# 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 am **not** an ML developer, but maybe a mildly sophisticated economist consumer

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  - Interpretability;
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  - 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 HD, seriously heterogeneous treatment effects, and solving large models;

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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 Partial 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”;
- $f : \mathbb{R}^p \to \mathbb{R}^k$ is some unknown function;
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- 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 $i = 1, \dots, n$:

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

- 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.

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# 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 $\lambda$, 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;

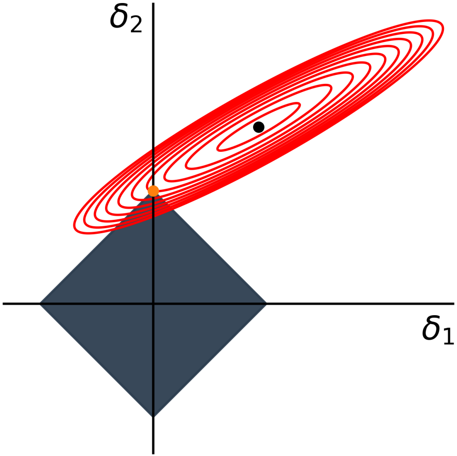
# The Geometry of LASSO

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 $\lambda$, there is a $c$ such that $\hat{\boldsymbol{\delta}} = \tilde{\boldsymbol{\delta}}$;



# Exploring Options

Recall our treatment effects model:

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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 $\gamma$ 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 $\sigma^2$ is complicated by consistently estimated.

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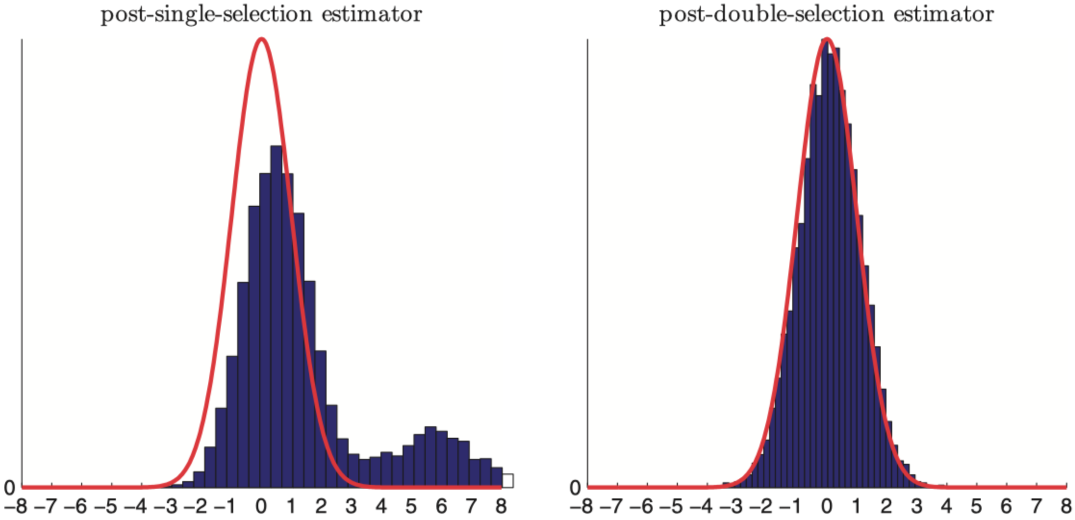
**The impressive stuff**:

- 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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- 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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# Generalization

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

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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 \\
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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:

$$\hat{\varepsilon}_i = y_i - \hat{g}_0(\boldsymbol{x}_i)$$
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- Regress $\hat{\varepsilon}_i$ on $\hat{u}_i$ to get $\hat{\theta}_0$;

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