**2.4 Personalised Treatment Effects**

Alicia Curth

[amc253@cam.ac.uk](mailto:amc253@cam.ac.uk)

**Personalised therapeutics**

* estimate effect of a treatment/intervention on an individual patient
* Tutorial goal:
  + Estimating the effect of a treatment on an individual
    - Will a given treatment work for an individual patient?
      * Age, weight, blood, pressure into observational data (offline)
  + Answering such questions from observational data is tricky
    - Missing counterfactual and confounding

**Observational data**

* Collected from actual clinical practice
  + Patient features - X
  + Treatment assignment - W
  + Outcome - Y
* This is not randomised
  + Depends on clinical practice
  + Based on observable characteristics
  + Propensity function
* Potential outcomes framework (Neyman-Rubin)
  + X: Each patient *i* has features
  + Two potential outcomes:
    - Treated outcome: treated
    - Control outcome: not treated
      * Will only observe factual outcomes – not the counterfactual outcomes
* Conditional average treatment effect (CATE)/ Individualised treatment effect (ITE)
  + <http://www.personal.ceu.hu/staff/Robert_Lieli/cate.pdf>

**Causal effect challenges**

* No labels – not supervised
* A solution:
  + Modelling potential outcome regressions
  + Data from treated
* Challenges:
  + Confounding -> covariate shift
    - Training distribution != testing distribution
    - Solutions:
      * Domain-adversarial training
      * Importance weighting
      * Not focus
  + Unobserved labels: can target outcomes but not treatment effect
* Potential outcomes framework
  + Main assumptions:
    - no unmeasured confounders (ignorability)
      * E.g. smoking is not recorded but treatment was assigned based on smoking status
    - Common support
      * Some randomness across treatment and not treatment
      * Treatment can be deterministically assigned

**How to model individualized treatment effects? – potential outcome regression**

* <https://arxiv.org/abs/2106.03765>
* Indirect learners: PO regression for CATE estimation
  + T-learner
  + Fit two separate regression surfaces using any ML method and only data of each treatment group, then use difference
* PO-sepcific regression heads
* T-learner
* TARnet
* Implicit inductive biases in existing indirect learners

**CATE estimation**

* Soft, Hard, and flexible approach
* Soft:
  + Generic indirect learner loss function > change regularization scheme

**Evaluation**

* Semi-synthetic simulation studies
* <https://datasets-benchmarks-proceedings.neurips.cc/paper/2021/hash/2a79ea27c279e471f4d180b08d62b00a-Abstract-round2.html>

**Meta-learner**

* Meta-learning != Meta-learner
* Two approaches
  + Indirect approach
    - For CATE: T-learner/ S-learner/ Hybrid S-learner
  + Direct approach

**Key takeaways:**

**What’s next?**

Handling unobserved confounding?

<https://proceedings.mlr.press/v119/bica20a.html>

Survival outcomes

Treatment outcome: multiple and continuous

Longitudinal data

**Additional notes:**

* Nonparametric Estimation of Heterogeneous Treatment Effects: From Theory to Learning Algorithms
  + <https://arxiv.org/abs/2101.10943>
* On Inductive Biases for Heterogeneous Treatment Effect Estimation
  + <https://arxiv.org/abs/2106.03765>
* Metalearners for estimating heterogeneous treatment effects using machine learning
  + <https://www.pnas.org/doi/10.1073/pnas.1804597116>
* Towards optimal doubly robust estimation of heterogeneous causal effects
  + <https://arxiv.org/abs/2004.14497>
* Estimating individual treatment effect: generalization bounds and algorithms
  + <https://arxiv.org/abs/1606.03976?context=stat>
* CATENets: <https://github.com/AliciaCurth/CATENets>
* Learn more:
  + <https://www.vanderschaar-lab.com/individualized-treatment-effect-inference/>