

# Machine Learning for Econometrics

## Introduction

Anthony Strittmatter

# Lecturers

- ▶ Bruno Crépon (CREST)
- ▶ Anthony Strittmatter (CREST)

# Course Outline

February 2 (Anthony Strittmatter)

- ▶ Introduction
- ▶ Regularized Regression

February 9 (Anthony Strittmatter)

- ▶ Trees and Forests

February 16 (Bruno Crépon)

- ▶ Policy Prediction Problems

March 2 (Anthony Strittmatter)

- ▶ Double Selection Procedure

# Course Outline

March 9 (Anthony Strittmatter)

- ▶ Double Machine Learning
- ▶ Causal Forest (maybe)

March 16 (Bruno Crépon)

- ▶ Optimal Policy Learning
- ▶ Generic Machine Learning

March 23 (Bruno Crépon)

- ▶ Fairness
- ▶ Aversion to algorithms

March 30 (Bruno Crépon)

- ▶ Bandits
- ▶ Optimal Transportation (maybe)

# Grading

- ▶ Final exam
- ▶ Open book

# References

- ▶ Mullainathan and Spiess (2017): "Machine Learning: An Applied Econometric Approach", Journal of Economic Perspectives, 31 (2), pp. 87-106, [download](#).
- ▶ Athey (2019): "Beyond Prediction: Using Big Data for Policy Problems", Science, 355 (6324), pp. 483-485, [download](#).

Introductory textbooks:

- ▶ James, Witten, Hastie, and Tibshirani (2013): "An Introduction to Statistical Learning", Springer, [download](#).
- ▶ Hastie, Tibshirani, and Friedman (2009): "Elements of Statistical Learning", 2nd ed., Springer, [download](#).

# What is Machine Learning (ML)?

- ▶ ML (or statistical learning) methods exist already since decades.
- ▶ Currently "Machine Learning" is a buzz word
- ▶ Probably most people think of ML as some computational intensive methods that make data-driven modelling decisions and/or can deal with large data amounts.
- ▶ However, relevant textbooks consider even OLS/Logit as a statistical learning tool.

# Purpose of Machine Learning

- ▶ Consider the structural model

$$Y = f(X) + \epsilon = X\beta + \epsilon,$$

with  $E[\epsilon] = 0$ .

- ▶ Causal analysis has the purpose to estimate  $\hat{\beta}$ , with  $plim(\hat{\beta}) = \beta$ .
- ▶ **Machine learning** has the purpose to predict  $Y$ .
- ▶ There is a clear link between causal analysis and machine learning, because

$$\hat{Y} = \hat{f}(X) = X\hat{\beta}$$

is a potential predictor for  $Y$ .

- ▶ Parameter consistency has not the highest priority when it comes to predictions.



# Potential Advantages and Disadvantages of ML

- ▶ ML methods can be very powerful to predict  $Y$ , even when  $\hat{\beta}$  is biased.
- ▶ ML methods can incorporate many (or even high-dimensional) covariates  $X$  in a convenient way.
- ▶ ML methods can model  $\hat{f}(\cdot)$  in a very flexible and data-driven way.
- ▶ **Main disadvantage:** ML is a black-box approach and we lose the interpretability of  $\hat{f}(\cdot)$  or  $\hat{\beta}$ .

# Causal vs. Predictive Questions

## Predictive Questions:

- ▶ How will the oil price change tomorrow (forecasting)?
- ▶ How high is the current unemployment rate (nowcasting)?
- ▶ Which adolescents have a high probability of becoming addicted to drugs (policy prediction)?

## Causal Questions:

- ▶ What is the effect of a tweet by president Donald Trump on oil prices?
- ▶ How does inflation affect the unemployment rate?
- ▶ Can prevention programs reduce the probability of drug addiction among high risk youths?

# Assessing the Model Accuracy

## Causal Analysis:

- ▶ True  $\beta$  is unobservable.
- ▶ Assess the model with asymptotic properties

$$\sqrt{N}(\hat{\beta} - \beta) \xrightarrow{d} N(0, \sigma^2).$$

- ▶ Finite sample biases are mostly neglected.

# Assessing the Model Accuracy

## Prediction:

- ▶ We observe  $Y$  for each unit (e.g. individual).
- ▶ We can assess the model accuracy directly in the sample of our analysis, for example, using the mean-squared-error (MSE)

$$\frac{1}{N} \sum_{i=1}^N (Y_i - \hat{Y}_i)^2.$$

- ▶ MSE accounts for finite sample biases.

## Example: Prediction of Used Car Prices

- ▶ We have access to web-scraped data from the online advertisement platform *myLemons*.
- ▶ We want to predict asking prices of used cars based on observable characteristics.
- ▶ We observe around 40 covariates about car brand, mileage, age, emissions, maintenance certificate, seller type, guarantee, etc. (including several non-linear and interaction terms)

# In-Sample MSE

- ▶ Partition data into training and test sample
- ▶ In the training sample, we estimate the empirical model

$$Y_{tr} = \hat{f}_{tr}(X_{tr}) + \hat{\epsilon}_{tr} = X_{tr}\hat{\beta}_{tr} + \hat{\epsilon}_{tr}$$

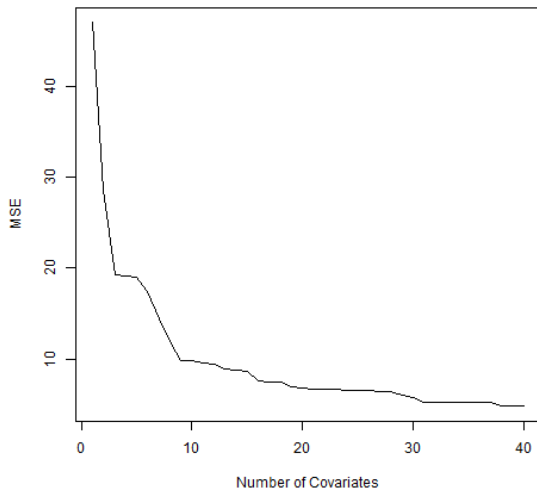
- ▶ In the training sample, we predict the fitted values

$$\hat{Y}_{tr} = \hat{f}_{tr}(X_{tr}) = X_{tr}\hat{\beta}_{tr}$$

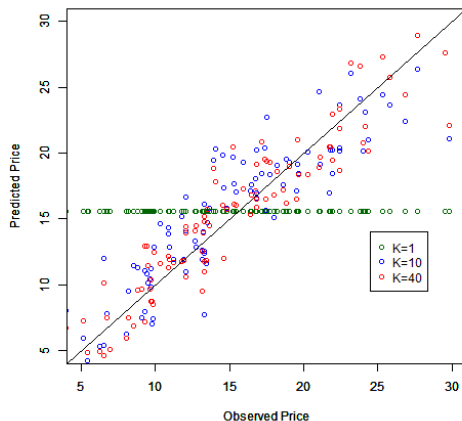
and calculate the MSE

$$\widehat{MSE}_{tr} = \frac{1}{N_{tr}} \sum_{i=1}^{N_{tr}} (Y_{i,tr} - \hat{Y}_{i,tr})^2.$$

# MSE in Training Sample



# Predicted Car Prices in Training Sample



Number of Covariates	1	10	40
MSE	46.948	9.819	4.866



# Out-of-Sample MSE

- In the training sample, we estimate the empirical model

$$Y_{tr} = \hat{f}_{tr}(X_{tr}) + \hat{\epsilon}_{tr} = X_{tr}\hat{\beta}_{tr} + \hat{\epsilon}_{tr}$$

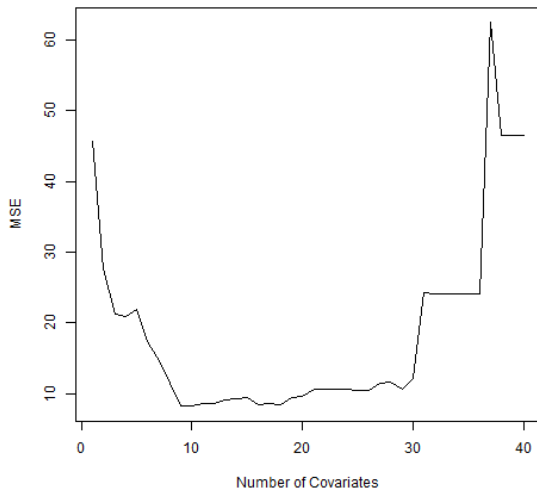
- In the test sample, we predict the fitted values

$$\hat{Y}_{te} = \hat{f}_{tr}(X_{te}) = X_{te}\hat{\beta}_{tr}$$

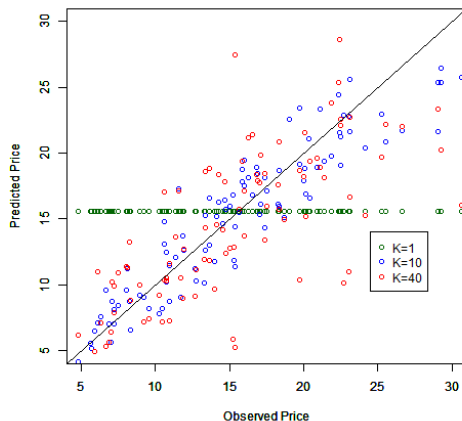
and calculate the MSE

$$\widehat{MSE}_{te} = \frac{1}{N_{te}} \sum_{i=1}^{N_{te}} (Y_{i,te} - \hat{Y}_{i,te})^2.$$

# MSE in Test Sample



# Predicted Car Prices in Test Sample



Number of Covariates	1	10	40
MSE	45.742	8.222	46.499

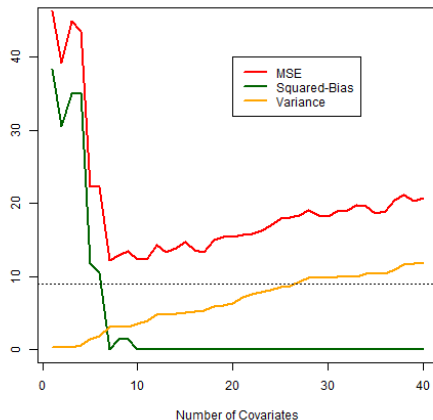
# Bias-Variance Trade-Off

- When we assess the model for one randomly drawn individual from the test sample with fixed characteristics  $x_{te}$ , then we can decompose the MSE to

$$\begin{aligned}MSE_{te} &= E[(Y_{te} - \hat{Y}_{te})^2] \\&= E[(f(x_{te}) + \epsilon_{te} - \hat{f}_{tr}(x_{te}))^2] \\&= \underbrace{E[(f(x_{te}) - \hat{f}_{tr}(x_{te}))^2]}_{\text{Reducible}} + \underbrace{Var(\epsilon_{te})}_{\text{Irreducible}} \\&= \underbrace{E[f(x_{te}) - \hat{f}_{tr}(x_{te})]^2}_{\text{Squared-Bias}} + \underbrace{Var(\hat{f}_{tr}(x_{te}))}_{\text{Variance}} + Var(\epsilon_{te})\end{aligned}$$

- For i.i.d. data,  $\hat{f}_{tr}(\cdot)$  and  $\epsilon_{te}$  are independent of each other.

# Simulation of Bias-Variance Trade-Off



- Only the first ten covariate have an impact on car prices in the simulation.
- Horizontal dashed line is the simulated noise  $Var(\epsilon_{te})$ .

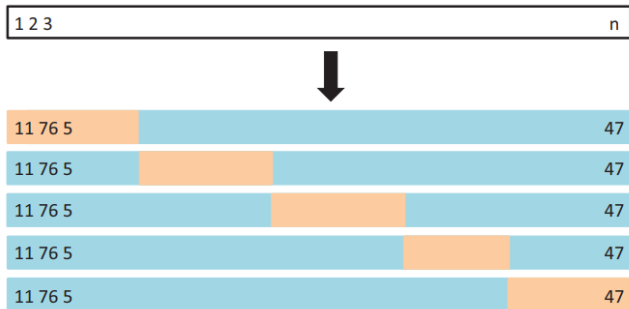
# Lasso Example

$$\arg \min_{\beta} \left\{ \sum_{i=1}^N \left( Y_i - \beta_0 - \sum_{j=1}^p X_{ij} \beta_j \right)^2 + \lambda \sum_{j=1}^p |\beta_j| \right\}$$

	OLS	Lasso
Intercept	21.246	22.776
diesel	2.075	.
other_car_owner	0.730	.
pm_green	1.635	.
private_seller	6.100	0.076
guarantee	-2.440	-0.437
inspection	-0.813	.
maintenance_cert	1.481	.
mileage	-0.049	-0.031
age_car_years	-1.291	-1.012
$R^2$ training	0.655	0.543
$R^2$ test	0.606	0.611

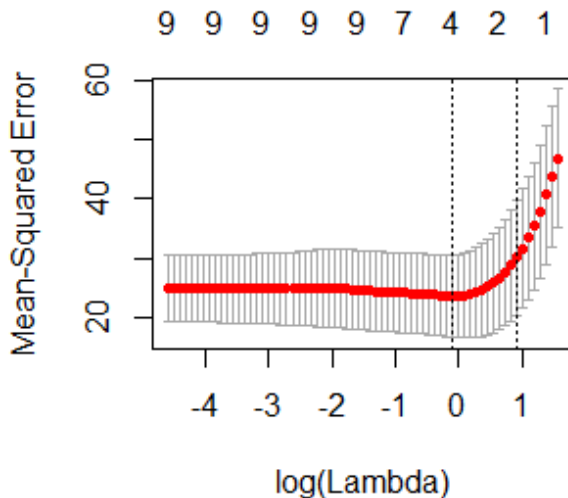
# Selection of Optimal Penalty Parameter

## k-fold Cross-Validation (CV) Algorithm



Source: James et al. (2013), p. 181

# Cross-Validated MSE





# Stability of the Lasso Model

	Lasso 1	Lasso 2	Lasso 3	Lasso 4	Lasso 5
Intercept	22.776	25.947	24.937	27.309	25.116
diesel	.	.	2.387	.	0.886
other_car_owner	.	-1.257	0.393	.	.
pm_green	.	2.871	.	.	.
private_seller	0.076	5.094	.	-1.037	.
guarantee	-0.437	1.677	15.939	.	.
inspection	.	-0.666	-0.374	.	.
maintenance_cert	.	-2.579	-0.868	.	.
mileage	-0.031	-0.037	-0.041	-0.069	-0.062
age_car_years	-1.012	-1.347	-1.416	-0.874	-1.115

- We do not learn the “true” structural model from ML
- ML is a black-box approach

# Stability of the Lasso Predictions

## Correlation of Predicted Car Prices in Test Sample:

	Lasso 1	Lasso 2	Lasso 3	Lasso 4
Lasso 2	0.94			
Lasso 3	0.85	0.81		
Lasso 4	0.97	0.91	0.85	
Lasso 5	0.99	0.94	0.87	0.99

# Examples of Business and Economic Studies

## Prediction Tasks:

- ▶ [Chandler, Levitt, and List \(2011\)](#) predict shootings among high-risk youth to target mentoring interventions.
- ▶ [Kleinberg, et al. \(2018\)](#) predict the crime probability of defendants released from investigative custody to improve judge decisions.

## Pre-Processing Unstructured Data:

- ▶ [Glaeser et al. \(2016\)](#) use images from Google Street View to measure block-level income in New York City and Boston.
- ▶ [Kang et al. \(2013\)](#) use restaurant reviews on Yelp.com to predict the outcome of hygiene inspections.
- ▶ [Kogan et al. \(2009\)](#) predict volatility of firms from market-risk disclosure texts (annual 10-K forms).

# Predictions vs. Causal Inference

- ▶ Outcome (e.g., earnings):  $Y$
  - ▶ Binary Treatment (e.g., participation in training program):  
 $D \in \{0, 1\}$
  - ▶ Potential Outcome:
    - ▶  $Y(1)$  potential earnings under participation
    - ▶  $Y(0)$  potential earnings under non-participation
    - Only one potential earnings can be observed
  - ▶ Causal effect:  $\delta = Y(1) - Y(0)$
- Predictions have the observable estimation target  $\hat{Y}$
- Causal inference has the (partly) unobservable estimation target  $\hat{\delta}$

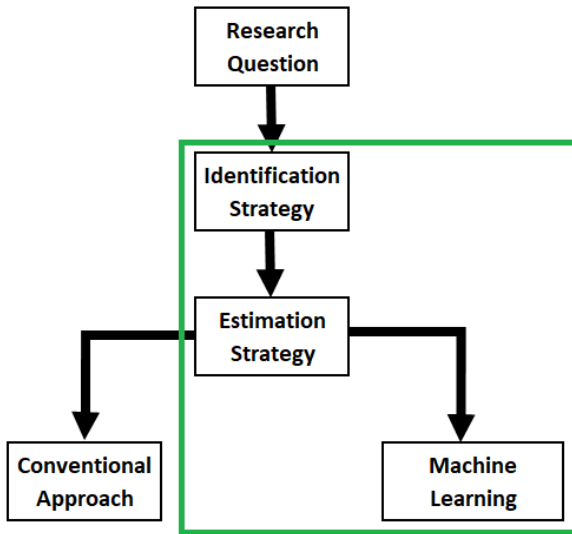
# Training of ML Algorithms

Out-of-Sample Mean-Squared-Error (MSE):

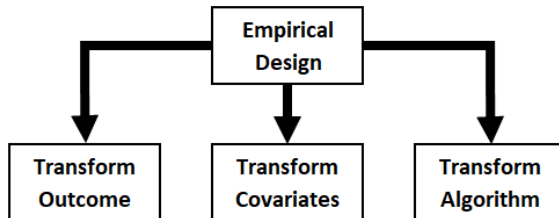
$$MSE_{\hat{\delta}} = E \left[ (\hat{\delta} - \delta)^2 \right] = \underbrace{E \left[ (\hat{\delta} - E[\hat{\delta}])^2 \right]}_{\text{Variance}} + \underbrace{E[\hat{\delta} - \delta]^2}_{\text{Squared Bias}}$$

→  $\delta$  is unobservable

# Research Design



# Causal Machine Learning (CML) Designs



⇒ [Knaus, Lechner, Strittmatter \(2018\)](#) provide a comparison of all designs.

# Potentials of Causal Machine Learning (CML)

## Four potential applications of CML:

1. Account for (very) many instruments in IV or Heckit approach (prediction problem, issues with inference).

References:

- ▶ [Belloni, Chen, Chernozhukov, and Hansen \(2012\)](#)
- ▶ [Hansen and Kozbur \(2014\)](#)

2. Account for confounders, e.g., in matching, IV, or difference-in-difference approaches:

- ▶ ML enables the incorporation of (very) many covariates which can make the exclusion restriction more credible.
- ▶ Some ML approaches make little functional form assumptions.

Reference:

- ▶ [Chernozhukov et al. \(2017\)](#)



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# Potentials of Causal Machine Learning (CML)

## 3. Heterogeneous effects:

- ▶ Principled approach makes it less likely to overlook important heterogeneity.
- ▶ Problems: Issues with interpretability and works only for the low-dimensional case.

References:

- ▶ [Wager and Athey \(2018\)](#)
- ▶ [Chernozhukov, Demirer, Duflo, and Fernández-Val \(2018\)](#)

## 4. Optimal policy rules (e.g. Bandits):

- ▶ Focus on the (discrete) treatment decision instead on the effect size.

Reference:

- ▶ [Athey and Wager \(2019\)](#)

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# Limitations of Causal Machine Learning (CML)

- ▶ ML algorithms cannot distinguish between causation and correlation.
  - CML will not select the relevant causal parameters automatically.
  - We have to provide some structure to the CML algorithm.
- ▶ CML can estimate causal effects only for a few (usually only one) endogenous variables.
  - We will not obtain the (complete) structural model.
- ▶ Identifying assumptions do not change, no matter if we use ML or conventional methods.
- ▶ We should resist the temptation to interpret prediction models in a causal way.

# Applications of CML Methods

- ▶ [Davis and Heller \(2017\)](#) investigate the effects of summer jobs on the probability to commit a violent crime.
- ▶ [Taddy et al. \(2016\)](#) investigate the heterogeneous effects of A/B-experiments in online-auctions (EBay) on customer responses (experimental study).
- ▶ [Bertrand et al. \(2017\)](#) and [Knaus, Lechner, and Strittmatter \(2020\)](#) estimate heterogeneous employment effects of training programmes for unemployed persons.

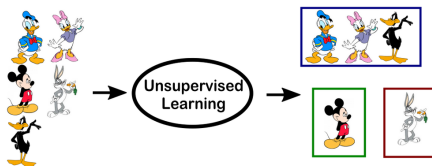
# Supervised vs. Unsupervised Machine Learning

## Supervised Machine Learning:

- ▶ We observe data on  $Y$  and  $X$  and want to learn the mapping  $\hat{Y} = \hat{f}(X)$
- ▶ Classification when  $\hat{Y}$  is discrete, regression when  $\hat{Y}$  is continuous

## Unsupervised Machine Learning:

- ▶ We observe only data on  $X$  and want to learn something about its structure
- ▶ Clustering: Partition data into homogeneous groups based on  $X$



- ▶ Principal component analysis