

# Invited Discussion on Bayesian Causal Forests

Arman Oganisian<sup>1</sup> and Jason A. Roy<sup>2</sup>

<sup>1</sup>University of Pennsylvania

<sup>2</sup>Rutgers University

*Bayesian Analysis* Webinar

September 25, 2020

# General Comments on BCF

Many contributions of this work:

- ▶ Clear discussion of regularization-induced confounding (RIC) within a nonparametric context.
- ▶ Nice illustrations of why targeted selection can be problematic if the propensity score is not included.
- ▶ Different BART priors for two functions.

## General Comments on BCF

Tempting to stratify and specify priors for  $f(x_i, Z_i = 0)$  and  $f(x_i, Z_i = 1)$ .

- ▶ Drawback: lack of direct control over prior for causal effects

Hahn et al. make compelling case for the model:

$$f(x_i, z_i) = \mu(x_i) + \tau(x_i)z_i$$

- ▶ Separating out prognostic score and treatment effect clearly.
- ▶ Flexible, yet interpretable shrinkage towards homogeneous effects.

## General Comments on BCF

If we start with  $f(x_i, z_i) = \mu(x_i) + \tau(x_i)z_i$

- ▶ could specify any priors over functions for  $\mu(\cdot)$  and  $\tau(\cdot)$

BCF is more specific. They propose

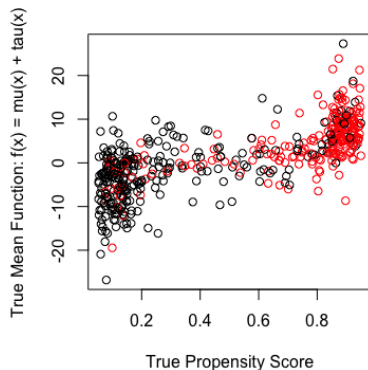
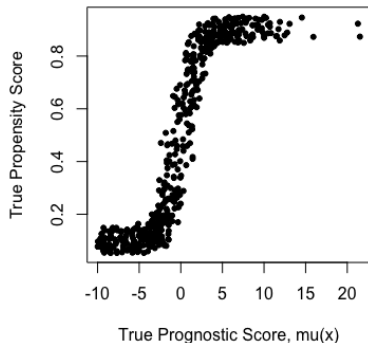
$$f(x_i, z_i) = \mu(x_i, \hat{\pi}(x_i)) + \tau(x_i)z_i$$

with BART priors on the functions, where  $\hat{\pi}$  is the propensity score.

- ▶ Is BART the right choice?
- ▶ Why include the propensity score?

# Targeted Selection

Targeted selection occurs when the treatment probability depends heavily on the prognostic score (risk if untreated). An example of this is in one of their simulation scenarios:



# Targeted Selection

However, ideally selection should be based on the expected benefit of treatment  $E(Y(1) - Y(0)|X)$ .

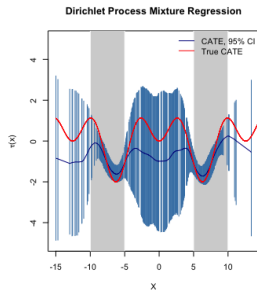
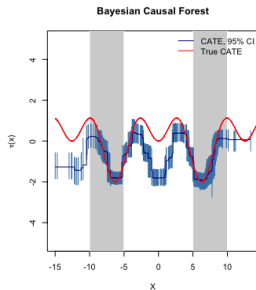
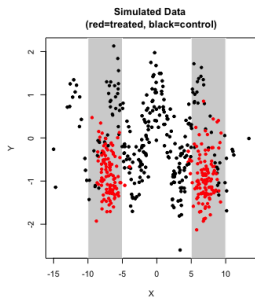
e.g., a clinician should recommend a treatment to patients that they suspect would benefit most from treatment, rather simply basing recommendations on who is the most (or least) frail

How common is targeted selection in practice?

# Uncertainty Estimation in Non-overlap Regions

- ▶ Overlap must hold:  $P(Z | X)$  be bounded  $\forall X$ .
- ▶ Model extrapolates in nonoverlap regions where  $P(Z | X) \approx 1$ .
- ▶ Trade-off between ignorability and overlap.

# Uncertainty Estimation in Non-overlap Regions



BCF inherits some features of BART:

- ▶ Non-smooth.
- ▶ Homoskedastic.



# Some Options

- ▶ Ignore it:
  - ▶ Underestimates uncertainty (and bias).
- ▶ Trimming:
  - ▶ Not properly Bayes.
  - ▶ For ITE, we “give up” on subjects.
  - ▶ For ATE, changes estimand.
- ▶ Modified BART ?
  - ▶ Smoothed BART [Linero and Yang, 2018].
  - ▶ BART with DP prior on errors [George et al., 2018].

# References I



George, E., Laud, P., Logan, B., McCulloch, R., and Sparapani, R. (2018).  
Fully nonparametric bayesian additive regression trees.



Linero, A. R. and Yang, Y. (2018).

Bayesian regression tree ensembles that adapt to smoothness and sparsity.  
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