ML in Economics and Finance: Where do We Go Now? - Part I

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Intro

Who is this guy?

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- I got my PhD in Finance at Northwestern University;
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I am **not** an ML developer, but maybe a mildly sophisticated economist consumer

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  - Interpretability;
  - Sophisticated notions of equilibrium;
  - Time series dynamics;

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Right now:

- Better understanding of the limitations of "plug and play" ML;
- Great stuff: new hybrid methods designed by and for economists;
- Bad stuff: we are flooded with tutorials, books, videos, bootcamps...

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- Three very cool agendas where ML can help economists
- Causality in HD, seriously heterogeneous treatment effects, and solving large models;

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What I will not do:

- Teach you how to code;
- Pretend I know how to prove the complicated theorems and walk you through proofs;
- Lie to you and say you can easily perform any of this in Stata! 🙄

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- Fellow empirical researchers trying to grasp what kind of ML tools might be useful;
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DISCLAIMER: These are **my** own views, based on **my** experience, and **my** own readings. Other people will disagree.

Flight Plan ✈️

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

$\Big\}$ **Today**

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

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Please bring questions at any time!

Questions?

A General Framework

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(Supervised) **Machine Learning** is a set of tools that enable computationally-feasible data-driven search over high-dimensional functional spaces.

A General Framework

$$y = f(\boldsymbol{x}) + \varepsilon$$

- $y \in \mathbb{R}^k$ is some "target" or "outcome";
- $\boldsymbol{x} \in \mathbb{R}^p$ is a vector of "features", or "predictors", or "covariates";
- $f : \mathbb{R}^p \to \mathbb{R}^k$ is some unknown function;
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Question: given a function space $\mathcal{F}$, how to find $\hat{f} \in \mathcal{F}$ that approximates f well?

- Collect data $\{(y_1, \boldsymbol{x}_1), \ldots, (y_n, \boldsymbol{x}_n)\}$;
- Define some notion of "approximates well" $\implies$ (a loss function);
- Be explicit about $\mathcal{F}$;
- Be explicit about your optimization mechanism;

You are already doing ML!

Consider an outcome y_i, and a set of covariates $\boldsymbol{x}_i$ for $i = 1, \ldots, n$:

$$y_i = \alpha + \boldsymbol{x}_i' \boldsymbol{\beta} + \varepsilon_i$$

- This is a linear regression model;
- The function space $\mathcal{F}$ is the set of all affine functions of the treatment and covariates;
- The loss function is the MSE: $\mathcal{L}(y_i, \hat{y}_i) = (y_i - \hat{y}_i)^2$;
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Conclusion: Linear regression is a (very simple) ML method! But there is so much more...

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OLS

- Leverages linearity (strong!);
- Easy to compute and interpret;

Fully Non-Parametric Methods

- Extreme flexibility;
- Super data hungry!

Machine Learning $=$ a *compromise*: richer parametrizations while still computationally feasible in high dimensions.

Questions?

Causality in High Dimensions

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- Kleinberg et al. (2015): many policy-relevant questions are prediction problems!
- Belloni 🇧🇷, Chernozhukov, Hansen and co-authors took it even further:
    - Computing the propensity score *is* forecasting!
    - The first-stage regression in an IV context *is* forecasting!

Treatment Effects in High Dimensions

Suppose you're interested in the treatment effect $\theta_0 \in \mathbb{R}$:

$$y_i = d_i\theta_0 + \boldsymbol{x}_i'\boldsymbol{\beta} + \varepsilon_i$$

- $y_i \in \mathbb{R}$ is an outcome;
- $d_i \in \mathbb{R}$ is a treatment;
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Question: what will happen if you try OLS here?

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    - You might get lost in a sea of robustness checks...
- Good news: ML researchers devoted a lot of attention to *sparse regressions*!

Welcome to SBE, Mr. LASSO

The Least Absolute Shrinkage and Selection Operator (LASSO) estimator solves:

$$\hat{\boldsymbol{\delta}} \equiv \arg\min_{\boldsymbol{\delta} \in \mathbb{R}^p} \left\{ \frac{1}{n} \sum_{i=1}^{n} (y_i - \boldsymbol{w}_i' \boldsymbol{\delta})^2 + \lambda \sum_{j=1}^{p} |\delta_j| \right\}$$

- $\lambda \geq 0$ is a tuning parameter that controls the amount of penalization ("*regularization*");
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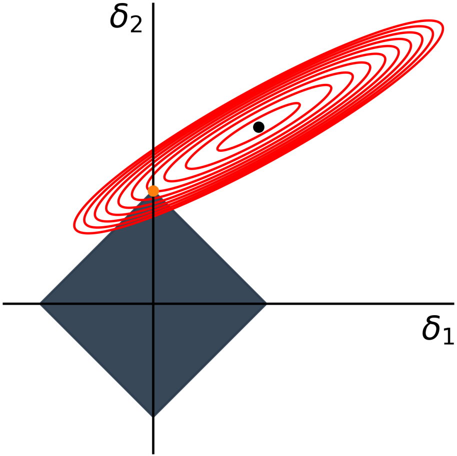
- For intermediate values of λ, some $\hat{\delta}_j$'s will be exactly zero!
- $\hat{\boldsymbol{\delta}}$ is gives up unbiasedness for much lower variance;
- This problem is still feasible if $p \gg n$ and it is convex $\implies$ fast computation;

The Geometry of LASSO

For $c > 0$, consider the following:

$$\tilde{\boldsymbol{\delta}} \equiv \arg\min_{\boldsymbol{\delta}\in\mathbb{R}^p} \left\{ \frac{1}{n} \sum_{i=1}^{n} (y_i - \boldsymbol{w}_i'\boldsymbol{\delta})^2 \right\}$$

$$\text{subject to } \sum_{j=1}^{p} |\delta_j| \leq c$$



- Think about the Lagrangian of this problem!
- For every λ, there is a c such that $\hat{\boldsymbol{\delta}} = \tilde{\boldsymbol{\delta}}$;

Exploring Options

Recall our treatment effects model:

$$y_i = d_i\theta_0 + \boldsymbol{x}_i'\boldsymbol{\beta} + \varepsilon_i$$

- **Approach 1**: run LASSO of y_i on d_i and $\boldsymbol{x}_i$. Is this a good idea?

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- **Approach 3**: do Approach 2, but then run OLS on the selected x_i and d_i. Is this good?
- Leeb and Pötscher (2008a) and Leeb and Pötscher (2008b): terrible idea again!
- Main problem: *omitted variable bias* if some relevant controls are not selected!
- If some x_j is correlated with d_i and affects y_i, omitting it biases $\hat{\theta}_0$!

Something That Finally Works!

Belloni et al. (2014a) thought about how d_i and $\boldsymbol{x}_i$ interact:

$$d_i = \boldsymbol{x}_i'\gamma + u_i, \quad \mathbb{E}[u_i \mid \boldsymbol{x}_i] = 0$$

- What if γ is also sparse, i.e., only a few x_j's affect d_i?
- Can we find a small subset of $\boldsymbol{x}_i$ that *predicts* treatment well?

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They proposed the **Double LASSO** procedure:

1. Run LASSO of y_i on $\boldsymbol{x}_i$ to select controls $\hat{S}_y$;
2. Run LASSO of d_i on $\boldsymbol{x}_i$ to select controls $\hat{S}_d$;
3. Run OLS of y_i on d_i and $\boldsymbol{x}_i$ with $x_j \in \hat{S}_y \cup \hat{S}_d$;

A Really Cool Result

Belloni et al. (2014b) provide conditions under which:

$$\sqrt{n}(\hat{\theta}_0 - \theta_0) \xrightarrow{d} \mathcal{N}(0, \sigma^2)$$

where σ^2 is complicated by consistently estimated.

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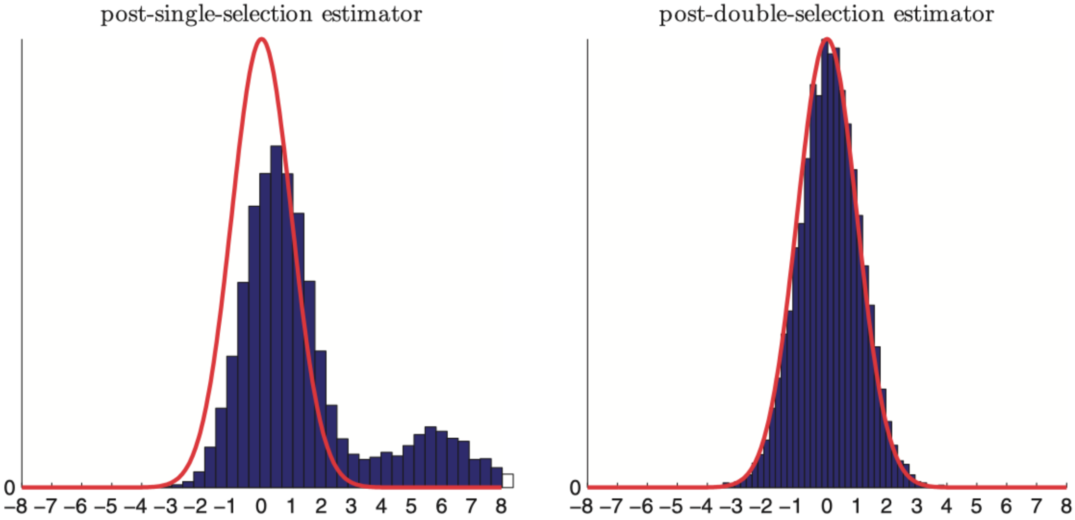
The impressive stuff:

- This convergence is uniform over a large class of DGPs;
- Convergence still happens at the rate $\sqrt{n}$, even if $p \gg n$!
- Under homoskedasticity, it attains semi-parametric efficiency!
- Construct confidence intervals in the usual ways;

Key assumption: sparse representation;

Some Monte-Carlo Reassurance



Questions?

Limitations and Generalizations

Limitations

- What if we want to allow for non-linearities?
- What if we want to use other ML methods?
- What if sparsity is not a good assumption?
- What if treatment has heterogenous effects?
- What if outcomes are function-valued?

Generalization

Belloni et al. (2017) and Chernozhukov et al. (2018) generalize all of this:

$$y_i = g_0(d_i, \boldsymbol{x}_i) + \varepsilon_i, \quad \mathbb{E}[\varepsilon_i \mid d_i, \boldsymbol{x}_i] = 0$$
$$d_i = m_0(\boldsymbol{x}_i) + u_i, \quad \mathbb{E}[u_i \mid \boldsymbol{x}_i] = 0$$

- $g_0(\cdot)$ and $m_0(\cdot)$ are unknown (possibly non-linear) functions;
- You can use several different ML method to estimate $g_0(\cdot)$ and $m_0(\cdot)$;
- Sparsity is not necessary anymore;

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- Secrete sauce I: <u>Neyman Orthogonal Scores</u> ψ

$$\mathbb{E}\left[\psi(\text{data}, \underbrace{\text{param of interest}}_{\equiv\theta_0}, \underbrace{\text{nuisance params}}_{\equiv\eta_0})\right] = 0, \qquad \frac{\partial}{\partial\eta}\mathbb{E}\left[\psi(\text{data}, \theta_0, \eta)\right]\Big|_{\eta=\eta_0} = 0$$

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$$y_i = g_0(d_i, \boldsymbol{x}_i) + \varepsilon_i, \quad \mathbb{E}[\varepsilon_i \mid d_i, \boldsymbol{x}_i] = 0$$
$$d_i = m_0(\boldsymbol{x}_i) + u_i, \quad \mathbb{E}[u_i \mid \boldsymbol{x}_i] = 0$$

- $g_0(\cdot)$ and $m_0(\cdot)$ are unknown (possibly non-linear) functions;
- You can use several different ML method to estimate $g_0(\cdot)$ and $m_0(\cdot)$;
- Sparsity is not necessary anymore;
- Secrete sauce I: Neyman Orthogonal Scores ψ

$$\mathbb{E}\left[\psi(\text{data}, \underbrace{\text{param of interest}}_{\equiv\theta_0}, \underbrace{\text{nuisance params}}_{\equiv\eta_0})\right] = 0, \qquad \frac{\partial}{\partial\eta}\mathbb{E}\left[\psi(\text{data}, \theta_0, \eta)\right]\Big|_{\eta=\eta_0} = 0$$

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- Secrete sauce II: <u>cross-fitting</u> $\implies$ efficiency vs strict assumptions;
- Independence across i is <u>essential</u>;

A Concrete Example (A Partially Linear Model)

$$y_i = d_i\theta_0 + g_0(\boldsymbol{x}_i) + \varepsilon_i, \quad \mathbb{E}[\varepsilon_i \mid d_i, \boldsymbol{x}_i] = 0$$
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Steps:

- Divide the data into two folds;
- On fold 1, estimate $\hat{g}_0(\boldsymbol{x}_i)$ and $\hat{m}_0(\boldsymbol{x}_i)$ using ML methods;
- On fold 2, compute residuals:

$$\hat{\varepsilon}_i = y_i - \hat{g}_0(\boldsymbol{x}_i)$$
$$\hat{u}_i = d_i - \hat{m}_0(\boldsymbol{x}_i)$$

- Regress $\hat{\varepsilon}_i$ on $\hat{u}_i$ to get $\hat{\theta}_0$;

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- Repeat switching folds and average $\hat{\theta}_0$'s;
- In practice you can use K folds!
- See Chernozhukov et al. (2017) for a practical guide!

Where do we go now?

Some open problems:

- Weak identification, in special in the IV context (see Scheidegger et al. (2025));
- Time series $\implies$ it's impossible to do cross-fitting (see Lewis and Syrgkanis (2021));
- Panel data $\implies$ usual estimators leverage linearity (see Chernozhukov et al. (2021) and Clarke and Polselli (2025));

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Good news! Plenty of dissertation topics!

Questions?

Thank you!

See you tomorrow, stay tuned!

🤙

Appendix and References

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