

Day 2, Practical 1, Hely's solution

Helene Charlotte Wiese Rytgaard

May 15, 2023

Task 1: Simulation function from the practical from yesterday:

```
set.seed(15)
(sim.data <- sim.fun(1000))
```

```
      id      X1      X2 X3 A Y
1:    1 0.4084562 0.38996075 0 0 0
2:    2 -1.2198243 -1.67449303 1 0 0
3:    3  1.8658349 -2.22881407 0 1 1
4:    4  0.6036221 -0.01388672 0 0 0
5:    5 -0.5317124  0.57686435 0 0 0
---
996: 996  1.6989517  0.14755236 0 1 1
997: 997 -1.5151272  0.22514534 0 0 1
998: 998 -1.4508899  0.31307290 0 0 1
999: 999 -0.1766132 -1.60064177 0 0 0
1000: 1000  0.6122651  0.79204417 0 1 1
```

1 Implementing the targeting step for the treatment-specific mean $\Psi_a(P_0)$

Task 2:

```
target.fun <- function(d, a) {

  ##-- 1:
  fit.f <- glm(Y~A+X1+X2+X3, family=binomial, data=d)
  fit.pi <- glm(A~X1+X2+X3, family=binomial, data=d)

  ##-- 2:
  d[, pred.fa:=predict(fit.f, type="response", newdata=copy(d)[, A:=a])]
  d[, pred.f:=predict(fit.f, type="response", newdata=d)]

  ##-- 3:
  d[, pred.pi1:=predict(fit.pi, type="response", newdata=d)]

  ##-- 4:
  d[, Ha:=(A==a)/(pred.pi1^a*(1-pred.pi1)^(1-a))]

  ##-- 5:
  fit.tmle <- glm(Y ~ offset(qlogis(pred.f)) + Ha -1, family=binomial, data=d)
  eps.hat <- fit.tmle$coef
```

```

##-- 6:
d[, pred.fa.1:=plogis(qlogis(pred.fa) + eps.hat/(pred.pi1^a*(1-pred.pi1)^(1-a)))]
d[, pred.f.1:=plogis(qlogis(pred.f) + eps.hat*Ha)]

##-- 7:
tmle.est <- d[, mean(pred.fa.1)]

##-- 8:
print(paste0("eic solved at level = ", d[, mean(Ha*(Y-pred.f.1) + pred.fa.1 - tmle
.est)]))

##-- 9:
tmle.se <- d[, sqrt(mean((Ha*(Y-pred.f.1) + pred.fa.1 - tmle.est)^2)/nrow(d))]

return(c(tmle.est=tmle.est, tmle.se=tmle.se))
}

```

Task 3.

```

(est.0 <- target.fun(d=sim.data, a=0))
(est.1 <- target.fun(d=sim.data, a=1))

```

```

[1] "eic solved at level = 0.0000000000000363650352099834"
tmle.est tmle.se
0.69462449 0.02091243
[1] "eic solved at level = 7.30553088184628e-15"
tmle.est tmle.se
0.7605273 0.0210355

```

Task 4:

```

target.fun <- function(d, a, weighted=FALSE) {

##-- 1:
fit.f <- glm(Y~A+X1+X2+X3, family=binomial, data=d)
fit.pi <- glm(A~X1+X2+X3, family=binomial, data=d)

##-- 2:
d[, pred.fa:=predict(fit.f, type="response", newdata=copy(d)[, A:=a])]
d[, pred.f:=predict(fit.f, type="response", newdata=d)]

##-- 3:
d[, pred.pi1:=predict(fit.pi, type="response", newdata=d)]

##-- 4:
d[, Ha:=(A==a)/(pred.pi1^a*(1-pred.pi1)^(1-a))]

##-- 5:
if (!weighted) {
fit.tmle <- glm(Y ~ offset(qlogis(pred.f)) + Ha -1, family=binomial, data=d)
} else {
fit.tmle <- glm(Y ~ offset(qlogis(pred.f)), weights=Ha, family=binomial, data=d)
}
eps.hat <- fit.tmle$coef

```

```

##-- 6:
if (!weighted) {
d[, pred.fa.1:=plogis(qlogis(pred.fa) + eps.hat/(pred.pi1^a*(1-pred.pi1)^(1-a)))]
d[, pred.f.1:=plogis(qlogis(pred.f) + eps.hat*Ha)]
} else {
d[, pred.fa.1:=plogis(qlogis(pred.fa) + eps.hat)]
d[, pred.f.1:=plogis(qlogis(pred.f) + eps.hat)]
}

##-- 7:
tmle.est <- d[, mean(pred.fa.1)]

##-- 8:
print(paste0("eic solved at level = ", d[, mean(Ha*(Y-pred.f.1) + pred.fa.1 - tmle
.est)]))

##-- 9:
tmle.se <- d[, sqrt(mean((Ha*(Y-pred.f.1) + pred.fa.1 - tmle.est)^2)/nrow(d))]

return(c(tmle.est=tmle.est, tmle.se=tmle.se))
}

```

```

target.fun(d=sim.data, a=0, weighted=TRUE)
target.fun(d=sim.data, a=1, weighted=TRUE)

```

```

[1] "eic solved at level = 0.00000000000098107623896582"
tmle.est tmle.se
0.6946408 0.0209782
[1] "eic solved at level = 0.0000000000321081363349095"
tmle.est tmle.se
0.76090428 0.02087738

```

Note: Warnings can be removed by using quasibinomial family rather than binomial.

2 Computing the variances of the ATE, the log RR and the log OR

Task 5.

```

print(paste0("est ate = ", est.ate <- est.1["tmle.est"] - est.0["tmle.est"]))
print(paste0("est rr = ", est.rr <- est.1["tmle.est"] / est.0["tmle.est"]))
print(paste0("est or = ", est.or <- (est.1["tmle.est"] / (1-est.1["tmle.est"])) / (est
.0["tmle.est"] / (1-est.0["tmle.est"]))))

```

```

[1] "est ate = 0.0659028514677774"
[1] "est rr = 1.09487550876992"
[1] "est or = 1.39618513268535"

```

Task 6. We can write the log-RR as

$$\log \Psi_{\text{RR}}(P) = \log \left(\frac{\Psi_1(P)}{\Psi_0(P)} \right) = \log(\Psi_1(P)) - \log(\Psi_0(P)) = h(\Psi_1(P)) - h(\Psi_0(P)),$$

where h is defined as

$$h(\psi) = \log \psi.$$

We compute the derivative

$$h(\psi) = \frac{1}{\psi},$$

thus, we have that,

$$\phi_{1,h}^*(P) = \frac{1}{\Psi_1(P)} \phi_1^*(P) \quad \text{and} \quad \phi_{0,h}^*(P) = \frac{1}{\Psi_0(P)} \phi_0^*(P).$$

Similarly, we can write the **log odds ratio** as

$$\log \Psi_{RR}(P) = \log \left(\frac{\Psi_1(P)}{1 - \Psi_1(P)} \right) - \log \left(\frac{\Psi_0(P)}{1 - \Psi_0(P)} \right) = h(\Psi_1(P)) - h(\Psi_0(P)),$$

where h is defined as

$$h(\psi) = \log \left(\frac{\psi}{1 - \psi} \right) = \log(\psi) - \log(1 - \psi).$$

We compute the derivative as

$$\frac{d}{d\psi} h(\psi) = \frac{1}{\psi} + \frac{1}{1 - \psi} = \frac{1 - \psi + \psi}{\psi(1 - \psi)} = \frac{1}{\psi(1 - \psi)},$$

so that

$$\phi_{1,h}^*(P) = \frac{1}{\Psi_1(P)(1 - \Psi_1(P))} \phi_1^*(P) \quad \text{and} \quad \phi_{0,h}^*(P) = \frac{1}{\Psi_0(P)(1 - \Psi_0(P))} \phi_0^*(P).$$

Task 7.

```
target.fun <- function(d, a) {

  ##-- 1:
  fit.f <- glm(Y~A+X1+X2+X3, family=binomial, data=d)
  fit.pi <- glm(A~X1+X2+X3, family=binomial, data=d)

  ##-- 2:
  d[, pred.fa:=predict(fit.f, type="response", newdata=copy(d)[, A:=a])]
  d[, pred.f:=predict(fit.f, type="response", newdata=d)]

  ##-- 3:
  d[, pred.pi1:=predict(fit.pi, type="response", newdata=d)]

  ##-- 4:
  d[, Ha:=(A==a)/(pred.pi1^a*(1-pred.pi1)^(1-a))]

  ##-- 5:
  fit.tmle <- glm(Y ~ offset(qlogis(pred.f)) + Ha -1, family=binomial, data=d)
  eps.hat <- fit.tmle$coef

  ##-- 6:
```

```

d[, pred.fa.1:=plogis(qlogis(pred.fa) + eps.hat/(pred.pi1^a*(1-pred.pi1)^(1-a)))]
d[, pred.f.1:=plogis(qlogis(pred.f) + eps.hat*Ha)]

##-- 7:
tmle.est <- d[, mean(pred.fa.1)]

##-- 8:
print(paste0("eic solved at level = ", d[, mean(Ha*(Y-pred.f.1) + pred.fa.1 - tmle
.est)]))

##-- 9:
tmle.se <- d[, sqrt(mean((Ha*(Y-pred.f.1) + pred.fa.1 - tmle.est)^2)/nrow(d))]

return(list(tmle.est=tmle.est, tmle.se=tmle.se, eic=d[, (Ha*(Y-pred.f.1) + pred.fa
.1 - tmle.est)]))
}

```

Task 8.

```

eic.0 <- target.fun(d=sim.data, a=0)[["eic"]]
eic.1 <- target.fun(d=sim.data, a=1)[["eic"]]

```

```

print(paste0("ate eic solved at level = ", (mean(eic.1 - eic.0))))
print(paste0("log-rr eic solved at level = ",
  mean(1/est.1[["tmle.est"]]*eic.1 - 1/est.0[["tmle.est"]]*eic.0)))
print(paste0("log-or eic solved at level = ",
  mean(1/(est.1[["tmle.est"]]*(1-est.1[["tmle.est"]]))*eic.1 -
  1/(est.0[["tmle.est"]]*(1-est.0[["tmle.est"]]))*eic.0)))

```

```

[1] "ate eic solved at level = -0.0000000000000290592405010909"
[1] "log-rr eic solved at level = -0.00000000000000427494452326632"
[1] "log-or eic solved at level = -0.0000000000000131309035693306"

```

```

print(paste0("ate var = ", mean((eic.1 - eic.0)^2/nrow(sim.data))))
print(paste0("log-rr var = ",
  mean((1/est.1[["tmle.est"]]*eic.1 - 1/est.0[["tmle.est"]]*eic.0)^2/nrow(sim.
  data))))
print(paste0("log-or var = ",
  mean((1/(est.1[["tmle.est"]]*(1-est.1[["tmle.est"]]))*eic.1 -
  1/(est.0[["tmle.est"]]*(1-est.0[["tmle.est"]]))*eic.0)^2/nrow(sim.data))))

```

```

[1] "ate var = 0.000861914952736296"
[1] "log-rr var = 0.00163750576793132"
[1] "log-or var = 0.022596156195927"

```

```

print(paste0("est ate = ", est.ate))
print(paste0("est log-rr = ", log(est.rr)))
print(paste0("est log-or = ", log(est.or)))

```

```

[1] "est ate = 0.0659028514677774"
[1] "est log-rr = 0.0906406661841214"
[1] "est log-or = 0.333743612084167"

```

Task 9.

```
library(tmle)
fit.tmle <- tmle(Y=sim.data$Y, A=sim.data$A,
  cbind(X1=sim.data$X1,X2=sim.data$X2,X3=sim.data$X3),
  gform=A~X1+X2+X3, ## treatment model
  Qform=Y~A+X1+X2+X3, ## outcome model
  family="binomial",
  cvQinit=FALSE)
```

```
fit.tmle
```

Additive Effect

```
Parameter Estimate: 0.066263
Estimated Variance: 0.00085811
p-value: 0.023694
95% Conf Interval: (0.0088482, 0.12368)
```

Additive Effect among the Treated

```
Parameter Estimate: 0.072104
Estimated Variance: 0.0009739
p-value: 0.020862
95% Conf Interval: (0.010938, 0.13327)
```

Additive Effect among the Controls

```
Parameter Estimate: 0.059976
Estimated Variance: 0.0009839
p-value: 0.055869
95% Conf Interval: (-0.0015039, 0.12146)
```

Relative Risk

```
Parameter Estimate: 1.0954
p-value: 0.024072
95% Conf Interval: (1.012, 1.1856)

log(RR): 0.091113
variance(log(RR)): 0.0016311
```

Odds Ratio

```
Parameter Estimate: 1.399
p-value: 0.025166
95% Conf Interval: (1.0427, 1.877)

log(OR): 0.33574
variance(log(OR)): 0.022488
```

3 Simulation study

Task 10.

```
fit.tmle1.est <- list()
```

```

fit.tmle2.est <- list()
fit.tmle3.est <- list()
fit.tmle1.se <- list()
fit.tmle2.se <- list()
fit.tmle3.se <- list()

for (m in 1:500) {

  set.seed(m+110)
  sim.data <- sim.fun(1000)

  fit.tmle1 <- tmle(Y=sim.data$Y, A=sim.data$A,
    cbind(X1=sim.data$X1,X2=sim.data$X2,X3=sim.data$X3),
    gform=A~X1+X2+X3, ## treatment model
    Qform=Y~A+X1+X2+X3, ## outcome model
    family="binomial",
    cvQinit=FALSE)

  fit.tmle1.est[[m]] <- fit.tmle1$estimates$ATE$psi
  fit.tmle1.se[[m]] <- sqrt(fit.tmle1$estimates$ATE$var.psi)

  fit.tmle2 <- tmle(Y=sim.data$Y, A=sim.data$A,
    cbind(X1=sim.data$X1,X1.squared=sim.data$X1^2,X2=sim.data$X2,X3=sim.data
    $X3),
    gform=A~X1+X2+X3, ## treatment model
    Qform=Y~A+X1.squared+X2+X3, ## outcome model
    family="binomial",
    cvQinit=FALSE)

  fit.tmle2.est[[m]] <- fit.tmle2$estimates$ATE$psi
  fit.tmle2.se[[m]] <- sqrt(fit.tmle2$estimates$ATE$var.psi)

  fit.tmle3 <- tmle(Y=sim.data$Y, A=sim.data$A,
    cbind(X1=sim.data$X1,X2=sim.data$X2,X3=sim.data$X4),
    Q.SL.library=c("SL.glm", "SL.mean", "SL.gam"),
    g.SL.library=c("SL.glm", "SL.mean", "SL.gam"),
    family="binomial")

  fit.tmle3.est[[m]] <- fit.tmle3$estimates$ATE$psi
  fit.tmle3.se[[m]] <- sqrt(fit.tmle3$estimates$ATE$var.psi)

}

```

Task 11. See Figure 1 and comments further below.

```

message(paste0("EY1 = ", E.Y1 <- sim.fun(1e6, a=1)))
message(paste0("EY0 = ", E.Y0 <- sim.fun(1e6, a=0)))
message(paste0("ATE = ", ATE <- E.Y1 - E.Y0))

```

```

EY1 = 0.749266
EY0 = 0.683064
ATE = 0.066202

```

```

setwd("~/Undervisning/TMLE/beamer/day2/")

```

```
library(ggplot2)

pdat <- data.table(estimator=c(rep("TMLE estimator (misspecified initial)",
                                  length(fit.tmle1.est)),
                              rep("TMLE estimator (correctly specified initial)",
                                  length(fit.tmle2.est)),
                              rep("TMLE estimator (simple super learner for initial)",
                                  length(fit.tmle3.est))),
                  est=c(unlist(fit.tmle1.est),
                        unlist(fit.tmle2.est),
                        unlist(fit.tmle3.est)))

ggplot(pdat) +
  theme_bw(base_size=25) +
  geom_boxplot(aes(x=est)) +
  facet_wrap(. ~ estimator, ncol=2) +
  geom_vline(aes(xintercept=ATE), linetype="dashed", color="red") +
  xlab(expression(hat(psi)[n])) + ylab("")
```

```
message(paste0("bias tmle1 = ", mean(unlist(fit.tmle1.est))-ATE))
message(paste0("bias tmle2 = ", mean(unlist(fit.tmle2.est))-ATE))
message(paste0("bias tmle3 = ", mean(unlist(fit.tmle3.est))-ATE))
message(paste0("variance tmle1 = ", var(unlist(fit.tmle1.est))))
message(paste0("variance tmle2 = ", var(unlist(fit.tmle2.est))))
message(paste0("variance tmle3 = ", var(unlist(fit.tmle3.est))))
message(paste0("coverage tmle1 = ", mean(ATE>=unlist(fit.tmle1.est)-1.96*unlist(fit.
  tmle1.se) &
  ATE<=unlist(fit.tmle1.est)+1.96*unlist(fit.tmle1.se))))
message(paste0("coverage tmle2 = ", mean(ATE>=unlist(fit.tmle2.est)-1.96*unlist(fit.
  tmle2.se) &
  ATE<=unlist(fit.tmle2.est)+1.96*unlist(fit.tmle2.se))))
message(paste0("coverage tmle3 = ", mean(ATE>=unlist(fit.tmle3.est)-1.96*unlist(fit.
  tmle3.se) &
  ATE<=unlist(fit.tmle3.est)+1.96*unlist(fit.tmle3.se))))
```

```
bias tmle1 = 0.00141930436233162
bias tmle2 = 0.000594083168194162
bias tmle3 = 0.000852184104645035
variance tmle1 = 0.000896527774711243
variance tmle2 = 0.000557961015161351
variance tmle3 = 0.000579126141824112
coverage tmle1 = 0.938
coverage tmle2 = 0.958
coverage tmle3 = 0.95
```

Comments for Task 11. The simulation study illustrates a number of points:

1. The TMLE estimator is consistent when either π or f is estimated consistently.
2. Inference for the TMLE estimator is only valid when based on correctly specified models (or a SL capturing the same information well enough).

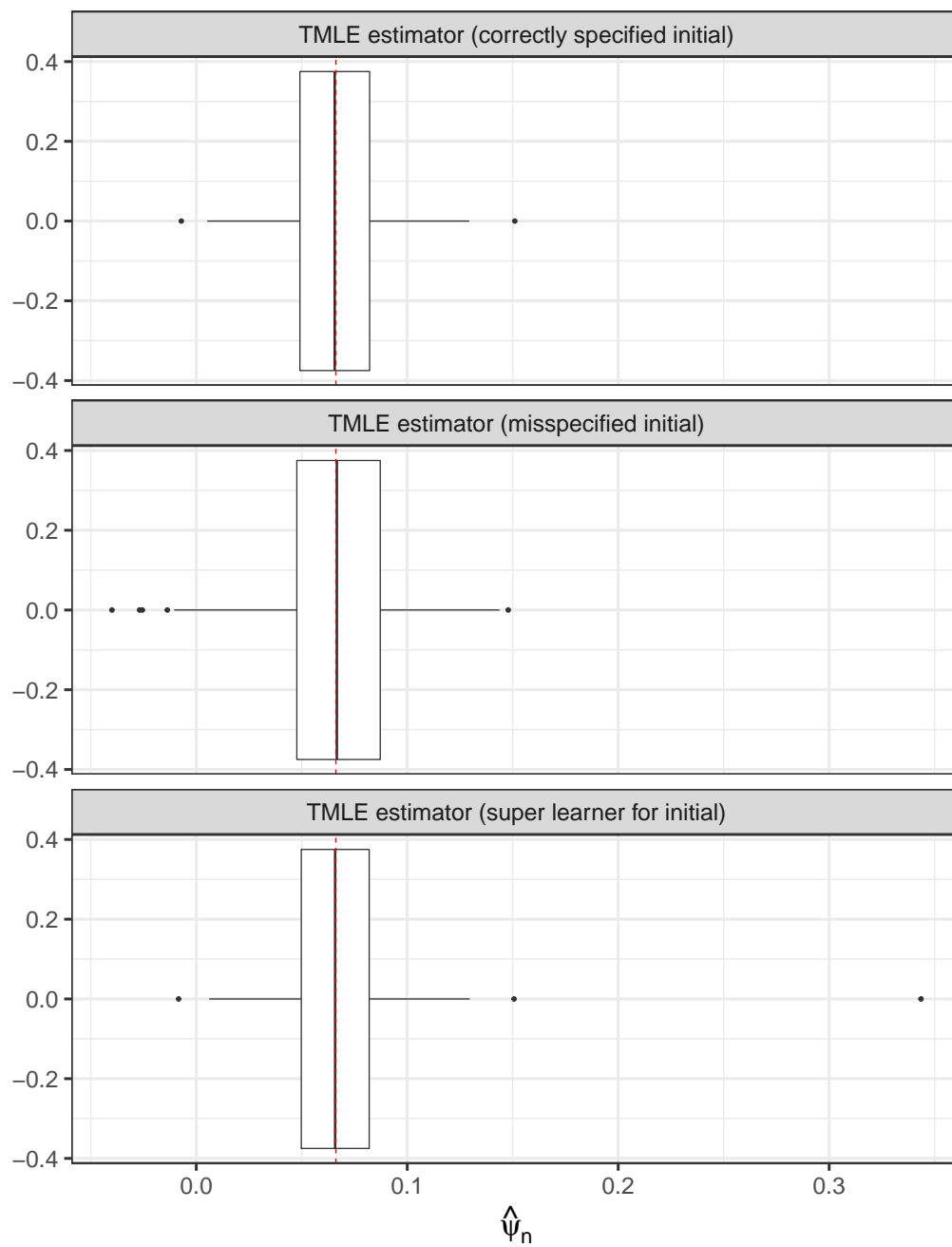


Figure 1