

Social Data Science: Machine Learning & Econometrics

Exercise class 4

March 11, 2020

Important information

Novel coronavirus

Exercise classes will move online, beginning immediately. When we return to normal classroom exercises you will be notified.

- ▶ Online learning is new territory for us, but we will try to learn quickly. Your feedback can help us fix mistakes faster.
- ▶ **Organization:** (read [this information!](#))
 - ▶ A weekly problem set will still be posted on github.
 - ▶ 1 week later you must “hand in” your progress on both the exercises and the quick warmup.
 - ▶ I will keep you updated on any further teaching (cf. the questionnaire)!
 - ▶ I will communicate important information and changes via Absalon.

Today's quick warmup

Q: Implement a class `Clock` that mimicks a n -hour clock. Assume that all clocks start at hour 0. Implement a `.tick()` method that ticks the clock forward one hour. The clock should also store the number of cycles it has run through since initialization.

Implement the `__eq__` method, to check if the same total amount of hours have elapsed on two different clocks.

Last lecture in a nutshell

Two related approaches to causal inference in random forests:

- ▶ Causal Forests
- ▶ Generalized random forest

... a way to solve estimating equations of the form

$$\mathbb{E}[\psi_{\theta(x), \nu(x)}(O_i) | X_i = x] = 0 \quad \forall x \quad (1)$$

In linear regression we solve for (β, δ) in

$$\mathbb{E}[Y_i - \delta W_i - \beta_k X_{ki}] = 0 \quad (2)$$

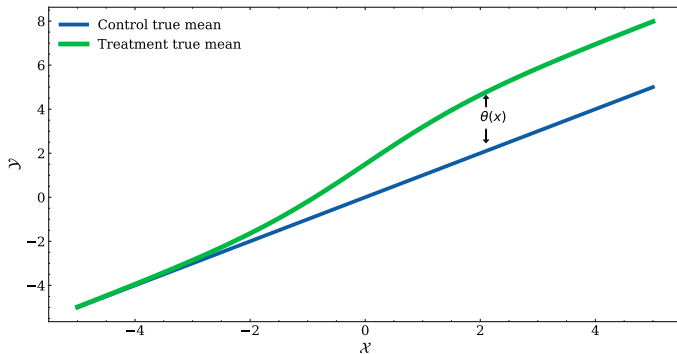
Build a (generalized) random forest and compute weights

$$\alpha_i(x) = \frac{1}{B} \sum_{b=1}^B \frac{\mathbb{1}_{(X_i \in L_b(x))}}{|L_b(x)|}, \quad (3)$$

then solve (1) globally (fix θ, ν) using these weights.

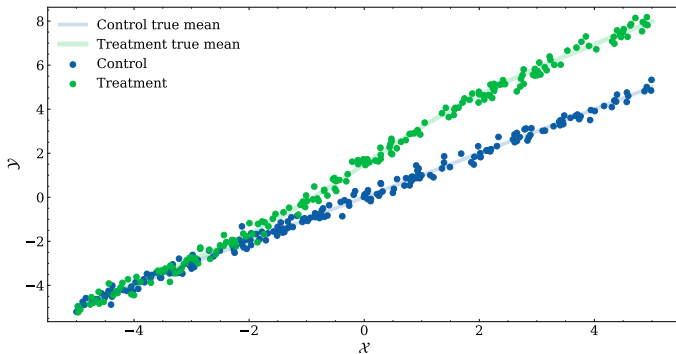
Last lecture in a nutshell

This is the “true” treatment effect, note it is heterogeneous in \mathcal{X}



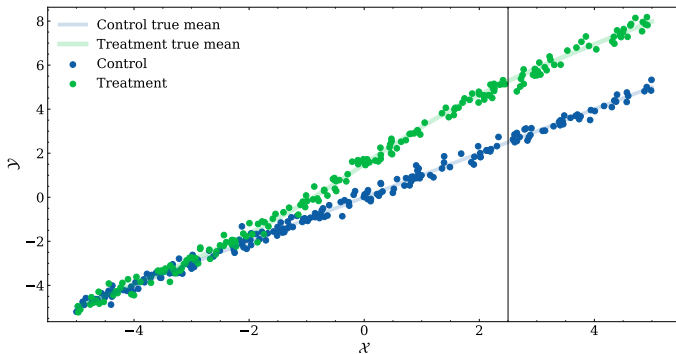
Last lecture in a nutshell

... of course in reality we only observe finite data.



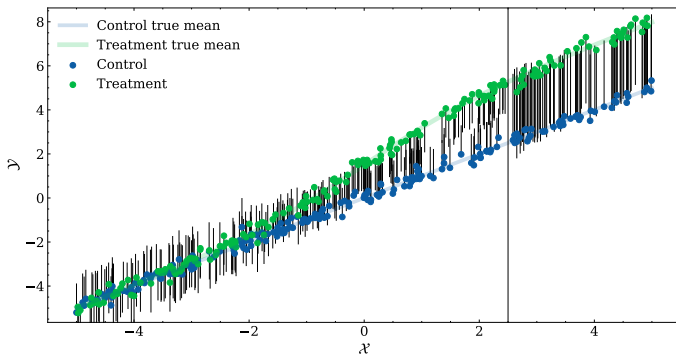
Last lecture in a nutshell

... this is the first split of a decision tree, splitting \mathcal{X}



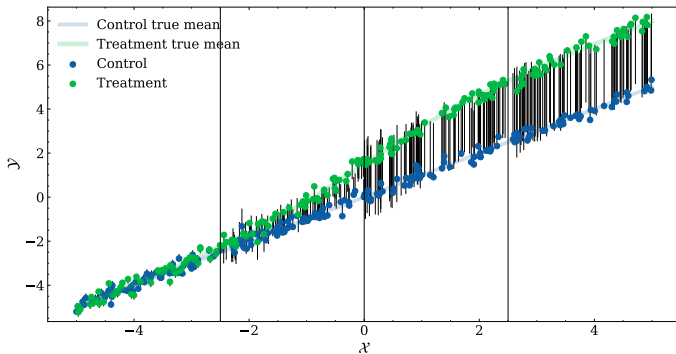
Last lecture in a nutshell

... and these are within-leaf treatment effects estimated as $\mu_{T=1}^{\ell(x)} - \mu_{T=0}^{\ell(x)}$



Last lecture in a nutshell

... continue growing the tree to refine the estimates of $\tau(x)$



Last lecture in a nutshell

... repeat the above n times, and weight observations by how often they land in the same leaf. Use these weights to estimate θ

