BART For Causal Inference

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Learning Objectives

- What are the benefits of framing questions causally?
- What are the traps of applying machine learning to causal inference?
  - Prior Dogmatism
  - Treatment Effect Heterogeneity Priors
- What are BCFs and why do we parameterize them the way we do?
- How do we summarize the posterior?
- What is the workflow for applying BART to causal inference?

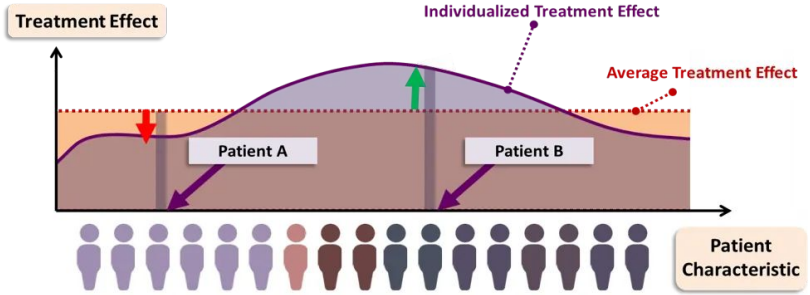
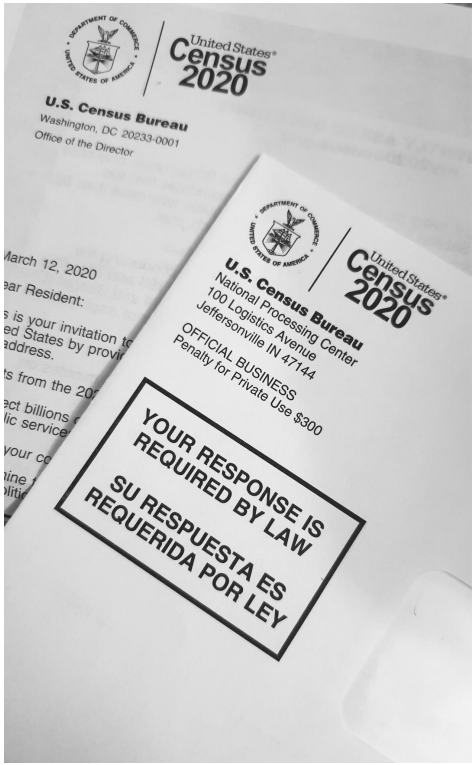


Image from https://www.vanderschaar-lab.com/individualized-treatment-effect-inference/

What is Causal Inference

Types of Studies

RANDOMIZED



NOT RANDOMIZED

Why Do Causal Inference?

- Forces us to ask good/clear questions
  - Causal questions are *model free*
  - Causal questions can directly lead to policy recommendations, or actions
- Forces us to clarify our assumptions
  - Encourages transparency
  - Forces us to think carefully about identification, sensitivity analysis, and being explicit about confounders

Why Focus on Treatment Effect Heterogeneity

- **In RCTs**: Not all treatments are useful for all people, and we might want to target treatments to individuals who will benefit the most.

- **In Observational Studies:** Can motivate different/better policies, but also **causal effects in observational studies tend to be more robust when they are large!** So finding treatments highly effective in subgroups can motivate better follow up studies and more robust conclusions.

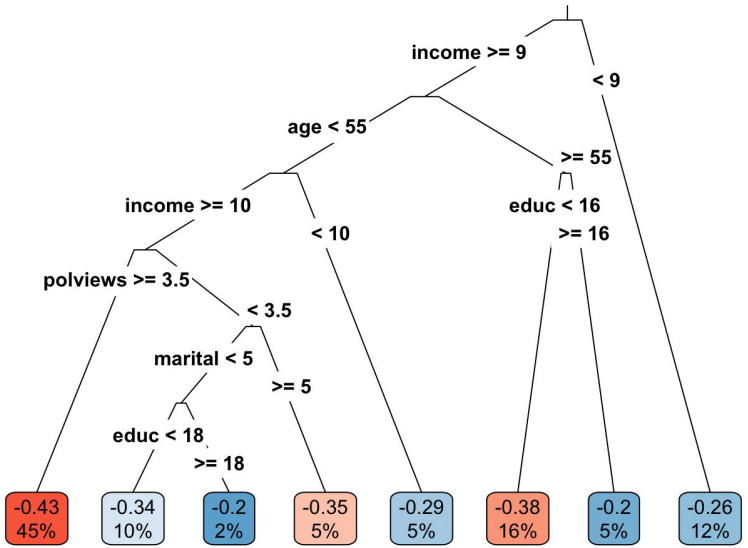
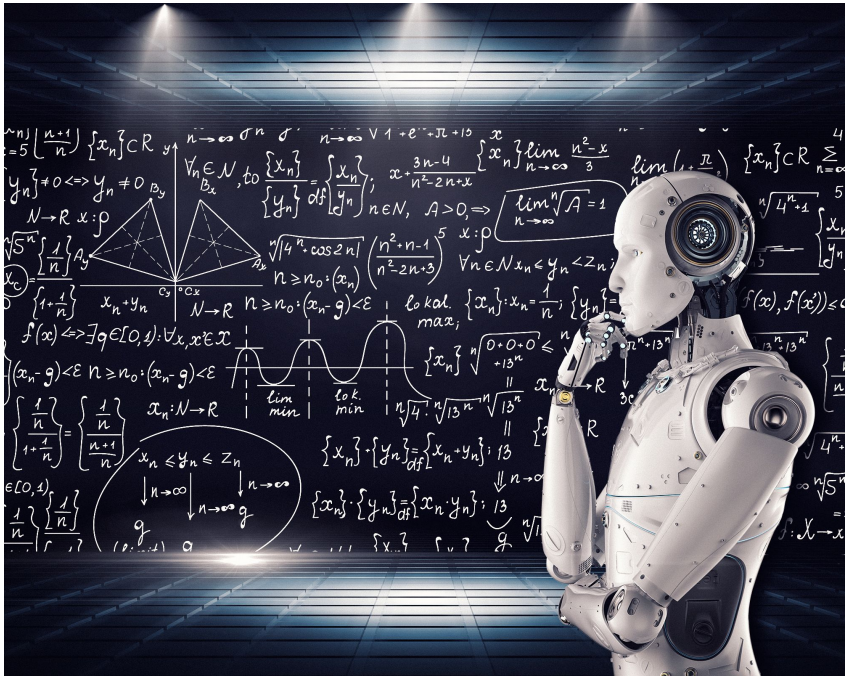


Image from
https://bookdown.org/stanfordgsbsilab/ml-ci-tutorial/hte-i-binary-treatment.html

Why Machine Learning?



- Reduces risks of model misspecification
- Avoids needing to specify interactions
- **But comes with its own catches due to regularization!**

Causal Framework

$A_i \sim \text{Bernoulli}\{e(X_i)\}$ Exposure Model

$\{Y_i(0), Y_i(1)\} \sim F_{X_i}$ Outcome Model

$\text{Observe } \{Y_i(A_i), A_i, X_i\}$ Always missing one…

Our Goal: Estimate the Treatment Effect

$$\tau(x) = \mathbb{E}\{Y_i(1) - Y_i(0) \mid X_i = x\}$$

Causal Assumptions

No Interference:

$$Y_i(\mathbf{a}) = Y_i(a_i)$$

Positivity:

$$\delta \leq e(x) \leq \delta^{-1} \qquad \text{for all } x$$

Unconfoundedness:

$$A_i \perp \{Y_i(0), Y_i(1)\} \mid X_i$$

Software Options

- **bcf** package on CRAN
- **SoftBart** package on CRAN (*softbart_vc_regression)*

Two Bad Approaches

S-Learner:

Use treatment as “just another covariate”

$$Y_i(a) = \mu(a, x) + \epsilon_i$$

Unclear what the prior on HTEs are!

T-Learner:

Stratify on the treatment

$$Y_i(a) = \mu_a(x) + \epsilon_i$$

Prefers to attribute to treatment that which can be explained by confounders! Also, assumes a lot of heterogeneity!

Regularization Leads to Prior Dogmatism

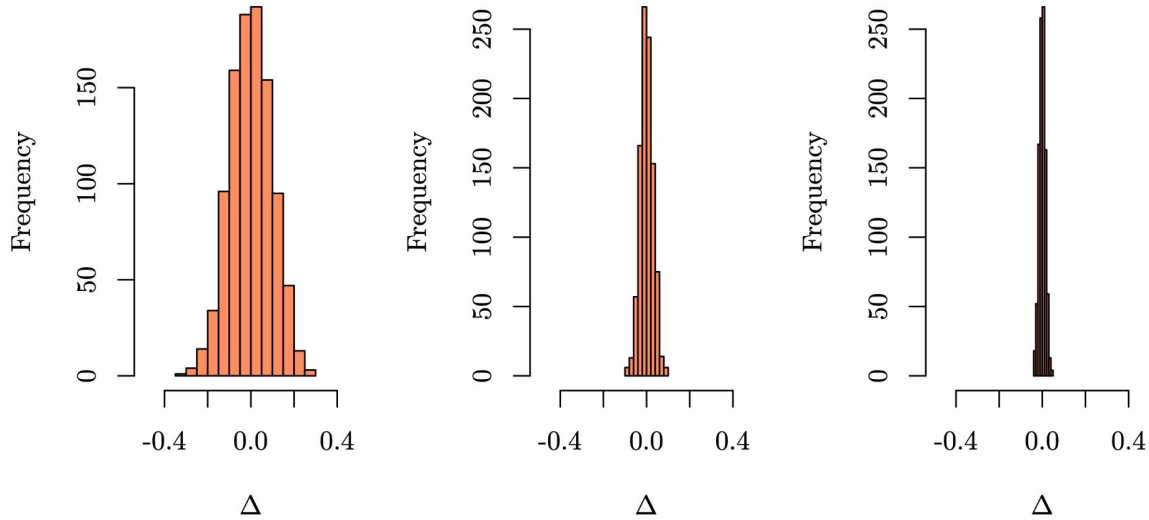


Figure 2: Prior distribution of Δ for the BART model in Section 2.2 for $P \in \{1, 10, 50\}$.

$$\Delta = \text{amount of selection bias}$$

Quirks of the T-Learner

$$\mu_0(x) \sim N(0, a)$$
$$\mu_1(x) \sim N(0, b)$$
$$\tau(x) = \mu_1(x) - \mu_0(x) \sim N(0, a + b)$$

Large treatment effects

$$\mathrm{Var}\{\tau(X)\} \asymp \frac{\mathrm{Var}\{\mu_1(X) + \mu_0(X)\}}{2}$$

Heterogeneity scales with complexity of prognostic effect

A Bayesian Causal Forest

$$Y_i(a) = \mu(X_i) + \{a - \hat{e}(X_i)\}\,\tau(X_i) + \epsilon_i(a)$$

Prognostic effect

Debiasing term

Treatment effect

Put BARTS on all unknown functions!

(Can also include PS in prognostic effect)

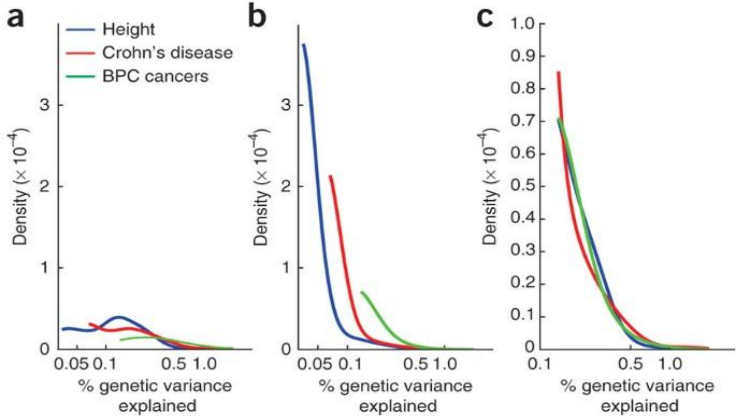
The Treatment Effect Prior

Prior on HTE function is very important!!!

Desirable properties

1. Shrink towards small effect sizes
2. Shrink towards homogeneous effects

Failure to do this correctly can lead to overly-optimistic identification of subgroups and poor estimation of the HTE!



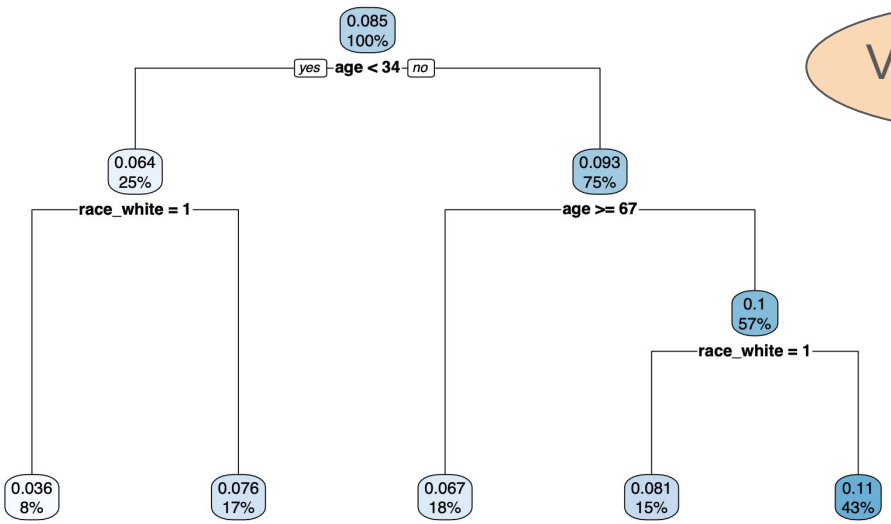
Posterior Summarization

Question: How do I extract scientific insight from the models?

Possible Goals:

- Subgroup identification (who benefited most from treatment?)
- Find an interpretable surrogate for $\tau(x)$

Subgroup Identification



Virtual Twins

Figure 3: Posterior summarization of the indirect effect using a single regression tree.

Best Tree-Based Approximation to HTE

Projection Summary, As Before

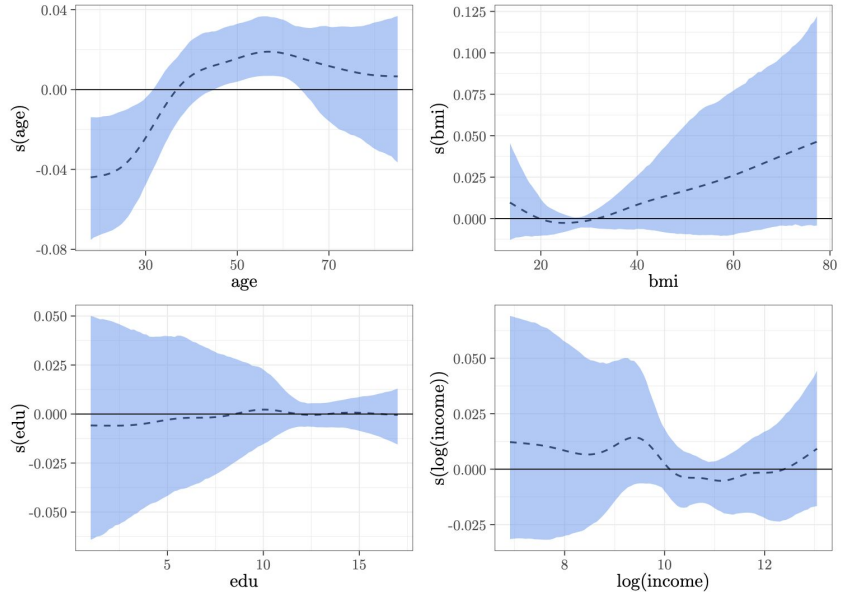
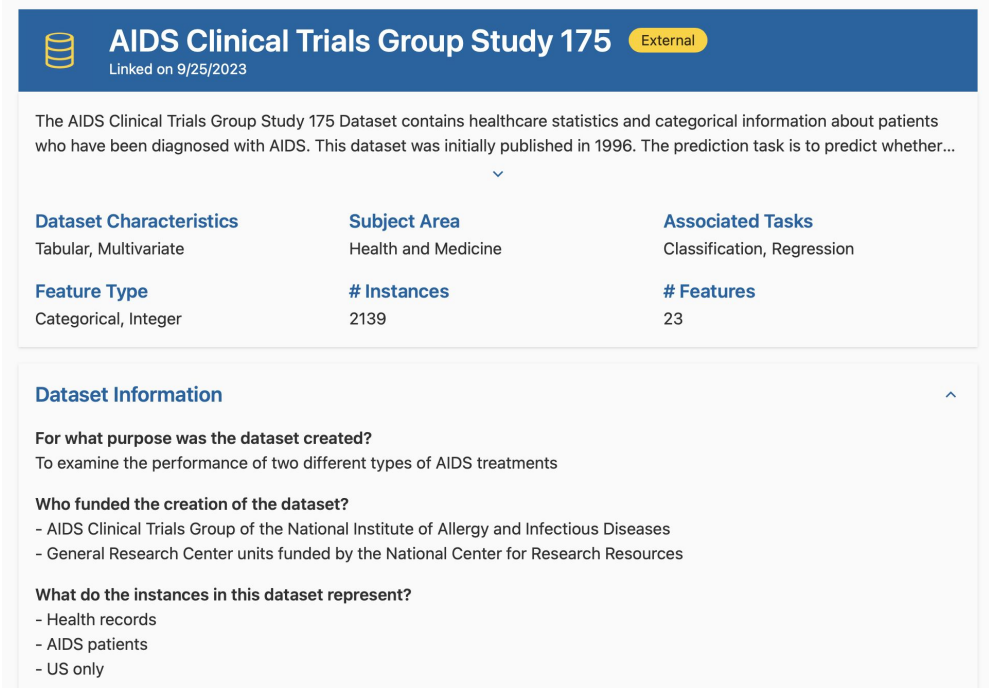


Figure 5: Posterior summarization of the indirect effect using a GAM for the continuous variables. The projection of the posterior mean is given by the dashed line while the shaded area gives a posterior 95% credible band of the projection.

Case Study: an RCT

Question: is treatment more effective at reducing CD4 count change in certain subpopulations?



AIDS Clinical Trials Group Study 175

External

Linked on 9/25/2023

The AIDS Clinical Trials Group Study 175 Dataset contains healthcare statistics and categorical information about patients who have been diagnosed with AIDS. This dataset was initially published in 1996. The prediction task is to predict whether...

Dataset Characteristics	Subject Area	Associated Tasks
Tabular, Multivariate	Health and Medicine	Classification, Regression

Feature Type	# Instances	# Features
Categorical, Integer	2139	23

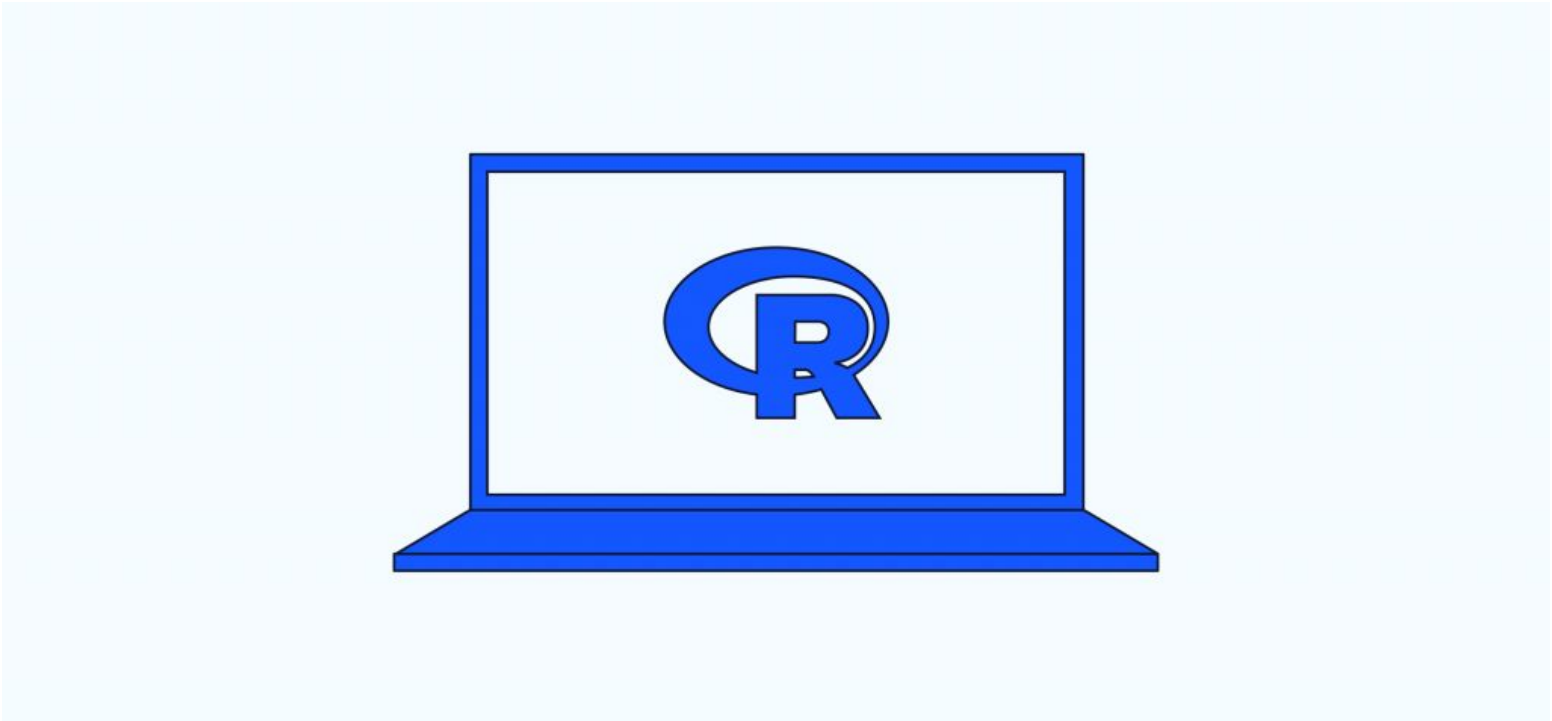
Dataset Information

For what purpose was the dataset created?
To examine the performance of two different types of AIDS treatments

Who funded the creation of the dataset?
- AIDS Clinical Trials Group of the National Institute of Allergy and Infectious Diseases
- General Research Center units funded by the National Center for Research Resources

What do the instances in this dataset represent?
- Health records
- AIDS patients
- US only

Go Over Code



Case Study: MEPS

Question: Is there heterogeneity in the degree to which smoking leads to bad health outcomes in some individuals?

Some variables: Age, Sex, Race, Measures of SES.

Go Over Code