Causal Machine Learning with DoubleML

Introduction to the R Package DoubleML

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Introduction to DoubleML



Building Principles



Key ingredient and Implementation

- Orthogonal Score
 - Object-oriented implementation with R6
 - \circ Exploit common structure being centered around a (linear) score function $\psi(\cdot)$
- High-quality ML
 - State-of-the-art ML prediction and tuning methods
 - Provided by mlr3 ecosystem
- Sample Splitting
 - Built-in resampling schemes of mlr3

Dependency







Dependencies and Installation



DoubleML package dependencies

- mlr3
- mlr3learners

Ro

™mlr

- mlr3tuning
- R6
- data.table





Why an Object-Orientated Implementation?

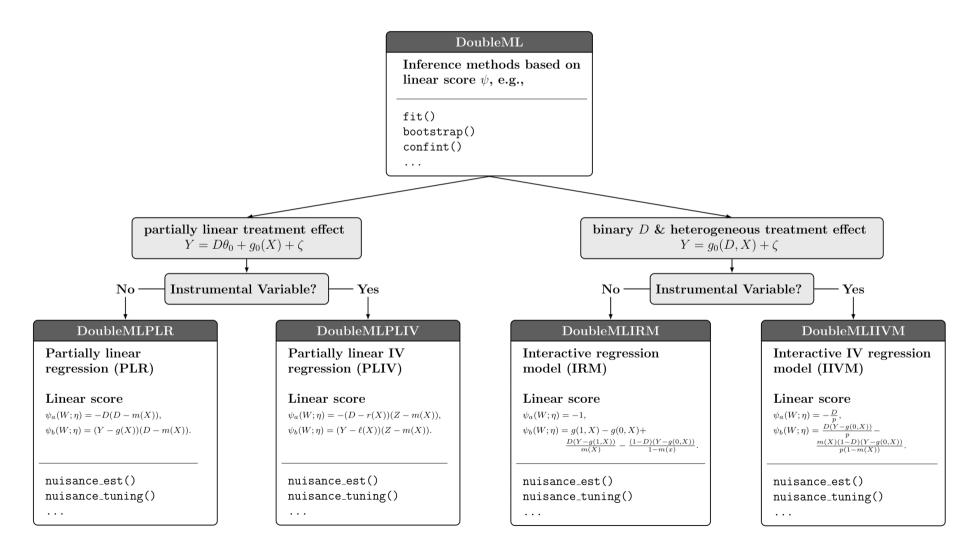


- Given the components $\psi^a(\cdot) \otimes \psi^b(\cdot)$ of a linear Neyman orthogonal score function $\psi(\cdot)$, a general implementation is possible for
 - The estimation of the orthogonal parameters
 - \circ The computation of the score $\psi(W; \theta, \eta)$
 - The estimation of standard errors
 - The computation of confidence intervals
 - A multiplier bootstrap procedure for simultaneous inference
- The sample splitting can be implemented in general as well
- → Implemented in the abstract base class DoubleML

- The score components and the estimation of the nuisance models have to be implemented modelspecifically
- → Implemented in model-specific classes inherited from DoubleML

Class Structure and Causal Models





Advantages of the Object-Orientation



- DoubleML gives the user a high flexibility with regard to the specification of DML models:
 - Choice of ML methods for approximating the nuisance functions
 - Different resampling schemes (repeated cross-fitting)
 - DML algorithms DML1 and DML2
 - Different Neyman orthogonal score functions

- DoubleML can be easily extended
 - New model classes with appropriate Neyman orthogonal score function can be inherited from DoubleML
 - The package features callables as score functions which makes it easy to extend existing model classes
 - The resampling schemes are customizable in a flexible way

Getting started with DoubleML!

Installation



• Latest CRAN release

```
install.packages("DoubleML")
```

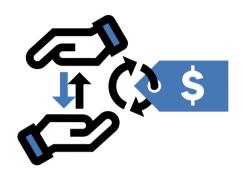
• Development version

```
remotes::install_github("DoubleML/doubleml-for-r")
```

• See the Getting Started page of the tutorial website for more information on prerequisites.

Data Example: Demand Estimation





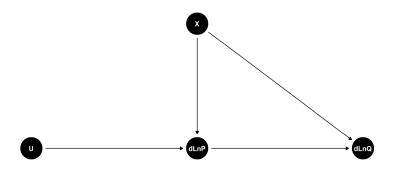
Data Source

- Data example based on a blogpost by Lars Roemheld (Roemheld, 2021)
- Original real data set publicly available via kaggle, preprocessing notebook available online

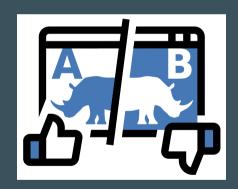
Causal Problem

- Price elasticity of demand: What is the effect of a price change, dLnP, on demanded quantity, dLnQ?
- ullet Observational study: Flexibly adjust for confounding variables X, e.g. product characteristics

Causal Diagram (DAG)

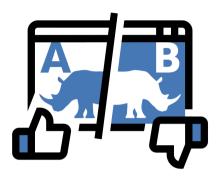


Hands on! Interactive Breakout Sessions



Data Example: A/B Testing





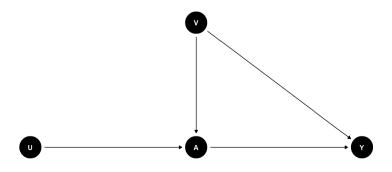
Data Source

Data example based on a randomly chosen
 DGP created for the 2019 ACIC Data Challenge.

Causal Problem

- Online shop: What is the effect of a new ad design A on sales Y (in \$\\$100\$)?
- ullet Observational study: Necessary to adjust for confounding variables V

Causal Diagram (DAG)



Online Resources



- The notebook is organized according to the **DoubleML Workflow**
- Extensive User Guide available via docs.doubleml.org
- Documentation for the R Package DoubleML available via docs.doubleml.org/r/stable/
- R vignette, Bach et al. (2021) available via arxiv

Quickstart in R6



- A short introduction to the R6 packages is available here.
- To create a new instance of a class, call the \$new() method.

Quickstart to R6



• Call methods and access fields

```
obj dml data$n obs
## [1] 500
obj_dml_data$print()
## ======= DoubleMLData Object ==========
##
###
  ----- Data summary
## Outcome variable: y
## Treatment variable(s): d
## Covariates: X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13, X14, X15, X16, X17, X18, X19, X20
## Instrument(s):
## No. Observations: 500
```

Quickstart to R6

Quickstart: Creating learners in mlr3



• Install and load mlr3 package

* Properties: loglik, weights

```
install.packages("mlr3")
library(mlr3)
```

• Create a learner

```
lm_learner = LearnerRegrLM$new()

lm_learner = lrn("regr.lm")
lm_learner

## <LearnerRegrLM:regr.lm>
## * Model: -
## * Parameters: list()
## * Packages: mlr3, mlr3learners, stats
## * Predict Type: response
## * Feature types: logical, integer, numeric, factor, character
```

Thank you UseR!2022



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References



Double Machine Learning Approach

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DoubleML Package for Python and R

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