

So many choices in Double Machine Learning!? Practical insights from a simulations study

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What is Double Machine Learning?



- Double/debiased machine learning (DML) introduced by Chernozhukov et al.
 (2018)
- General framework based on machine learning tools for causal inference and estimation of treatment effects
- Combines the strength of machine learning and econometrics
- Resulting estimator has good properties (\sqrt{N} -consistency, approx. Gaussian)
- Our object-oriented implementation DoubleML provides a general interface for models and methods for DML (in R and in Python)



The Key Ingredients of DML



1. Neyman Orthogonality

Inference is based on a method-of-moments estimator that obeys the **Neyman orthogonality** condition

2. High-Quality Machine Learning Estimators

The nuisance parameters are estimated with high-quality (fast-enough converging) machine learning methods

Sample Splitting

To avoid the biases arising from overfitting, a form of **sample splitting** is used at the stage of producing the estimator of the main parameter θ_0



Example: Partially Linear Regression Model

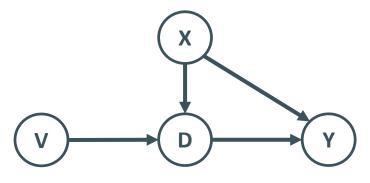


Partially linear regression (PLR) model

$$egin{aligned} Y &= D heta_0 + g_0(X) + \zeta, & & \mathbb{E}[\zeta|D,X] &= 0, \ D &= m_0(X) + V, & & \mathbb{E}[V|X] &= 0, \end{aligned}$$

with

- outcome variable Y
- Policy or Treatment variable of interest D
- High-dimensional vector of confounding covariates $X = (X_1, ..., X_p)$
- Stochastic errors ζ and V





Tuning in Double Machine Learning



■ PLR example: To estimate θ_0 , the following **Neyman orthogonal score** is used

$$\psi(W;\theta,\eta) = (Y - g(X) - \theta(D - m(X)))(D - m(X))$$

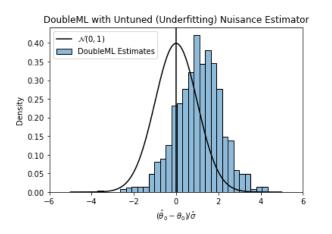
- The nuisance $\eta = (g(X) = \mathbb{E}[Y \mid X], m(X) = \mathbb{E}[D \mid X])$ is estimated by ML learners
- Double Machine Learning is inherently robust against small biases from regularization or overfitting
- Tuning DML nuisance predictors is an open question

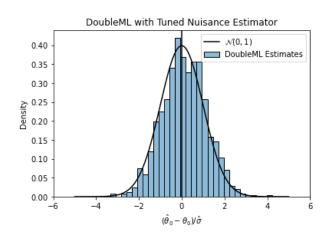


Tuning in Double Machine Learning



 Using untuned ML estimators for nuisance prediction however can lead to a severely biased estimation in the causal parameter of interest





How do we get to the right estimator?



Our Project



- Carry out large scale simulation study to answer important questions double machine learning users face
 - Which Machine Learning Methods to use?
 - Role of sample splitting in tuning?
 - How to assess the quality of fit?

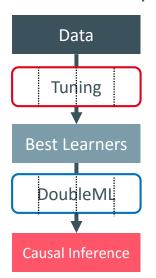


Our Simulation Study

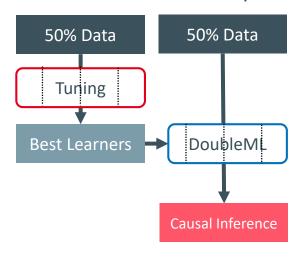


- We use plug-in Automated Machine Learning Estimators from the library flaml.
- Three different tuning approaches are tested high-dimensional datasets from the ACIC 2019

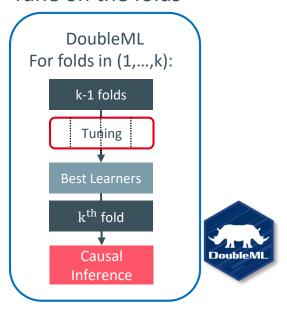
Tune on full sample



Tune on hold-out sample

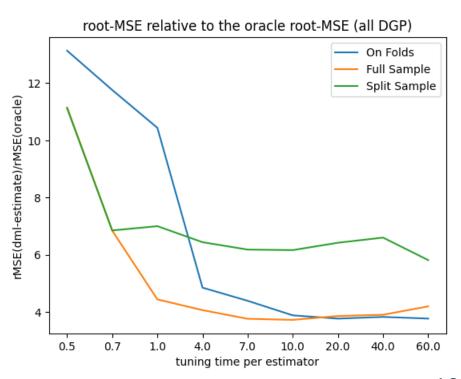


Tune on the folds



Results

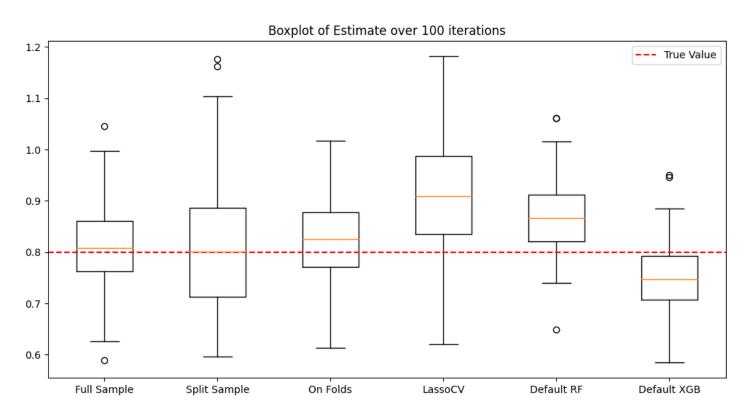




$$n = 1000, p = 200$$

Results





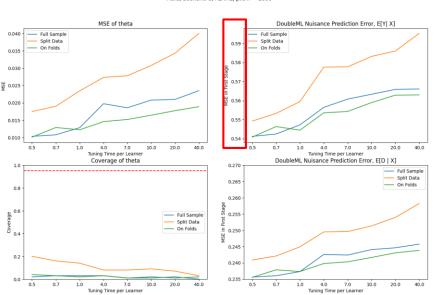
Results



Misspecified Model

(linear, additive effect)

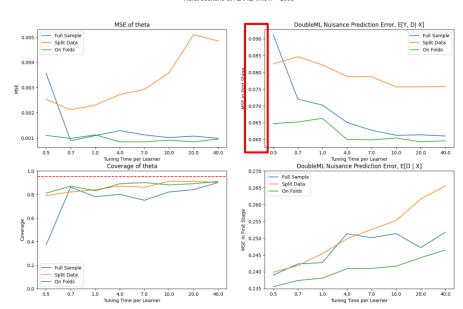
ACIC, Scenario 8, FLAML, plr, n = 1000



Correct Model

(heterogenous effect)

ACIC, Scenario 8, FLAML, irm, n = 1000



Key Take-Aways and Outlook



- Tuning the nuisance estimators has influence on inference accuracy in double machine learning
- Plug-in AutoML estimators work well here
- Tuning on hold-out data is in investigated cases not efficient
- We recommend monitoring the nuisance prediction error for assessment of causal inference quality
- Full results for all DGPs to be published / further studies on influence of cross-fitting
- Extension to further AutoML frameworks
- Extension module for DoubleML



Thank you for your attention!

Comments, ideas? Feel free to reach out!

More about **DoubleML**:

Https://docs.doubleml.org

https://github.com/DoubleML/doubleml-for-py https://github.com/DoubleML/doubleml-for-r



DoubleML

The Python and R package **DoubleML** provide an implementation of the double / debiased machine learning framework of Chemozhukov et al. (2018). The Python package is built on top of scikit-learn (Pedregosa et al., 2011) and the R package on top of mir3 and the mir3 ecosystem (Lang et al., 2019).





User auide



Getting started

New to **DoubleML**? Then check out how to get started! Want to learn everything about **DoubleML?** Then you should visit our extensive user guide with detailed explanations and further references.

Workflow

The **DoubleML** workflow demonstrates the typical steps to consider when using **DoubleML** in applied analysis.

To the getting started guide

To the user guide

To the DoubleML workflow







Python API

The Python API documentation.

R API
The R API documentation.

A gallery with examples demonstrating the functionalities of **DoubleML**.

Example gallery

