

**Arthur Gretton, UCL**

Econometrics Seminar, Monday April 8

**TITLE:** Causal Effect Estimation with Context and Confounders

**ABSTRACT:** A fundamental causal modelling task is to predict the effect of an intervention (or treatment) on an outcome, given context/covariates. Examples include predicting the effect of a medical treatment on patient health given patient symptoms and demographic information, or predicting the effect of ticket pricing on airline sales given seasonal fluctuations in demand. The problem becomes especially challenging when the treatment and context are complex (for instance, "treatment" might be a web ad design or a radiotherapy plan), and when only observational data is available (i.e., we have access to historical data, but cannot intervene ourselves). The challenge is greater still when the covariates are not observed, and constitute a hidden source of confounding.

I will give an overview of some practical tools and methods for estimating causal effects of complex, high dimensional treatments from observational data. The approach is based on conditional feature means, which represent conditional expectations of relevant model features. These features can be deep neural nets (adaptive, finite dimensional, learned from data), or kernel features (fixed, infinite dimensional, enforcing smoothness). When hidden confounding is present, a neural net implementation of instrumental variable regression can be used to correct for this confounding. The methods will be applied to modelling employment outcomes for the US Job Corps program for Disadvantaged Youth, and in policy evaluation for reinforcement learning.

**Further reading:**

For observed confounders, [Kernel Methods for Causal Functions: Dose, Heterogeneous, and Incremental Response Curves](#) (Biometrika 2023), [A Neural Mean Embedding Approach for Back-door and Front-door Adjustment](#) (ICLR 2023).

For hidden confounders, [Kernel Instrumental Variable Regression](#) (NeurIPS 2019), [Learning Deep Features in Instrumental Variable Regression](#) (ICLR 2021), [Proximal Causal Learning with Kernels: Two-Stage Estimation and Moment Restriction](#) (ICML 2021), [Deep Proxy Causal Learning and its Application to Confounded Bandit Policy Evaluation](#) (NeurIPS 2021).