

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](#);
- Asset Pricing + Macro-Finance + Econometrics;
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I am **not** an ML developer, but maybe a mildly sophisticated economist consumer

Where are we?

- Last 20-30 years: explosion of computation power and popularization of ML techniques;
- Last 15 years: we economists imported several techniques from CS and Stats;
- Many challenges in this translation:
 - Causality vs pattern recognition;
 - Sophisticated notions of equilibrium;
 - Interpretability;
 - 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 high dimensions, seriously heterogeneous treatment effects, and solving large-scale GE 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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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

What is *Machine Learning*?

- Different fields will have different definitions: CS, Stats, Operations Research, ...
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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: $\mathcal{L}(y_i, \hat{y}_i) = (y_i - \hat{y}_i)^2$;
- OLS: minimize a convex loss function over the space of parameters;

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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 methods are a *compromise*: they allow for richer parametrizations while still being computationally feasible in high dimensions.

Causality in High Dimensions
