

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

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Intro

Who is this guy?

- I have just joined [FGV EPGE](#) as an Assistant Professor;
- 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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 - Sophisticated notions of equilibrium;
 - Interpretability;
 - Time series dynamics;

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 - Time series dynamics;

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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- 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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DISCLAIMER: These are **my** own views, based on **my** experience, and **my** own readings.
Other people will disagree.

- 1. What is ML, anyway?
 - 2. Causality in High Dimensions
 - 3. (Seriously) Heterogeneous Treatment Effects
 - 4. Solving Large-Scale General Equilibrium Models
- } **Today**
- } **Tomorrow**

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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

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

- $y \in \mathbb{R}^k$ is some "target" or "outcome";
- $\mathbf{x} \in \mathbb{R}^p$ is a vector of "features", or "predictors", or "covariates";
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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 $\{(y_1, \mathbf{x}_1), \dots, (y_n, \mathbf{x}_n)\}$;
- 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 \mathbf{x}_i for $i = 1, \dots, n$:

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

- 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.


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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 $\theta_0 \in \mathbb{R}$:

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

- $y_i \in \mathbb{R}$ 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*!

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

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

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- For intermediate values of λ , some $\hat{\delta}_j$'s will be exactly zero!
- $\hat{\boldsymbol{\delta}}$ gives up unbiasedness for much lower variance;
- This problem is still feasible if $p \gg n$ and it is convex \implies fast computation;

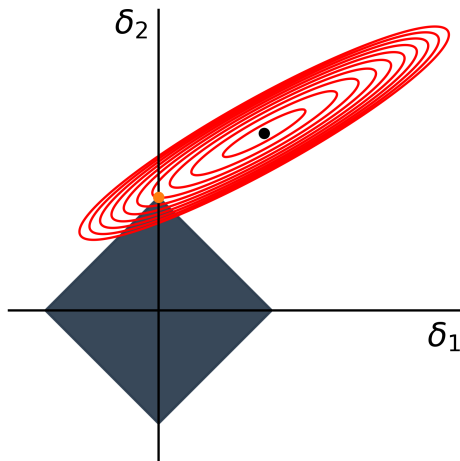
The Geometry of LASSO

For $c > 0$, consider the following:

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

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 $\hat{\delta} = \tilde{\delta}$;



Recall our treatment effects model:

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

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Exploring Options

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- **Approach 3:** do Approach 2, but then run OLS on the selected \mathbf{x}_i and d_i . Is this good?

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- [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 \mathbf{x}_i interact:

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

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

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- Can we find a small subset of \mathbf{x}_i that *predicts* treatment well?

They proposed the **Double LASSO** procedure:

1. Run LASSO of y_i on \mathbf{x}_i to select controls \hat{S}_y ;
2. Run LASSO of d_i on \mathbf{x}_i to select controls \hat{S}_d ;
3. Run OLS of y_i on d_i and \mathbf{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.

A Really Cool Result

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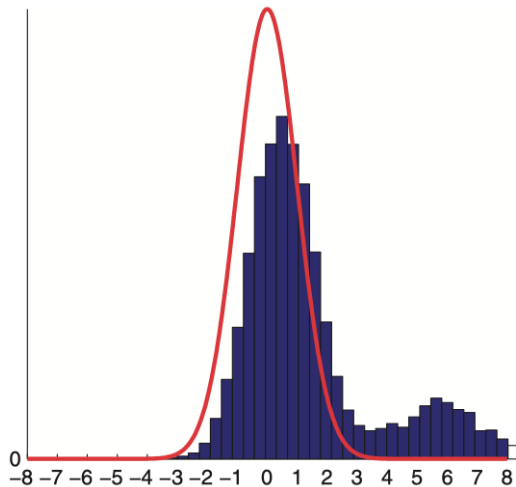
The impressive stuff:

- 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;

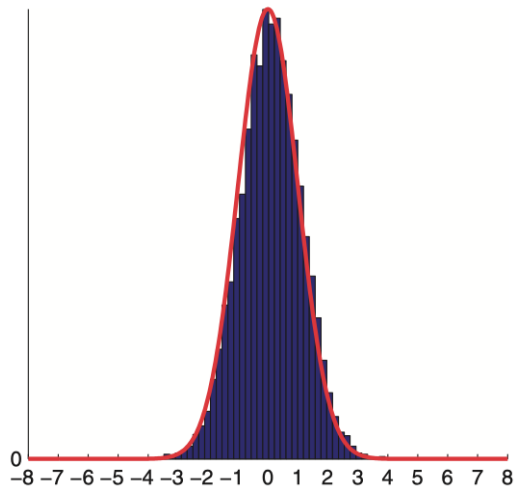
Key assumption: sparse representation;

Some Monte-Carlo Reassurance

post-single-selection estimator



post-double-selection estimator



Questions?

Limitations and Generalizations

- 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?

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

$$\begin{aligned}y_i &= g_0(d_i, \mathbf{x}_i) + \varepsilon_i, & \mathbb{E}[\varepsilon_i \mid d_i, \mathbf{x}_i] &= 0 \\d_i &= m_0(\mathbf{x}_i) + u_i, & \mathbb{E}[u_i \mid \mathbf{x}_i] &= 0\end{aligned}$$

- $g_0(\cdot)$ 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;

Generalization

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- Secrete sauce I: Neyman Orthogonal Scores ψ

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

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$$\begin{aligned}y_i &= g_0(d_i, \mathbf{x}_i) + \varepsilon_i, & \mathbb{E}[\varepsilon_i \mid d_i, \mathbf{x}_i] &= 0 \\d_i &= m_0(\mathbf{x}_i) + u_i, & \mathbb{E}[u_i \mid \mathbf{x}_i] &= 0\end{aligned}$$

- $g_0(\cdot)$ 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

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

- Secrete sauce II: cross-fitting \implies efficiency vs strict assumptions;

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- Secrete sauce II: cross-fitting \implies efficiency vs strict assumptions;
- Independence across i is essential;

A Concrete Example (A Partially Linear Model)

$$\begin{aligned}y_i &= d_i\theta_0 + g_0(\mathbf{x}_i) + \varepsilon_i, & \mathbb{E}[\varepsilon_i \mid d_i, \mathbf{x}_i] &= 0 \\d_i &= m_0(\mathbf{x}_i) + u_i, & \mathbb{E}[u_i \mid \mathbf{x}_i] &= 0\end{aligned}$$

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Steps:

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

$$\hat{\varepsilon}_i = y_i - \hat{g}_0(\mathbf{x}_i)$$

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- 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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