

The background of the slide features a large, light gray watermark of the University of Chicago seal. The seal includes a shield with a book and the text "Viva CatSci Excc entia latur", and a crest above it with the text "The University of Chicago".

Causal Machine Learning

Week 1

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Causality

The paradigmatic assertion in causal relationships is that manipulation of a cause will result in the manipulation of an effect. . . . Causation implies that by varying one factor I can make another vary.

(Cook & Campbell 1979: 36, emphasis in original)

Causal Constructs

- ▶ What types of outcomes do social scientists care about?
- ▶ What types of treatments?
- ▶ What objects do they wish to estimate?
- ▶ *Why* do they wish to estimate these?

Causal Constructs

- ▶ Consider the following:

$$w = \alpha + \beta \text{ Gender} + \delta'x + \epsilon$$

- ▶ What is the interpretation of β ?
- ▶ What would you include in x ? Does this change the interpretation of β ?
- ▶ How should we think of Bertrand & Mullainathan (AER 2004)?

Why estimate causal effects?

- ▶ Hypotesis testing
- ▶ Policy descriptors
- ▶ Counterfactual Policy evaluation
- ▶ Policy design

Models and Causality

- ▶ Q: Do we need models to get causal effects?
- ▶ Q: What exactly is a model?
- ▶ Q: Do we need a structural model? What's that?

Models: Some Examples

- ▶ The simple linear model

$$Y_i = \alpha + \beta T_i + \varepsilon_i$$

- ▶ What assumptions do we need here to complete this model and interpret β as a casual effect?
- ▶ What other assumptions would you make? Why?
- ▶ Let's talk about some other “models”

Heterogeneity

- ▶ **Q: What exactly is heterogeneity?**
 - ▶ Observed and Unobserved heterogeneity
 - ▶ Fixed and Random Effects
 - ▶ Random Coefficients

Parameteric Models

- ▶ Consider the standard difference in means estimator
- ▶ One can equivalently write this as

$$Y_i^{\text{obs}} \mid \mathbf{W}, \tilde{\theta} \sim \mathcal{N}(\mu_c + W_i \cdot \tau, \sigma^2)$$

- ▶ In this case (as in the difference in means) the **ATE** is simple τ

Parameteric Models: Extended Example

- Now consider the following:

$$\begin{pmatrix} \ln(Y_i(0)) \\ \ln(Y_i(1)) \end{pmatrix} | \theta \sim \mathcal{N} \left(\begin{pmatrix} \mu_c \\ \mu_t \end{pmatrix}, \begin{pmatrix} \sigma_c^2 & 0 \\ 0 & \sigma_t^2 \end{pmatrix} \right)$$

- What is the ATE here?

Parameteric Models: Extended Example

- Now consider the following:

$$\begin{pmatrix} \ln(Y_i(0)) \\ \ln(Y_i(1)) \end{pmatrix} \mid \theta \sim \mathcal{N} \left(\begin{pmatrix} \mu_c \\ \mu_t \end{pmatrix}, \begin{pmatrix} \sigma_c^2 & 0 \\ 0 & \sigma_t^2 \end{pmatrix} \right)$$

- The ATE is:

$$\tau = \tau(\theta) = \exp \left(\mu_t + \frac{1}{2} \cdot \sigma_t^2 \right) - \exp \left(\mu_c + \frac{1}{2} \cdot \sigma_c^2 \right)$$

Parameteric Models: Inference

- ▶ Define $\theta = \{\mu_c, \mu_t, \sigma_c, \sigma_t\}$
- ▶ Set up likelihood $\ell(\mathbb{D}|\theta)$ and obtain $\hat{\theta}$
- ▶ Compute the Hessian at $\hat{\theta}$: $\hat{\mathbf{H}} = \left\{ \frac{\partial^2 \ell}{\partial \theta_{jk}} \right\}$
- ▶ Use Delta method

$$\text{se}\left(\tau\left(\hat{\theta}\right)\right)=\left[\frac{\partial \tau(\theta)}{\partial \theta}\Big|_{\theta=\hat{\theta}}\right]^{\prime} \hat{\mathbf{H}}^{-1}\left[\frac{\partial \tau(\theta)}{\partial \theta}\Big|_{\theta=\hat{\theta}}\right]$$

Discussion Problem I

- ▶ Imagine a firm that sends customers catalogs
- ▶ They randomize the treatment so that 90% get the catalog and 10% are held out
- ▶ A firm wishes to figure out the causal effect of the catalog (x) on buying behavior (y)
- ▶ **What should the model be?**
- ▶ **What decisions do we make?**

Discussion Problem II

- ▶ Imagine a firm that charges a price for a product. Consumer buys a single unit or not at all.
- ▶ A firm wishes to set optimal prices. To do so they need to figure out the causal effect of prices (x) on purchase decision (y)
- ▶ **What should the model be?**
- ▶ **How should the firm set prices?**

Discussion Problem III

- ▶ Detailing refers to the act of pharma reps calling on physicians
- ▶ A firm wishes to figure out the causal effect of detailing (x) on prescribing behavior (y)
- ▶ Currently the average number of calls is 10.
- ▶ **What should the model be?**
- ▶ **Should the firm increase the number of calls?**