

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;
- Some of my papers use ML methods in different contexts;

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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;
 - 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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- But what else? What is worth knowing about ML in Econ and Finance?

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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 | <p>Today</p> <p>Tomorrow</p> |
|--|------------------------------|
- The diagram illustrates a flight plan with two main sections: "Today" and "Tomorrow". The "Today" section contains the first two items of the list. The "Tomorrow" section contains the last two items. Brackets on the right side of the list group the items under these headings.



- | | | |
|---|---|----------|
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| 2. Causality in High Dimensions | | Tomorrow |
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| 4. Solving Large-Scale General Equilibrium Models | | Tomorrow |

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";
- $f : \mathbb{R}^p \rightarrow \mathbb{R}^k$ 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 $\{(y_1, \mathbf{x}_1), \dots, (y_n, \mathbf{x}_n)\}$;
- 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 methods are a *compromise*: they allow for richer parametrizations while still being computationally feasible in high dimensions.

Causality in High Dimensions
