2.4 Personalised Treatment Effects

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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/