# Introduction to Machine Learning for Economists and Business Analysts

Anthony Strittmatter

# Zoom

Zoom Link:

https://uni-wuerzburg.zoom.us/j/95131181830?pwd=ZTE3WEZXRW5pb3RBOERYd3VBckJjZz09

ID: 951 3118 1830

Password: 570475

# 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 |

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# Teaching Assistants

Max Müller

Judith Vonberger

# Course Outline

- **Lecture 1:** Introduction to Statistical Learning
- **Lecture 2-4:** Supervised Machine Learning
  - Penalized Regression
  - Trees and Random Forest
  - Neural Networks
- **Lecture 5:** Unsupervised Machine Learning
  - Clustering
  - Principal Component Analysis
- **Lecture 6:** Reinforcement Learning
  - Bandit Algorithm

# Schedule

| | **Monday July 19** | **Tuesday July 20** | **Wednesday July 21** | **Thursday July 22** | **Friday July 23** |
|---|---|---|---|---|---|
| **3:15-4:45pm CEST** | Lecture 1 | Lecture 3 | Lecture 4 | Lecture 5 | Lecture 6 |
| **5:15-6:45pm CEST** | Lecture 2 | PC Lab 1 | PC Lab 2 | PC Lab 3 | PC Lab 4 |

# 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/Wuerzburg
- I will use interactive Jupyter notebooks during the PC labs: https://mybinder.org/v2/gh/AStrittmatter/Wuerzburg/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 on your PC. This are both open source softwares.

# Grading

- Grading is based on an *individual* home assignment.
- Deadline for submission: Sunday, August 1, 2021
- Solutions can be uploaded to the course platform *WueCampus*.

- It is allowed (and even desired) to support each other.
- But do not submit identical or copied home assignments, because then you will fail.

# General

- Feel free to interrupt 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.

# Course Participants

- $>$ 150 applications
- 75 admitted course participants
- International group with participants from 31 countries:

| | Participants | |
|---|---|---|
| Europe | 30 | 40% |
| South America | 25 | 33% |
| Asia | 12 | 16% |
| North America | 4 | 5% |
| Africa | 3 | 4% |
| Australia | 1 | 1% |

- 57% bachelor students, 31% master students, 12% business professionals

# References


- Mullainathan and Spiess (2017): "Machine Learning: An Applied Econometric Approach", Journal of Economic Perspectives, 31 (2), pp. 87-106, download.
- Athey (2017): "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 $\hat{\beta}$.

# Prediction vs. Causality

# 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

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

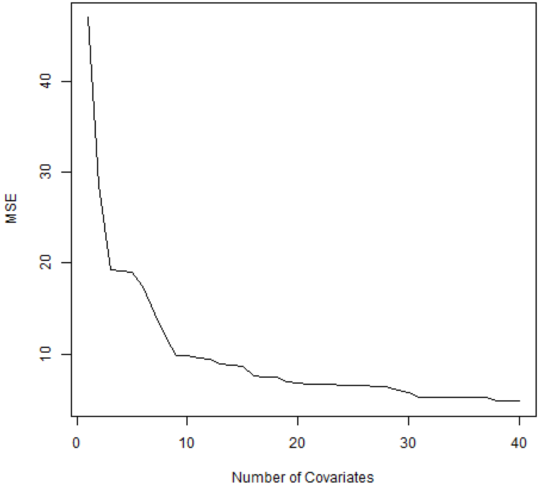
- In the training sample, we predict the fitted values

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

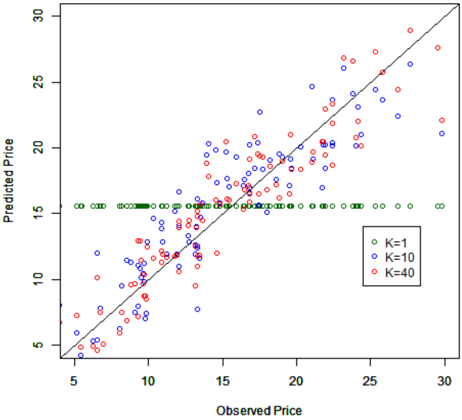
  and calculate the MSE

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

# 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

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

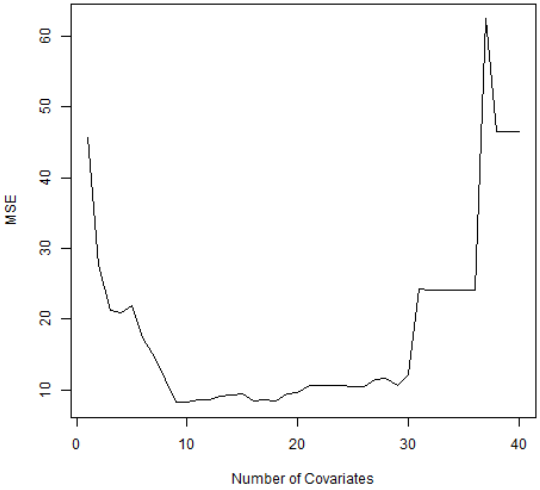
- In the test sample, we predict the fitted values

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

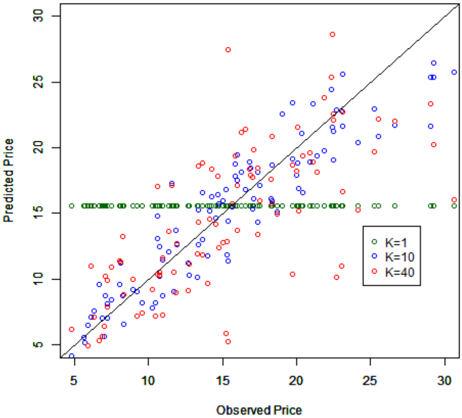
and calculate the MSE

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

# MSE in Test Sample



# Predicted Car Prices in Test Sample




| Number of Covariates | 1 | 10 | 40 |
|---|---|---|---|
| MSE | 45.742 | 8.222 | 46.499 |

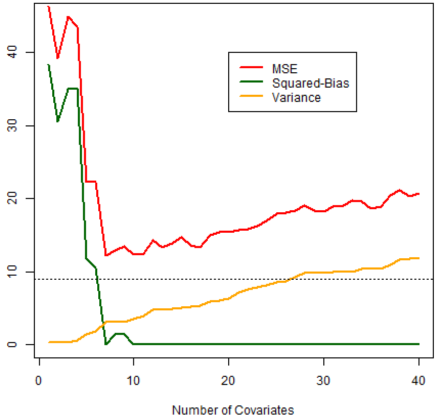
# Bias-Variance Trade-Off

- 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 $\epsilon_{te}$ are independent of each other.

# Simulation of Bias-Variance Trade-Off



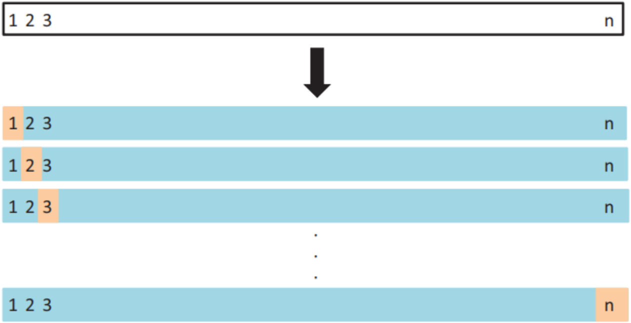

- Only the first ten covariate have an impact on car prices in the simulation.
- Horizontal dashed line is the simulated noise $Var(\epsilon_{te})$.

# 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 |

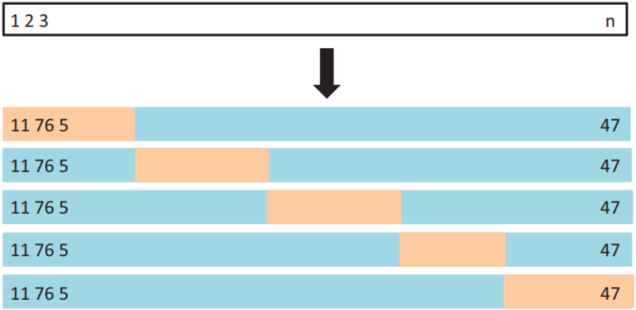
# Leave-One-Out Cross-Validation




Source: James et al. (2013), p. 179

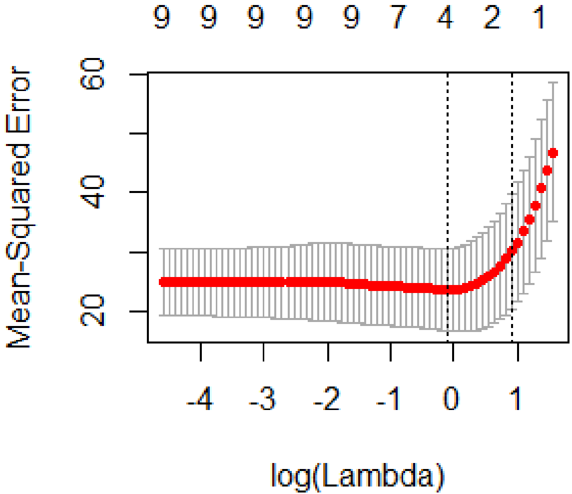
# Selection of Optimal Penalty Parameter

**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 |

# When could Predictions be Useful?

Tasks with a prediction purpose:

- Predict stock or commodity prices using Twitter data.
- Nowcasting unemployment rate or GDP using Google search queries.
- Pre-screening of job applications.
- Consumer demand (shipping before the order occurs).
- Movie recommendations on Netflix.
- Handwriting, image, face, or voice recognition.

# 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).