion

(a) S. Athey, M. Bayati, N. Doudchenko, G. Imbens, and K. Khosravi (2017) “Matrix Completion Methods for Causal Panel Data Models.” http://arXiv.org/abs/1710.10251.

(b) J. Bai (2009), “Panel data models with interactive fixed effects.” *Econometrica*, 77(4): 1229–1279.

(c) E. Cand`es and B. Recht (2009) “Exact matrix completion via convex optimization.” *Foundations of Computational Mathematics*, 9(6):717-730.