Causal Machine Learning

Introduction

Anthony Strittmatter

Zoom

Zoom Link:

https://unilu.zoom.us/j/94171293390?pwd=UmNMN2tCUmV3bDByYTVPMTZYci93UT09

ID: 941 7129 3390

Password: 260195

Lecturer

Anthony Strittmatter

Research Interests: Business, Labour, and Health Economics, Program Evaluation, Computational Data Analytics

Positions:

Since 2020	Assistant Professor at the Institut Polytechnique in Paris, Center for Research in Economics and Statistics (CREST)
2014-2020	University of St.Gallen, with research visits at UC Berkeley, Stanford University, and Ludwig Maximilian University of Munich
2009-2016	Albert-Ludwig University of Freiburg

- Email: anthony.strittmatter@ensae.fr
- Webpage: www.anthonystrittmatter.com

Course Outline

1. Prediction vs. Causality
2. Accounting for Confounders
   - Post-Double-Selection Procedure
   - Double/Debiased Machine Learning
3. Effect Heterogeneity
   - Causal Forest
   - Generic Machine Learning
4. Optimal Policy Learning
   - Explore and then Commit
   - Bandit Algorithms
   - Reinforcement Learning

PC Labs

- PC labs are integral part of the course.
- I will provide the entire course material on my GitHub repository: https://github.com/AStrittmatter/CML-Course
- I will use interactive Jupyter notebooks during the PC labs: https://mybinder.org/v2/gh/AStrittmatter/CML-Course/HEAD
- The advantage of the notebooks is that you do not need to install anything and the data is in the correct folder.
- However, in case the connection to the server is weak I also provide an R-file for download on my GitHub repository. To use it, you need to install R and RStudio.

Learning Objectives

1. Students can distinguish between questions that can be answered with predictive and causal methods.
2. Students can deploy machine learning methods to account for control variables.
3. Students can estimate heterogeneous effects with machine learning methods.
4. Students know different machine learning approaches that can be used to estimate decision rules and can apply these approaches to economic and business problems.

Pre-Requisites

- The courses "Causal Analysis" (Prof. Lukas Schmid) and "Supervised Machine Learning" (Dr. Massimo Mannino) are the best preparation for this course.
- Prerequisites are basic knowledge of machine learning methods (Lasso, Trees, Random Forests) and causal inference (potential outcome framework, multiple regression, inverse probability weighting).
- If a refresher is required, I recommend the relevant chapters from the following textbooks:
  - James, Witten, Hastie, and Tibshirani (2013): "An Introduction to Statistical Learning", Springer, download.
  - Angrist and Pischke (2015): "Mastering Metrics: The Path from Cause to Effect", Princeton University Press.

Grading

- Written final exam
- The material covered during the lectures and PC labs is relevant for the exam.
- 60 minutes
- Closed book
- Final exam: Friday, April 16, 4:15-5.15pm
- **Extraordinary registration period via Uni Portal: February 8 to March 5!**

General

- Feel free to interupt me at any time when you have questions.
- Tell me when I'm too slow or too fast. Ask me to repeat material in case something was not clear.
- You can also send me an email with questions: anthony.strittmatter@ensae.fr
- Proposals to improve the course are also welcome.
- Please try to interact as much as possible with your fellow students. Build learning groups. Use the chat function on OLAT.

Prediction vs. Causality

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.

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

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

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 loose 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 β 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

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

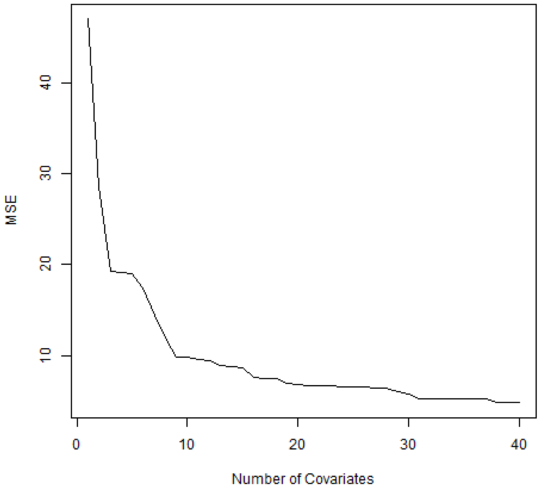
- In the training sample, we predict the fitted values

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

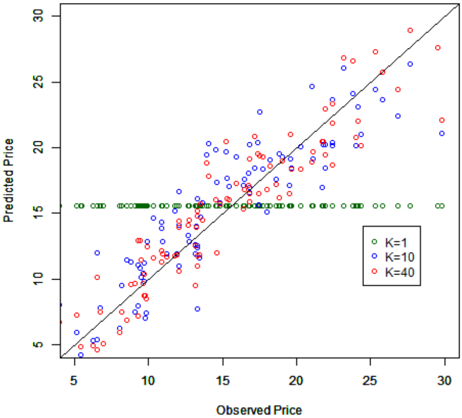
and calculate the MSE

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

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

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

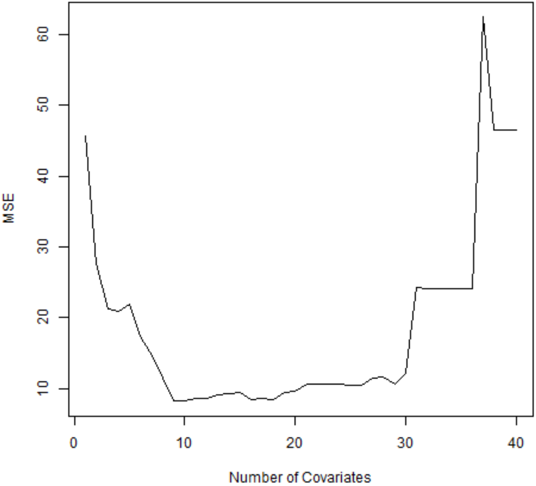
- In the test sample, we predict the fitted values

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

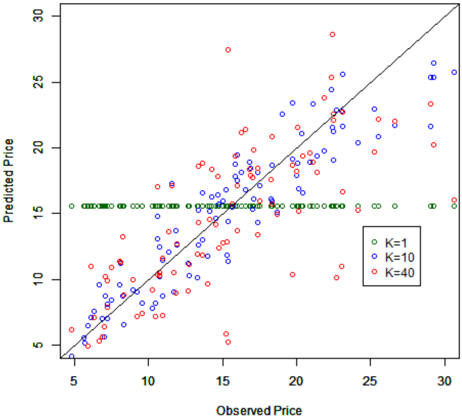
and calculate the MSE

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

MSE in Test Sample



Predicted Car Prices in Test Sample



Number of Covariates	1	10	40
MSE	45.742	8.222	46.499

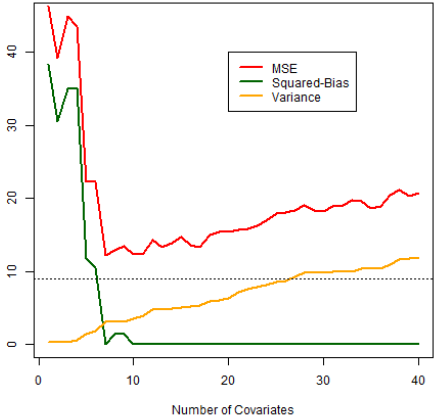
Bias-Variance Trade-Off

- 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

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

- For i.i.d. data, $\hat{f}_{tr}(\cdot)$ and ϵ_{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 $Var(\epsilon_{te})$.

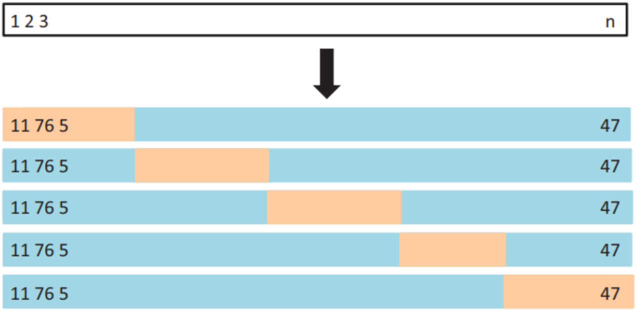
Lasso Example

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

	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

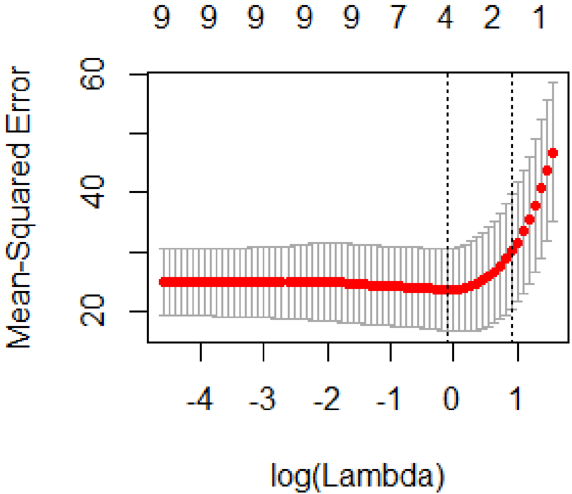
Selection of Optimal Penalty Parameter

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

$\rightarrow$ We do not learn the “true” structural model from ML

$\rightarrow$ 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

  $\rightarrow$ Only one potential earnings can be observed
- Causal effect: $\delta = Y(1) - Y(0)$

$\rightarrow$ Predictions have the observable estimation target $\widehat{Y}$

$\rightarrow$ Causal inference has the (partly) unobservable estimation target $\widehat{\delta}$

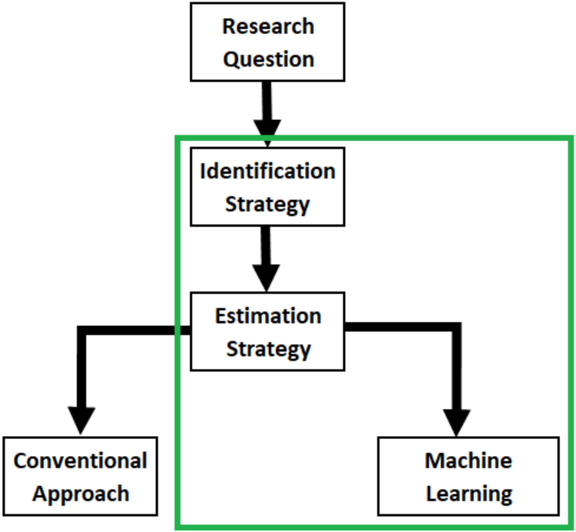
Training of ML Algorithms

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

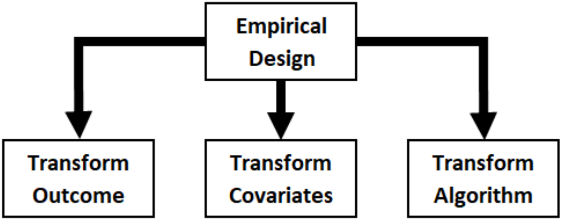
$$MSE_{\hat{\delta}} = E\left[(\hat{\delta} - \delta)^2\right] = \underbrace{E\left[(\hat{\delta} - E[\hat{\delta}])^2\right]}_{\text{Variance}} + \underbrace{E[\hat{\delta} - \delta]^2}_{\text{Squared Bias}}$$

$\rightarrow \delta$ 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.

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Limitations of Causal Machine Learning (CML)

- ML algorithms cannot distinguish between causation and correlation.
  - $\rightarrow$ CML will not select the relevant causal parameters automatically.
  - $\rightarrow$ We have to provide some structure to the CML algorithm.
- CML can estimate causal effects only for a few (usually only one) endogenous variables.
  - $\rightarrow$ 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.

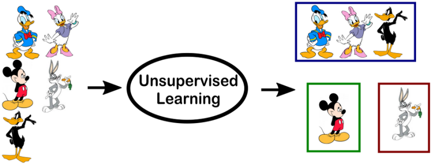
Supervised vs. Unsupervised Machine Learning

Supervised Machine Learning:

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