

Machine Learning for Economists (and Business Analysts)

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Contact and Schedule

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- ▶ Office Room: 5.31.1

	Monday Mar 9	Tuesday Mar 10	Wednesday Mar 11
Time	12:15-15:45	12:15-15:45	14:15-17:45
Room	S2 HG.35	S16 HG.39	S16 HG.39

	Wednesday Mar 18	Thursday Mar 19	Friday Mar 20
Time	14:15-17:45	12:15-15:45	12:15-15:45
Room	S14 HG.32	S16 HG.39	S2 HG.35

Course Outline

- ▶ **Lecture 1:** Introduction to Statistical Learning
 - ▶ Out-of-Sample Prediction
 - ▶ Prediction vs. Causal Analysis
- ▶ **Lecture 2:** Regularized Regression
 - ▶ Lasso, Ridge, Elastic Net
- ▶ **Lecture 3:** Non-parametric Supervised Machine Learning
 - ▶ Classification and Regression Trees
 - ▶ Forests
- ▶ **Lecture 4:** Unsupervised Machine Learning
 - ▶ Clustering
 - ▶ Principal Component Analysis

Course Outline (cont.)

- ▶ **Lecture 5:** High-Dimensional Confounding
 - ▶ Double Selection Procedure
 - ▶ Double Machine Learning
- ▶ **Lecture 6:** Effect Heterogeneity
 - ▶ Causal Forest
 - ▶ Optimal Policy Learning

Literature

- ▶ 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 with no clear definition.
- ▶ 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.

Purpose of Machine Learning

- ▶ Consider the linear 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 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?

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)

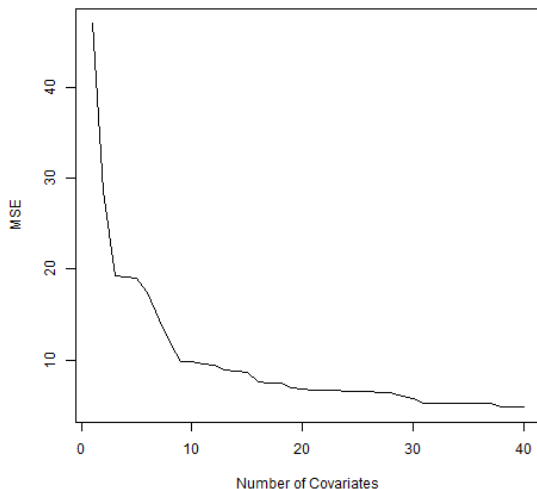
$$\frac{1}{N} \sum_{i=1}^N (Y_i - \hat{Y}_i)^2.$$

- ▶ MSE accounts for finite sample biases.

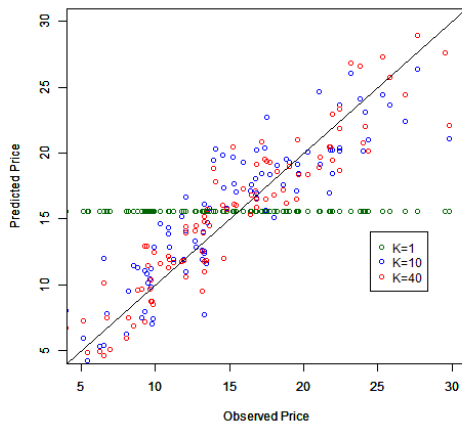
Example: Prediction of Used Car Prices

- ▶ 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)

MSE in Training Sample

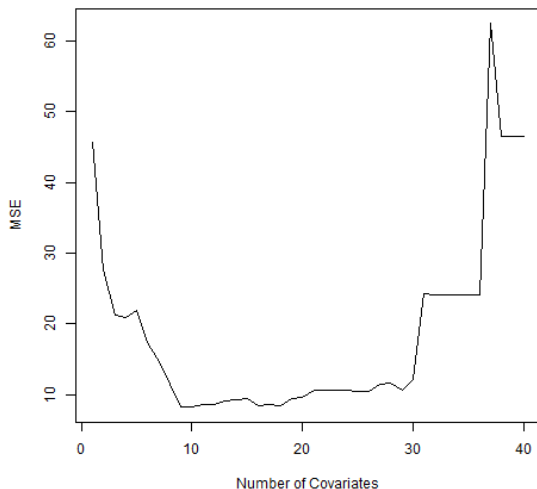


Predicted Car Prices in Training Sample

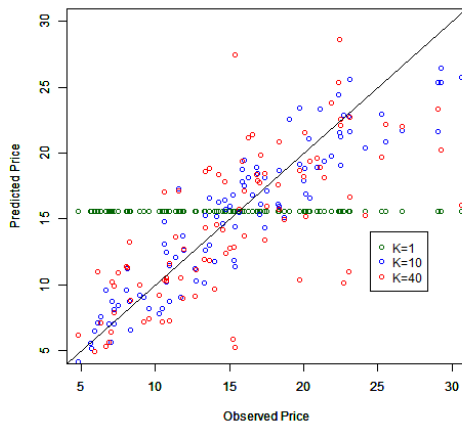


Number of Covariates	1	10	40
MSE	46.948	9.819	4.866

MSE in Test Sample



Predicted Car Prices in Test Sample



Number of Covariates	1	10	40
MSE	45.742	8.222	46.499

Estimation Procedure

- 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

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

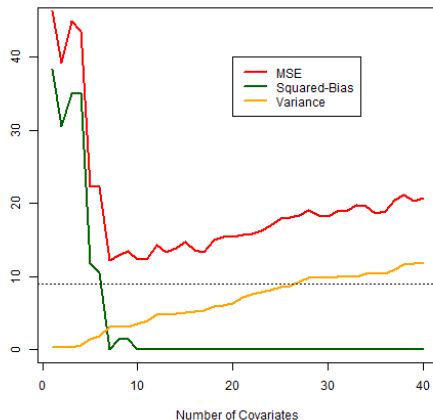
Bias-Variance Trade-Off

- 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 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 $Var(\epsilon_{te})$.

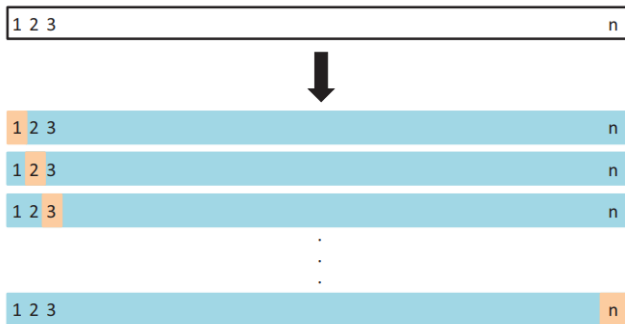
Lasso Example

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

	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

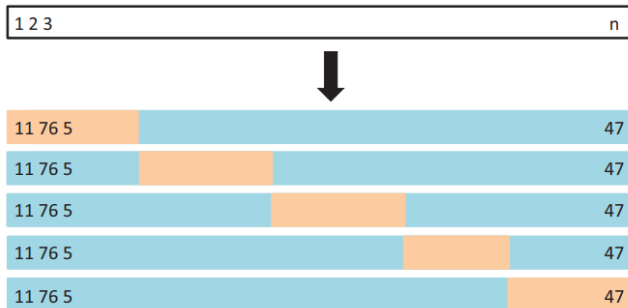
Leave-One-Out Cross-Validation



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

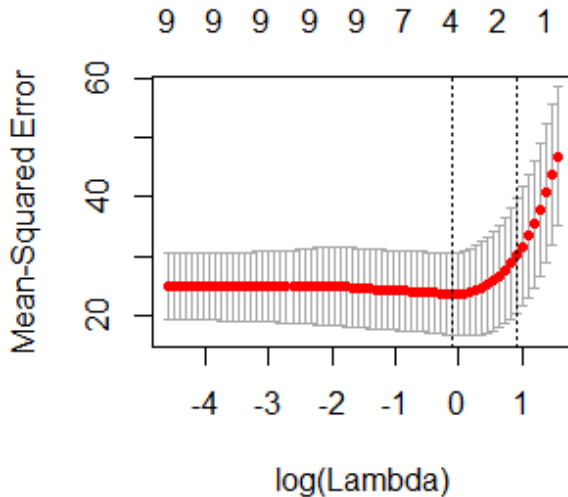
Selection of Optimal Penalty Parameter (cont.)

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

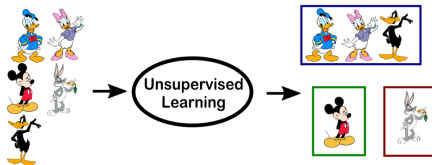
Supervised vs. Unsupervised Machine Learning

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



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.

Generate New 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 $\hat{\delta}$

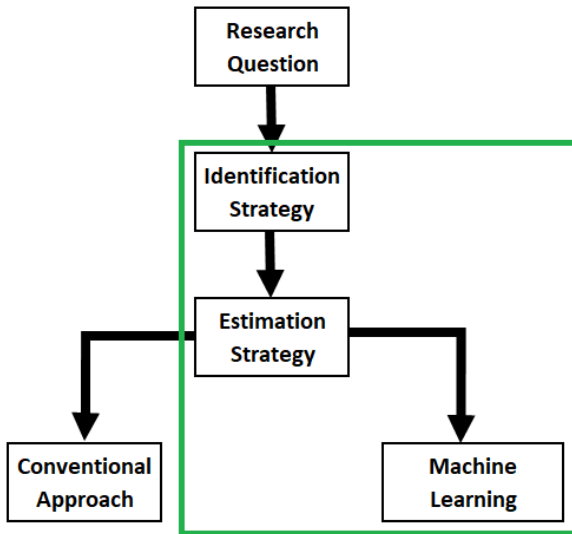
Training of ML Algorithms

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

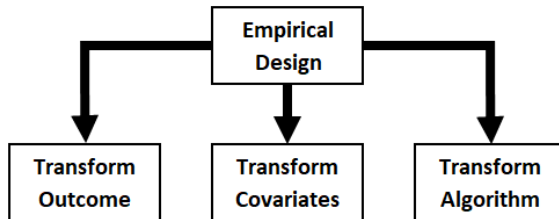
$$MSE_{\hat{\delta}} = E \left[(\hat{\delta} - \delta)^2 \right] = \underbrace{E \left[(\hat{\delta} - E[\hat{\delta}])^2 \right]}_{\text{Variance}} + \underbrace{(E[\hat{\delta}] - \delta)^2}_{\text{Squared Bias}}$$

→ δ 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. \(2017\)](#)

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:

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

Reference:

- ▶ [Athey and Wager \(2019\)](#)

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

- ▶ [Knaus \(2018\)](#) estimates the effects of musical practice on student's skills and selects confounders with ML methods.
- ▶ [Taddy et al. \(2016\)](#) investigate the heterogeneous effects of A/B-experiments in online-auctions (EBay) on customer responses (experimental study).
- ▶ [Bertrand et al. \(2017\)](#) estimate heterogeneous employment effects of training programmes for unemployed persons.
- ▶ [Strittmatter \(2019\)](#) estimates heterogeneous labour supply effects of a welfare reform.
- ▶ [Ascarza \(2018\)](#) targets marketing campaigns.