Estimating Causal Treatment Effects For Brain Bleed Patients

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Introduction

- Brain bleeds are a serious medical emergency with high risk of death or disability, and treatment decisions can be difficult and time sensitive
- Every year, there are 18.9 million cases of intracerebral hemorrhages, with 30-day mortality rates up to 40-50%. However, there is uncertainty regarding which treatment strategies lead to the best patient outcomes
- To explore this further, our project uses a subset of the MIMIC-III dataset, a publicly available ICU database from the Beth Israel Deaconess Medical Center in Boston, MA that contains clinical data for 1330 brain bleed patients

Research Goal

- Quantify the effect of two treatments (craniotomy/craniectomy and minimally invasive surgery) compared to the control (nonsurgical methods) on the 90-day survival of brain bleed patients
- Our research is centered around two estimands of interest:
  - Average Treatment Effect (ATE): What is the average effect of treatment type on survival?
  - Conditional Average Treatment Effect (CATE): How does the effect of treatment type on survival vary across patient subgroups?

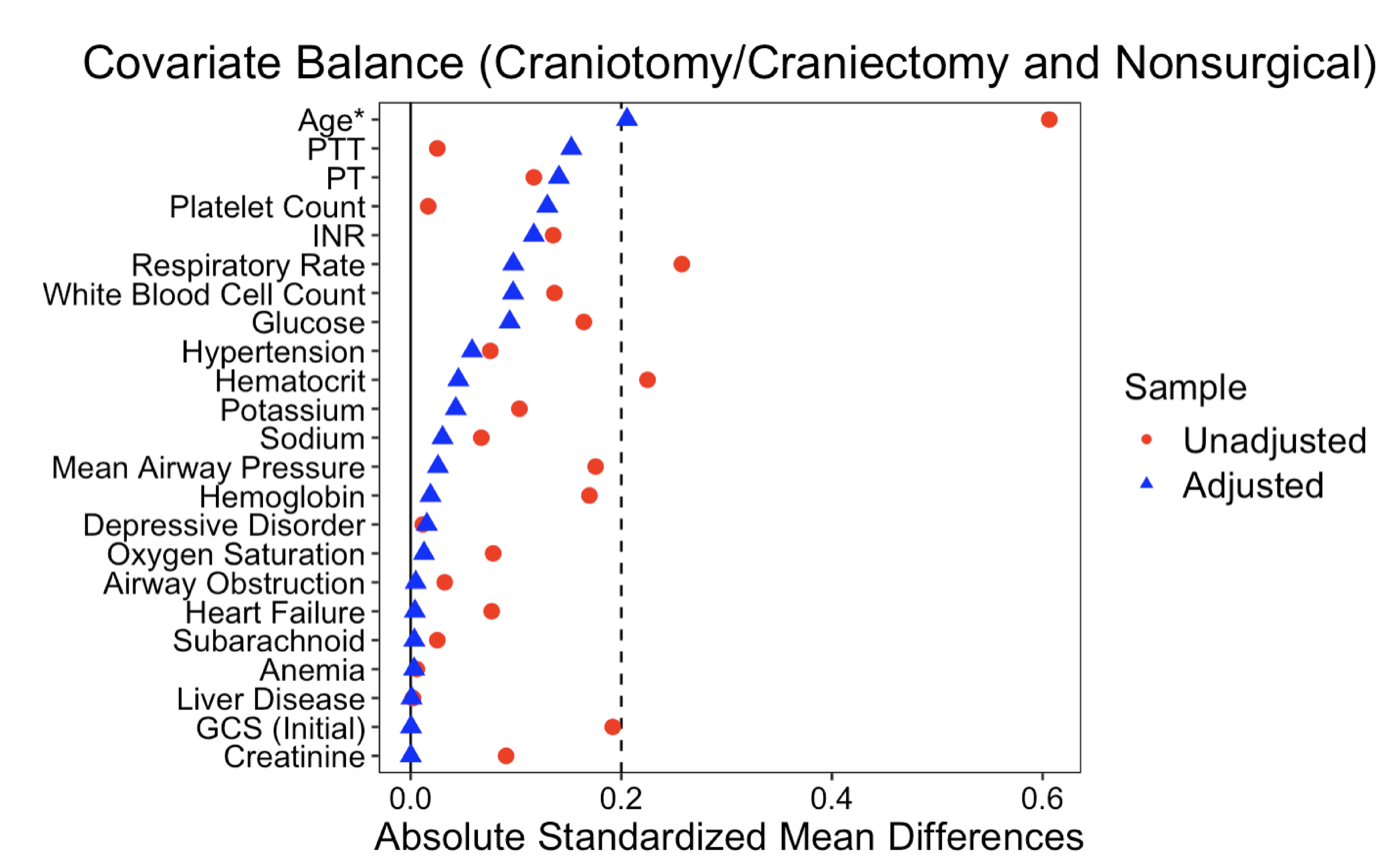
Methods – Average Treatment Effect

$$\tau_a := \mathrm{E}[Y_i(a) - Y_i(0)]$$

- Estimates the effect of treatment a compared to the control across the population

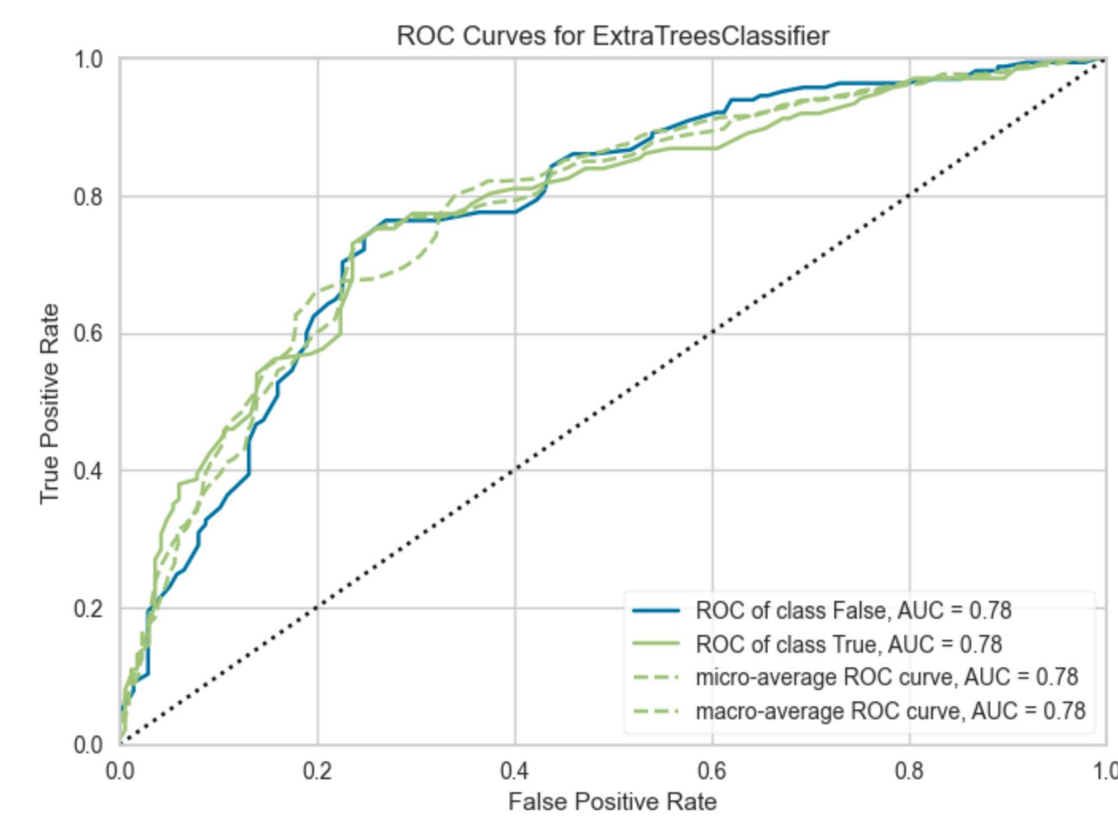
Propensity Score Model $e_a(x) := P[A_i = a | X_i = x]$

- Predicts probability of receiving treatment a given covariates x
- Propensity scores must be estimated in observational settings
- Used LASSO Logistic Regression for our propensity score model, chosen by metrics such as Area Under the Curve (AUC)



Outcome Model $\mu(x, a) := E[Y_i \mid X_i = x, A_i = a]$

- Predicts probability of mortality given covariates x, and assuming treatment a
- Used two Extra Trees Classifiers and a Support Vector Machine for our outcome models, selected by metrics such as AUC



Augmented Inverse-Propensity Weighted Estimator

$$\hat{\tau}_a := \frac{1}{n}\sum_{i=1}^{n}[\hat{\mu}(X_i, a) - \hat{\mu}(X_i, 0) + \frac{(\mathbb{1}_{A_i=a})}{\hat{e}_a(X_i)}(Y_i - \hat{\mu}(X_i, a)) - \frac{(\mathbb{1}_{A_i=0})}{(1-\hat{e}_a(X_i))}(Y_i - \hat{\mu}(X_i, 0))]$$

- AIPW combines the outcome model and propensity score model for a stable estimate of Average Treatment Effect
- Doubly Robust: estimator is consistent/unbiased if either the propensity score model or the outcome model is consistent/unbiased

Methods – Heterogeneous Treatment Effects

$$\tau_a := \mathrm{E}[Y_i(a) - Y_i(0) | X_i = x]$$

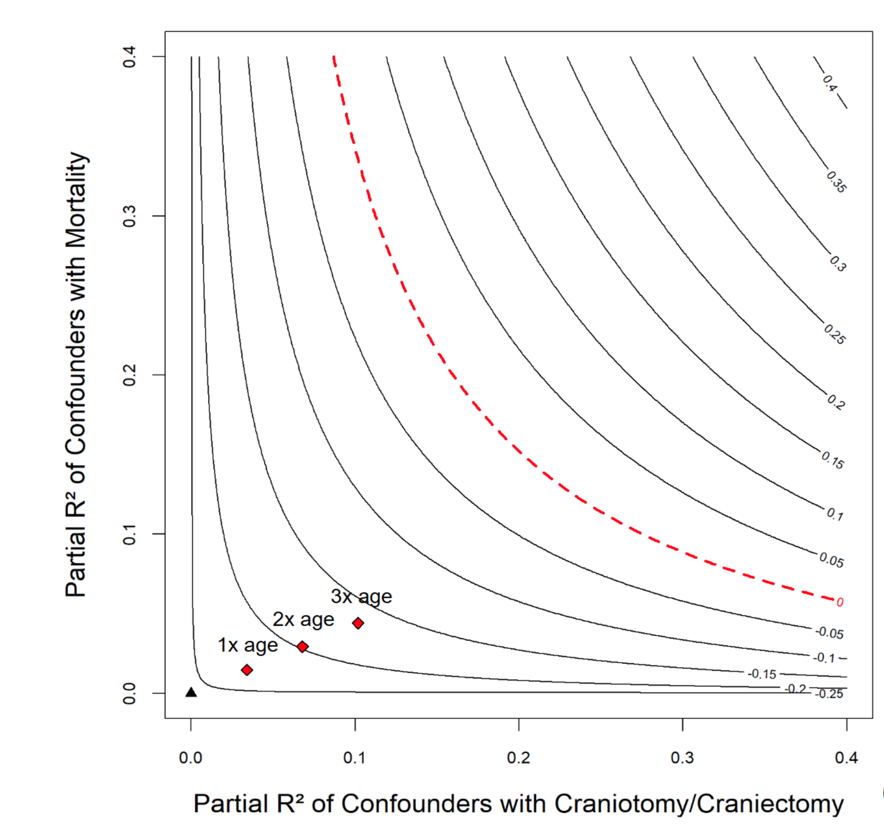
- Conditional Average Effect of Treatment (CATE) quantifies the expected effect of a treatment for individuals with specific characteristics
- Helps answer the question: "what is the treatment effect for an individual or groupwith certain characteristics?"
- Allows clinicians to give more personalized, or subgroup specific, treatment recommendations
- Allows for analysis of how optimal treatment assignment could improve patient outcomes, using a multi-armed causal forest

Mean Covariate Values by Model-Optimal Treatment
Rounded, with p-value significance

Covariate	Craniotomy/Craniectomy	Minimally Invasive Surgery	p_value
Age at Admission	74	59	0.000
Initial GCS	6	8	0.000
White Blood Cell Count	18	14	0.014
Glucose	168	159	0.019
Platelet Count	234	242	0.126
Hematocrit	30	30	0.428

Results

- Our AIPW estimates that receiving a craniotomy/craniectomy reduces patients' mortality risk by approximately **27.4%** at a statistically significant level
- Our AIPW also estimates that receiving minimally invasive surgery reduces patients' mortality risk by approximately **13.2%**, but not at a statistically significant level
- Optimal treatment modeling suggests that receiving an alternative to nonsurgical treatment can lower patients' mortality risk on average:
  - Patients who received nonsurgical treatment and were assigned a model-optimal treatment of craniotomy/craniectomy are predicted to have a **24% reduction** in mortality risk
  - Patients who received nonsurgical treatment and were assigned a model-optimal treatment of minimally invasive surgery are predicted to have a **27% reduction** in mortality risk
- Unmeasured confounders need to be **at least 7 times as strong** as our strongest confounder (age) to invalidate our results for our statistically significant model



Future Research

- Estimating Average Treatment Effect on the Treated (ATT) to focus on understanding the effect of treatments on brain bleed patients who actually received treatment
- Utilizing machine learning methods to conduct prediction analysis, which consists of forecasting future outcomes based on patterns in observed data

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