Flight Plan ✈️

1. What is ML, anyway?
2. Causality in High Dimensions

Yesterday

3. (Seriously) Heterogeneous Partial Effects
4. Solving Large-Scale General Equilibrium Models

Today

Heterogeneous Partial Effects

Motivation

Let Y be an outcome and X, Z be features (covariates). We frequently want to approximate

$$h(x, z) \equiv \mathbb{E}[Y|X = x, Z = z]$$

and the **partial effects**

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- Approach 1: impose a parametric model for h, e.g. linear regression. Pros and cons?
- Approach 2: use fully nonparametric methods. Pros and cons?

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- Approach 2: use fully nonparametric methods. Pros and cons?
- The third way is the charm: a bit of structure, a bit of ML!

Example I - Heterogenous Treatment Effects

- Outcomes Y_i depend on a treatment $X_i \in \mathbb{R}$ and covariates $Z_i \in \mathbb{R}^p$;
- The dose X_i depends on observables Z_i;
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- The dose X_i depends on observables Z_i;
- Potential outcomes $Y_i(x)$ for each dose $x \in \mathbb{R}$;
- The conditional average effect of increasing the dose is $\tau(x, z) \equiv \frac{\partial}{\partial x}\mathbb{E}[Y(x)|Z = z]$;
- If $\mathbb{E}[Y(x)|X = x, Z = z] = \mathbb{E}[Y(x)|Z = z]$ (common assumption in the literature), then

$$\tau(x, z) = \frac{\partial}{\partial x}\mathbb{E}[Y|X = x, Z = z] = \frac{\partial h(x, z)}{\partial x}$$

Example II - Grouped Heterogeneity

Consider the following model:

$$Y_i = \alpha(Z_i) + X_i'\beta + \varepsilon_i, \quad \mathbb{E}[\varepsilon_i | X_i, Z_i] = 0,$$

- X_i affects Y_i homogeneously;
- Intercept $\alpha(Z_i)$ varies with Z_i, maybe in a highly nonlinear way;
- Since Z_i and X_i can be correlated, this can affect inference about β;
- Bonhomme and Manresa (2015) studied how democracy affects national income using this model;
- In their case: $\alpha(Z_i)$ is constant across groups but Z_i defines membership;
- In our notation: $h(z, x) = \alpha(z) + x'\beta$

Questions?

Thank you!

See you tomorrow, stay tuned!

Appendix and References

References

Bonhomme, Stéphane and Elena Manresa (May 2015). "Grouped Patterns of Heterogeneity in Panel Data: Grouped Patterns of Heterogeneity". In: *Econometrica* 83.3, pp. 1147–1184. ISSN: 0012-9682. DOI: 10.3982/ecta11319. URL: http://dx.doi.org/10.3982/ECTA11319.