Segment 5: Analyzing Observational Studies

Section 06: Flexible Response Surface Modeling

Two General Approaches
(could be applied together)

1. Response Surface Modeling
   - $E[Y|X, Z] =$
   - E.g., Regression
   - **Advantages**: Heterogeneous treatment effects, predictive power (precision)
   - **Disadvantages**: Need to get the model "right", consequences of misspecification in observational studies

2. Two-stage (Propensity Score) Modeling
   2.1 Model the assignment mechanism (i.e., the propensity score)
   2.2 Compare means in groups defined by the propensity score

   - **Advantages:** Modeling the assignment mechanism can be easier (and iterative), balance/overlap during "design", can easily be nonparametric *after* "design"
   - **Disadvantages:** Heterogeneous effects are hard to specify/interpret, may leave predictive power "on the table"

Response Surface Modeling and Treatment Effect Heterogeneity

- Can easily specify a treatment effect that varies as a function of covariate(s)
  - E.g., `stan_glm(post_test ~ treatment + pre_test + treatment:pre_test, data=electric)`

- Compare with propensity score
  - $E[Y(1) - Y(0)|e(X) = e]$: Average effect in units with a certain propensity score
  - `stan_glm(y~ z + ps + z:ps)`
  - Difficult to interpret

Response Surface Modeling and Model Specification

But....

- But need to know *a priori* which interaction terms to include to encode TEH...
- And also the parametric model needs to be close to "right"
  - In a nonrandomized study, especially if there is strong confounding

General Question: Can we leverage more powerful/flexible predictive algorithms for response surface modeling for causal inference in a way that improves upon the above?

Enter BART!
(or other flexible prediction algorithm)

There are *many* powerful predictive algorithms available that can:

- "Automatically" model very flexible functions of treatments, covariates, in a response surface
  - Nonlinearity, interactions, etc.
  - Can detect them "automatically"
- Estimate treatment effect heterogeneity without having to know *exactly* which variables to interact with treatment
- Leverage strong predictive performance capabilities
- Bayesian Additive Regression Trees (BART) is one example
  - That is becoming popular for causal inference
- Some of the benefits of doing causal inference with BART extend to other predictive modeling technologies (CART, random forests, etc.)

General Predictive Procedure

0.

1. Fit a flexible response model for $Y|X, Z$
   - Possible two separate models: $(Y|X, Z = 1), (Y|X, Z = 0)$
   - BART, random forests, etc.
2. Predict the "other" potential outcome
   - For $Z = 1$ units, use model to predict $Y(0)$
   - For $Z = 0$ units, use model to predict $Y(1)$
3. Calculate causal effects
   - Individual-level causal effects (caution, lots of uncertainty)
   - Average causal effects

Bayesian Nonparametric Modeling for Causal Inference

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Researchers have long struggled to identify causal effects in nonexperimental settings. Many recently proposed strategies assume ignorability of the treatment assignment mechanism and require fitting two models—one for the assignment mechanism and one for the response surface. This article proposes a strategy that instead focuses on very flexibly modeling just the response surface using a Bayesian nonparametric modeling procedure, Bayesian Additive Regression Trees (BART). BART has several advantages: it is far simpler to use than many recent competitors, requires less guesswork in model fitting, handles a large number of predictors, yields coherent uncertainty intervals, and fluidly handles continuous treatment variables and missing data for the outcome variable. BART also naturally identifies heterogeneous treatment effects. BART produces more accurate estimates of average treatment effects compared to propensity score matching, propensity-weighted estimators, and regression adjustment in the nonlinear simulation situations examined. Further, it is highly competitive in linear settings with the "correct" model, linear regression. Supplemental materials including code and data to replicate simulations and examples from the article as well as methods for population inference are available online.

Key Words: Bayesian; Causal inference; Nonparametrics.