# News from Cyperspace

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### LPR

```
# Good old LPR2 until 2018
proc1 <- importSAS('X:/data/rawdata_hurtig/702773/opr.</pre>
    sas7bdat',
           where=....
           keep=c("pnr","opr","odto"),date.vars = "odto
    ")
# LPR2 remnants 2019
proc2_2019 <- importSAS('X:/data/rawdata_hurtig/703775/</pre>
   2022/t_sksube.sas7bdag',
           where=....,
           keep=c("pnr","c_opr","d_odto","recnum"))
setnames(proc2_2019,c("c_opr","d_odto"),c("opr","odto")
```

### LPR

```
#Great new LPR3
proc3 <- importSAS('X:/data/workdata_hurtig</pre>
    /703775/2022/procedurer.sas7bdat',
           where=...)
#make a filter, LPR3 is HUGE
filt <- unique(proc3[,.(kontakt_id)])</pre>
#Filtered version of adm3
adm3 <- importSAS('X:/data/rawdata_hurtig/703775/2022/</pre>
    kontakt.sas7bdat',,
          keep=c("kontakt_id","pnr"),filter=filt)
proc3 <- merge(proc3,adm3,by="kontakt_id")</pre>
proc3[,odto:=as.Date(starttidspunkt)]
proc3 <- proc3[,.(pnr,odto)]</pre>
proc <- rbind(proc1,proc2_2019,proc3,fill=TRUE)</pre>
```

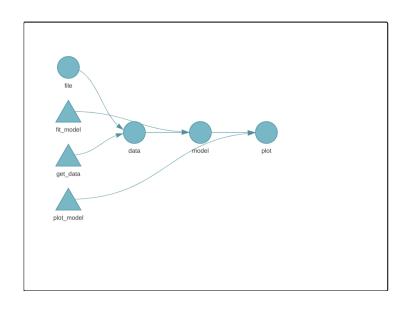
# **TARGETS**



R/functions.R contains our custom user-defined functions. (See the <u>functions chapter</u> for a discussion of function-oriented workflows.)

```
# R/functions.R
get_data <- function(file) {</pre>
  read_csv(file, col_types = cols()) %>%
    filter(!is.na(Ozone))
fit_model <- function(data) {</pre>
  lm(Ozone ~ Temp, data) %>%
    coefficients()
plot model <- function(model, data) {</pre>
  ggplot(data) +
    geom point(aes(x = Temp, v = Ozone)) +
    geom_abline(intercept = model[1], slope = model[2])
```

```
#_targets.R file
library(targets)
source("R/functions.R")
tar_option_set(packages = c("readr", "dplyr", "ggplot2"))
list(
   tar_target(file, "data.csv", format = "file"),
   tar_target(data, get_data(file)),
   tar_target(model, fit_model(data)),
   tar_target(plot, plot_model(model, data))
)
```



```
tar_make()
#> • start target file
#> • built target file
#> • start target data
#> • built target data
#> • start target model
#> • built target model
#> • built target plot
#> • built target plot
#> • end pipeline: 1.007 seconds
```

```
tar_make()

#> \script skip target file

#> \script skip target data

#> \script skip target model

#> \script skip target plot

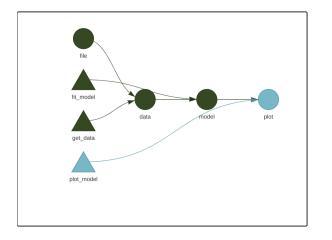
#> \script skip pipeline: 0.095 seconds
```

#### 2.6.1 Change code

If you change one of your functions, the targets that depend on it will no longer be up to date, and tar\_make() will rebuild them. For example, let's increase the font size of the plot.

```
# Edit functions.R...
plot_model <- function(model, data) {
   ggplot(data) +
      geom_point(aes(x = Temp, y = Ozone)) +
      geom_abline(intercept = model[1], slope = model[2]) +
      theme_gray(24) # Increased the font size.
}</pre>
```

#### tar\_visnetwork()





Up to date



Outdated







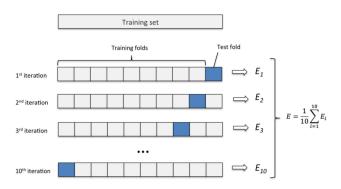
# Counterfactual



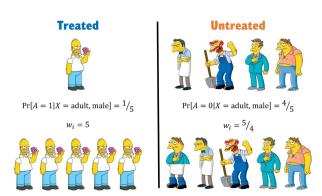
### Causal Inference

- ► Parametric G-formula
- Propensity matching
- Inverse probability weighting

# Superlearner

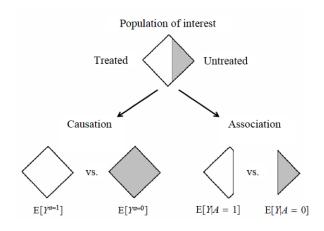


## Propensity adjustment



Our pseudo-population includes a similar number of adult males (note the duplicated Homer and the hybrid untreated), so when comparing the groups — the effect of adult-males will cancel it-self and we'll be left only with

### G-estimation



### TMLE - LTMLE

Targeted Maximum Likelihood Estimation

- Step-1 Outcome versus covariates using superlearner
- Step-2 Targeting using propensity of treatment
- Double robust G-estimation of target parameter

Target Parameter flexible such as calculating the benefit/risk of 5 ears of treatment with X versus no treatment

## PhD course: Targeted Register Analysis

Dates: 12, 13, 14 and 15 December 2022, all days 8.00-15.00

Course location: CSS

Registration: Please register before 7 November 2022

- Analysing Danish register data
- ► The roadmap of targeted statistical learning
- ➤ The transition from traditional epidemiological tools (cohort followup studies, case-control studies) which produce hazard ratios or odds ratios to average treatment effects defined in a dynamic causal framework
- Machine learning (random forests/recursive neural networks)
- Longitudinal minimum loss estimation (LTMLE)
- Use the R-package targets to setup and organize a reproducible analysis

#### Teachers

Christian Torp-Pedersen, Nothern Sealands Hospital and Section of Biostatistics, Department of Public Health, University of Copenhagen Marvin Wright, Leibniz Institute for Prevention Research and Epidemiology, Bremen, Germany Zeyi Wang, Postdoctoral scholar, Division of Biostatistics, University of California, Berkeley Andrew Mertens, postdoc, Division of Biostatistics, University of California, Berkeley Thomas A. Gerds, Section of Biostatistics, Department of Public Health, University of Copenhagen