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

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Intro

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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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- Pretend I know how to prove the complicated theorems and walk you through proofs;

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- Teach you how to code;
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- 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.

Flight Plan ✈️

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

Today

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

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

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

- $y \in \mathbb{R}^k$ is some "target" or "outcome";
- $\boldsymbol{x} \in \mathbb{R}^p$ is a vector of "features", or "predictors", or "covariates";
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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;
- $\boldsymbol{x}_i \in \mathbb{R}^p$ is a vector of available covariates;
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Question: what will happen if you try OLS here?

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- But you do not know which ones!

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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;

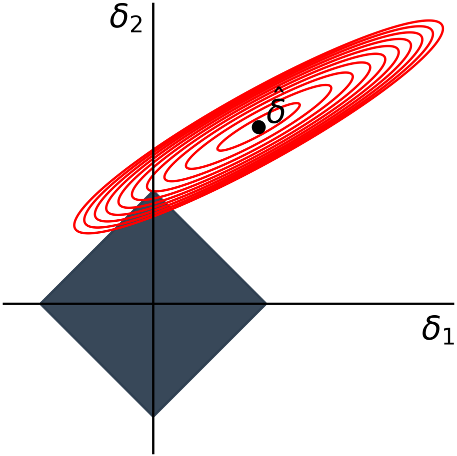
The Geometry of LASSO

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



Generalizations

Appendix and References

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