CES Lecture

Promises and Perils of Machine Learning

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Course Outline

1. Introduction to Machine Learning for Economic Research
2. High-Dimensional Confounding
3. Optimal Policy Learning

Prerequisites

Prerequisites:

- Next Tuesday: Lasso
- Next Thursday: Forest and classification tree

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.

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 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

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

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?

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)

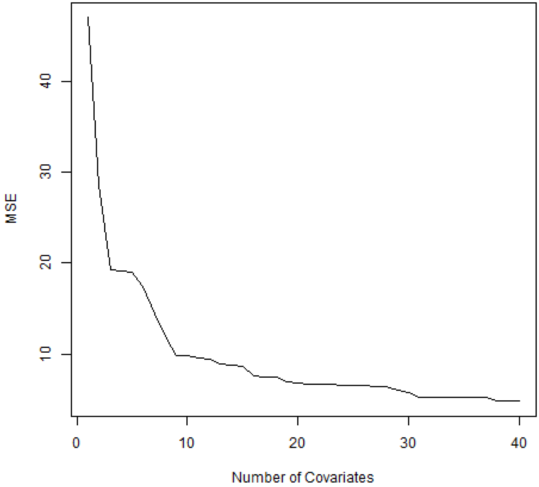
$$\frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2.$$

- MSE accounts for finite sample biases.

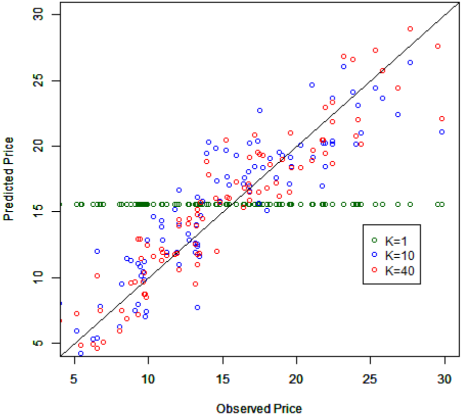
Example: Prediction of Used Car Prices

- 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

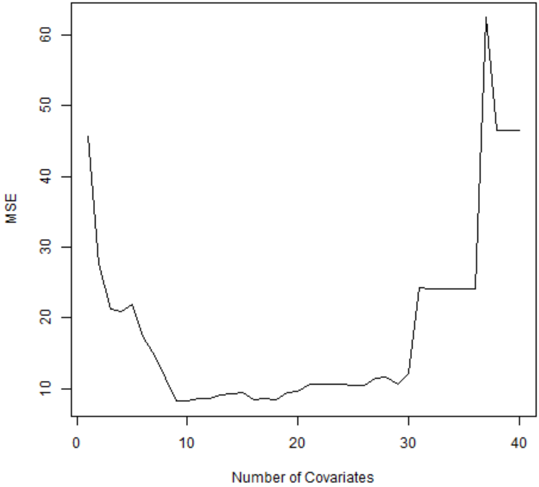


Predicted Car Prices in Training Sample

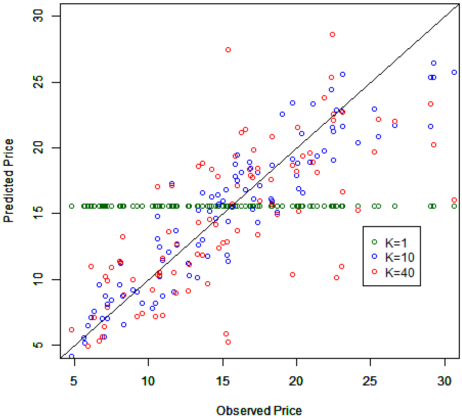


Number of Covariates	1	10	40
MSE	46.948	9.819	4.866

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

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

  and calculate the MSE

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

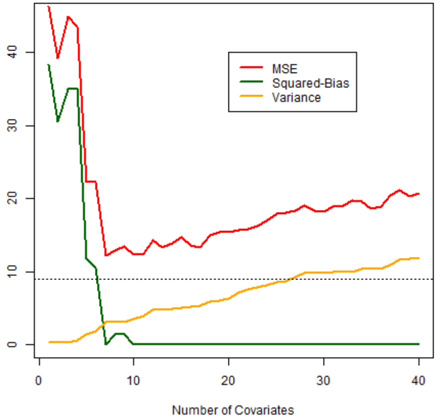
Bias-Variance Trade-Off

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

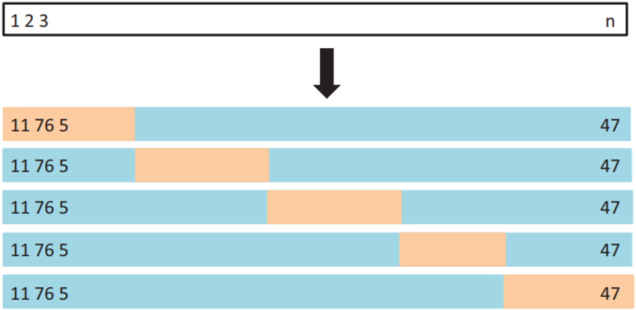
Lasso Example

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

	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

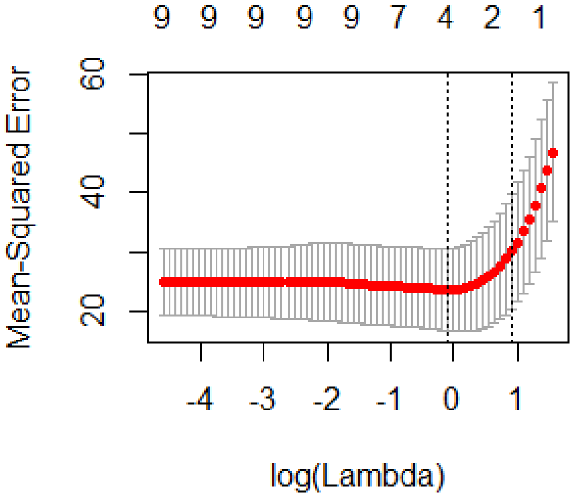
Selection of Optimal Penalty Parameter

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

→ 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.

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

  $\rightarrow$ 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 $\widehat{\delta}$

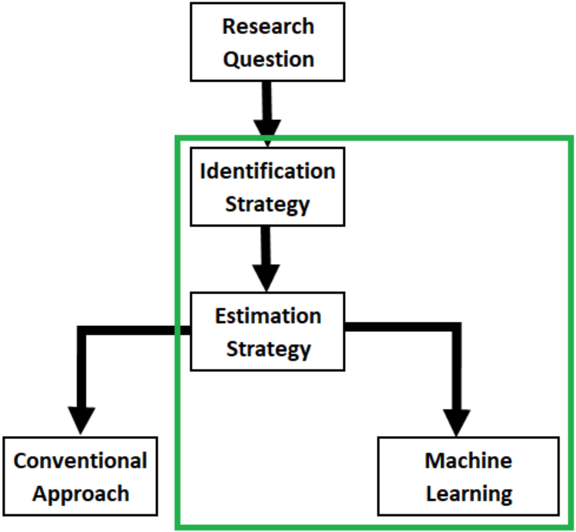
Training of ML Algorithms

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

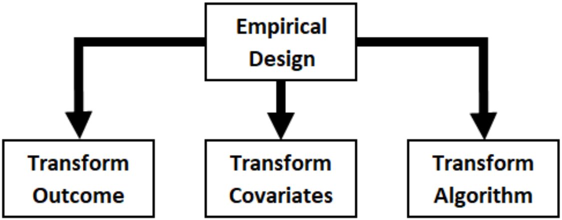
$$MSE_{\hat{\delta}} = E\left[(\hat{\delta}-\delta)^2\right] = \underbrace{E\left[(\hat{\delta}-E[\hat{\delta}])^2\right]}_{\text{Variance}} + \underbrace{E[\hat{\delta}-\delta]^2}_{\text{Squared Bias}}$$

$\rightarrow$ 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.
  - $\rightarrow$ 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

- 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.

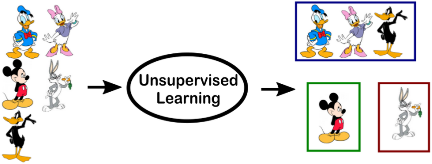
Supervised vs. Unsupervised Machine Learning

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



- Factor analysis (e.g., principal component analysis)