THE Winter School

Promises and Perils of Machine Learning

Anthony Strittmatter

Swiss Institute for Empirical Economic Research

University of St.Gallen

Course Outline

1. Introduction to Machine Learning for Economic and Business Research
2. Predictive Machine Learning: Regularized Regression
3. Causal Machine Learning: High-Dimensional Confounding

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 $plim(\hat{\beta}) \neq \beta$.
- 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)

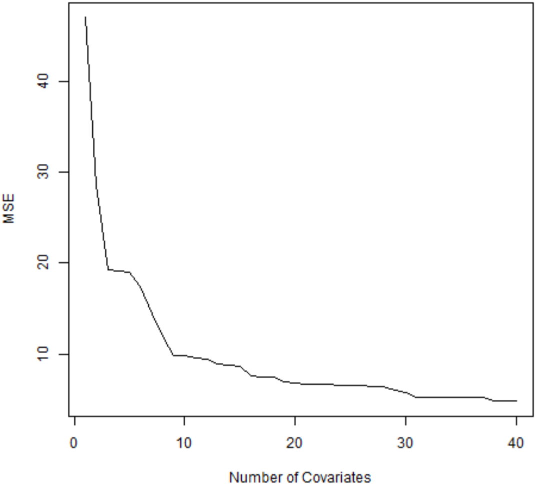
$$\frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2.$$

- MSE accounts for finite sample biases.

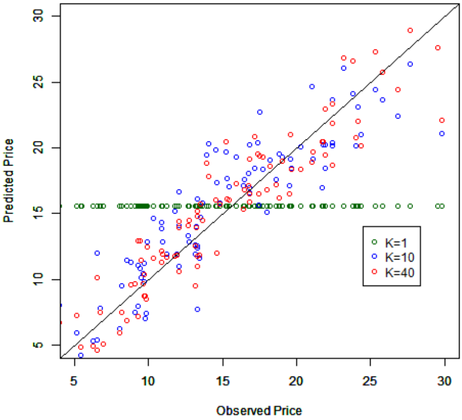
Example: Prediction of Used Car Prices

- 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

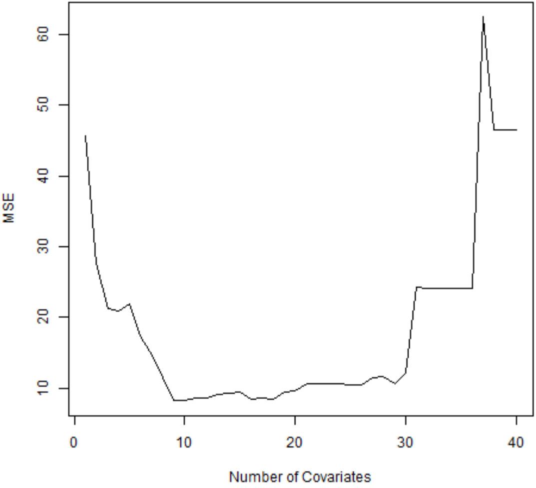


Predicted Car Prices in Training Sample

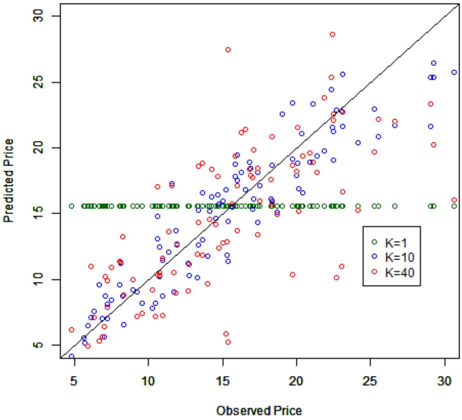


Number of Covariates	1	10	40
MSE	46.948	9.819	4.866

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

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

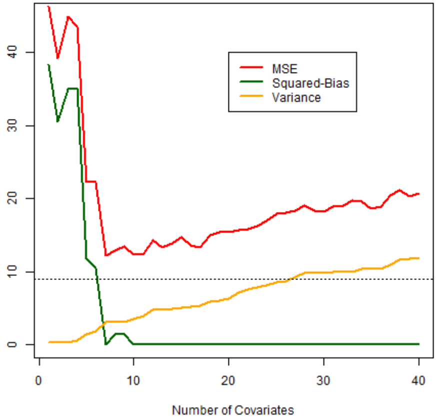
Bias-Variance Trade-Off

- 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	24.56	25.47
diesel	0.903	.
other_car_owner	0.304	.
pm_green	2.559	0.057
private_seller	-0.371	.
guarantee	-9.126	-5.246
inspection	-0.476	.
maintenance_cert	0.467	.
mileage	-0.073	-0.055
age_car_years	-0.942	-0.840
R^2 training	0.563	0.521
R^2 test	0.114	0.273

Stability of the Lasso Model

	Lasso 1	Lasso 2	Lasso 3	Lasso 4	Lasso 5
Intercept	25.47	22.94	21.59	20.03	23.29
diesel	.	2.290	2.077	0.805	.
other_car_owner	.	0.058	.	0.903	.
pm_green	0.057	.	.	2.078	.
private_seller	.	.	0.256	.	-1.100
guarantee	-5.246	.	-0.592	1.516	.
inspection	.	.	0.465	.	0.475
maintenance_cert	.	.	.	-0.666	.
mileage	-0.055	-0.039	-0.030	-0.031	-0.046
age_car_years	-0.840	-0.968	-1.327	-1.027	-0.897

→ 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	0.92			
Lasso 3	0.92	0.99		
Lasso 4	0.88	0.97	0.95	
Lasso 5	0.95	0.97	0.95	0.96

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 $\widehat{\delta}$

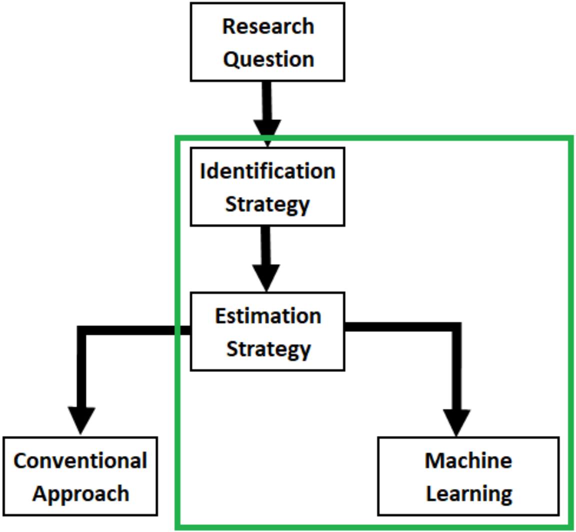
Training of ML Algorithms

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

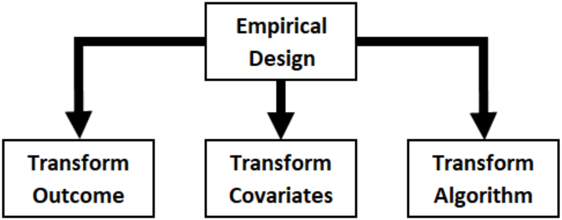
$$MSE_{\hat{\delta}} = E\left[(\hat{\delta} - \delta)^2\right] = \underbrace{E\left[(\hat{\delta} - E[\hat{\delta}])^2\right]}_{\text{Variance}} + \underbrace{E[\hat{\delta} - \delta]^2}_{\text{Squared Bias}}$$

$\rightarrow \delta$ 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)

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.

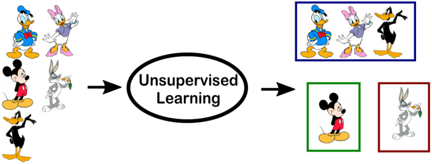
Supervised vs. Unsupervised Machine Learning

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)