

Statistical Learning in Mediation Analysis

Lab for Chapter 5: Estimating interventional randomized direct and indirect effects in R

David Benkeser
Emory University

Iván Díaz
Weill Cornell Medicine

MODULE 17

**Summer Institute in Statistics for
Clinical and Epidemiological Research**
August 2022

Contents of this lab

- 1 Illustration of estimation of the interventional direct and indirect effects using the `medoutcon` R package
- 2 Do-it-yourself analysis of a real dataset

Illustrative dataset

- Recall the dataset `weight_behavior` from the `mma` R package used in Lab 3.
- We set up the dataset the same way as for Lab 3, removing missing data:

```
library(mma)
library(tidyverse)
# load and examine data
data(weight_behavior)
dim(weight_behavior)

## [1] 691 15

# drop missing values
weight_behavior <- weight_behavior %>%
  drop_na() %>%
  as_tibble()
```

Setting up the problem

As before, we focus on the causal effects of participating in a sports team (`sports`) on the BMI of children (`bmi`), taking into consideration mediators given by (`exercises`, `overweigh`). All other measured covariates are taken to be potential baseline confounders.

For this lab we will use `snack` as an intermediate confounder.

The function `medoutcon()`

Recall the main function of the package: `medoutcon()`. In Lab 3 we discussed the arguments to this function, but left one pending: Z . This is the intermediate confounder of interest. In this function, if Z is null, the function estimates the NDE and NIE, if Z is a vector, the function estimates the interventional direct and indirect effects

Estimating the interventional direct effect

First, we set up the super learner libraries as in Lab 3:

```
library(sl3)
# instantiate learners
fglm_lrnr <- Lrnr_glm_fast$new()
lasso_lrnr <- Lrnr_glmnet$new(alpha = 1, nfolds = 3)
rf_lrnr <- Lrnr_ranger$new(num.trees = 200)
# create learner library and instantiate super learner ensemble
lrnr_lib <- Stack$new(fglm_lrnr, lasso_lrnr, rf_lrnr)
sl_lrnr <- Lrnr_sl$new(learners = lrnr_lib, metalearner = Lrnr_nnls$new())
```

Estimating the interventional direct effect

We now compute the effects:

```
library(medoutcon)
# compute one-step estimate of the natural direct effect
ide_onestep <- medoutcon(
  W = weight_behavior[, c("age", "sex", "race", "tvhours")],
  A = (as.numeric(weight_behavior$sports) - 1),
  Z = (as.numeric(weight_behavior$snack) - 1),
  M = weight_behavior[, c("exercises", "overweigh")],
  Y = weight_behavior$bmi,
  g_learners = lasso_lrnr,
  h_learners = lasso_lrnr,
  b_learners = lasso_lrnr,
  effect = "direct",
  estimator = "onestep",
  estimator_args = list(cv_folds = 5)
)
```

Estimating the interventional indirect effect

```
# compute one-step estimate of the natural indirect effect
iie_onestep <- medoutcon(
  W = weight_behavior[, c("age", "sex", "race", "tvhours)],
  A = (as.numeric(weight_behavior$sports) - 1),
  Z = (as.numeric(weight_behavior$snack) - 1),
  M = weight_behavior[, c("exercises", "overweigh)],
  Y = weight_behavior$bmi,
  g_learners = lasso_lrnr,
  h_learners = lasso_lrnr,
  b_learners = lasso_lrnr,
  effect = "indirect",
  estimator = "onestep",
  estimator_args = list(cv_folds = 5)
)
```

Results

```
summary(ide_onestep)
## # A tibble: 1 x 7
##   lwr_ci param_est upr_ci var_est eif_mean estimator param
##   <dbl>   <dbl> <dbl>  <dbl>   <dbl> <chr>   <chr>
## 1 -0.321     0.209  0.739  0.0732  1.98e-15 onestep direct~

summary(iie_onestep)
## # A tibble: 1 x 7
##   lwr_ci param_est upr_ci var_est eif_mean estimator param
##   <dbl>   <dbl> <dbl>  <dbl>   <dbl> <chr>   <chr>
## 1  0.431     0.989  1.55  0.0810  1.38e-15 onestep indire~
```

Note that, in contrast with the results of Lab 3 where the effect of snacking was part of the indirect effect, here the effect of snacking is part of the direct effect.

Do-it-yourself analysis of a real dataset

Please revisit the exercise at the end of Lab 4, and compute the estimate of the interventional direct and indirect effects for that problem/dataset.