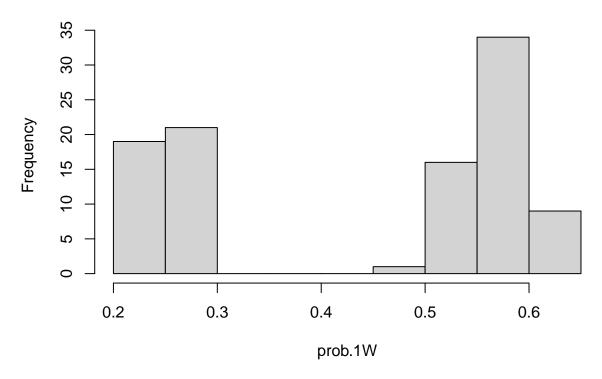
683 Final project

Ariane Stark, Minsu Kim, Diezhang Wu, Alona Muzikansky

11/6/2021

```
set.seed(123)
# simple substitution estimator (a.k.a. parameteric G-computation)
txt <- ObsData
control <- ObsData
txt$A <- 1
control$A <- 0
g.comp.reg \leftarrow glm(Y \sim W11 + W12 + W13 + W14 + W2 + A, family="binomial", data=ObsData)
pred.txt <- predict(g.comp.reg, newdata = txt, type = "response")</pre>
pred.control <- predict(g.comp.reg, newdata = control, type = "response")</pre>
psi.hat <- mean(pred.txt - pred.control)</pre>
psi.hat
## [1] -0.01454638
# IPTW estimator
prob.AW.reg <- glm(A ~ W11 + W12 + W13 + W14, family="binomial", data=ObsData)</pre>
prob.1W <- predict(prob.AW.reg, type= "response")</pre>
prob.0W \leftarrow 1 - prob.1W
hist(prob.1W)
```

Histogram of prob.1W

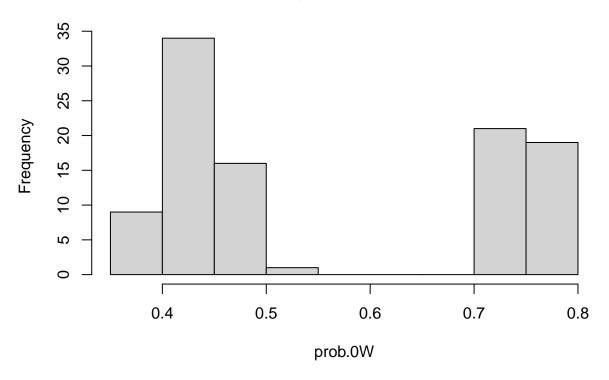


summary(prob.1W)

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 0.2216 0.2516 0.5358 0.4400 0.5727 0.6226
```

hist(prob.0W)

Histogram of prob.0W



summary(prob.OW)

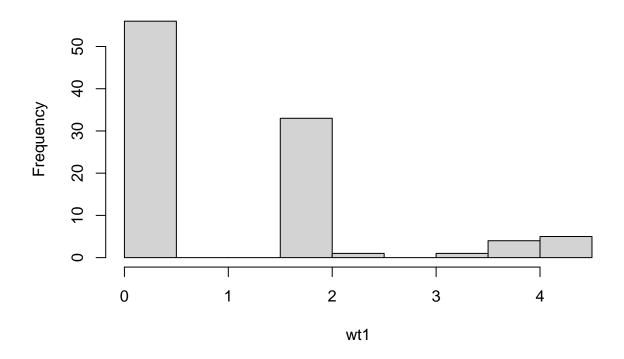
```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 0.3774 0.4273 0.4642 0.5600 0.7484 0.7784
```

```
wt1 <- as.numeric(ObsData$A==1)/prob.1W
wt0 <- as.numeric(ObsData$A==0)/prob.0W
summary(wt1)</pre>
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 0.000 0.000 0.000 1.004 1.766 4.452
```

hist(wt1)

Histogram of wt1

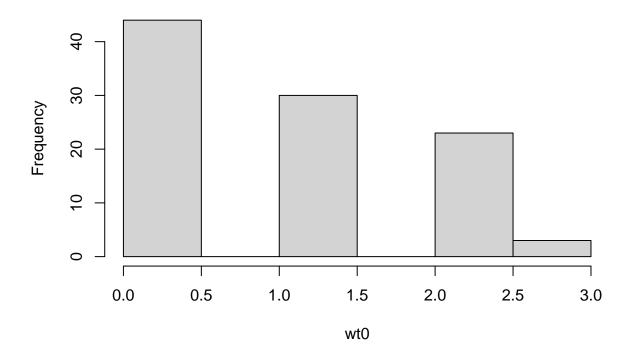


summary(wt0)

Min. 1st Qu. Median Mean 3rd Qu. Max. ## 0.000 0.000 1.312 0.998 2.074 2.594

hist(wt0)

Histogram of wt0



```
psi.iptw <- mean(wt1*ObsData$Y) - mean(wt0*ObsData$Y)
psi.iptw
## [1] 0.01002469</pre>
```

```
# Modified HT
psi.ht <- mean(wt1*ObsData$Y)/mean(wt1) - mean(wt0*ObsData$Y)/mean(wt0)
psi.ht</pre>
```

[1] 0.00916455

```
# Unadjusted estimator
wt1.ua <- as.numeric(ObsData$A==1)/mean(ObsData$A == 1)
wt0.ua <- as.numeric(ObsData$A==0)/mean(ObsData$A == 0)
psi.unadj <- mean(wt1.ua*ObsData$Y) - mean(wt0.ua*ObsData$Y)
psi.unadj</pre>
```

[1] 0.02922078

```
# TMLE estimator
```

SS, IPTW and TMLE estimator with super learner

```
library("SuperLearner")
SL.library<- c('SL.glm', 'SL.glm.interaction', "SL.step",
               "SL.randomForest", "SL.step.forward", "SL.stepAIC", "SL.mean")
run.tmle <- function(ObsData, SL.library){</pre>
  # Simple substitution estimator
  # dataframe X with baseline covariates and exposure
  X <- subset(ObsData, select=c(A, W11, W12, W13, W14,W2))</pre>
  # set the exposure=1 in X1 and the exposure=0 in X0
  X1 <- X0 <- X
  X1$A <- 1
 XO$A <- 0
  # Estimate E O(Y/A, W) with Super Learner
  SL.outcome <- SuperLearner(Y=ObsData$Y, X=X, SL.library=SL.library,</pre>
              family="binomial", cvControl=list(V=10))
  # get the expected outcome, given the observed exposure and covariates
  expY.givenAW <- predict(SL.outcome, newdata=ObsData)$pred</pre>
  # expected outcome, given A=1 and covariates
  expY.given1W <- predict(SL.outcome, newdata=X1)$pred</pre>
  # expected outcome, given A=O and covariates
  expY.givenOW <- predict(SL.outcome, newdata=X0)$pred</pre>
  # simple substitution estimator would be
  PsiHat.SS <- mean(expY.given1W - expY.given0W)
  # Inverse probability of txt weighting
  # Super Learner for the exposure mechanism P_0(A=1/W)
  SL.exposure <- SuperLearner(Y=ObsData$A,</pre>
                               X=subset(ObsData, select= -c(A,Y,W2)),
                               SL.library=SL.library, family="binomial",
                               cvControl=list(V=10, stratifyCV = TRUE))
  # generate the predicted prob of being exposed, given baseline cov
  probA1.givenW <- SL.exposure$SL.predict</pre>
  # generate the predicted prob of not being exposed, given baseline cov
  probA0.givenW <- 1- probA1.givenW</pre>
  # clever covariate
 H.AW <- as.numeric(ObsData$A==1)/probA1.givenW - as.numeric(ObsData$A==0)/probA0.givenW
  # also want to evaluate the clever covariate at A=1 and A=0 for all participants
 H.1W <- 1/probA1.givenW
 H.OW <- -1/probAO.givenW
```

```
# IPTW estimate
  PsiHat.IPTW <- mean(H.AW*ObsData$Y, na.rm = TRUE)
  #-----
  # Targeting & TMLE
  # Update the initial estimator of E O(Y/A, W)
  # run logistic regression of Y on H.AW using the logit of the esimates as offset
  expY.givenAW <- expY.givenAW - 0.000001</pre>
  logitUpdate<- glm( ObsData$Y ~ -1 +offset(qlogis(expY.givenAW)) +</pre>
                       H.AW, family='binomial')
  epsilon <- logitUpdate$coef</pre>
  # obtain the targeted estimates
  expY.givenAW.star<- plogis( qlogis(expY.givenAW)+ epsilon*H.AW )</pre>
  expY.given1W.star<- plogis( qlogis(expY.given1W)+ epsilon*H.1W )</pre>
  expY.givenOW.star<- plogis( qlogis(expY.givenOW)+ epsilon*H.OW )</pre>
  # TMLE point estimate
  PsiHat.TMLE<- mean(expY.given1W.star - expY.given0W.star)
  # Return a list with the point estimates, targeted estimates of E_{-}O(Y/A,W),
  # and the vector of clever covariates
  estimates <- data.frame(cbind(PsiHat.SS=PsiHat.SS, PsiHat.IPTW, PsiHat.TMLE))
  predictions <- data.frame(cbind(expY.givenAW.star, expY.given1W.star, expY.given0W.star))</pre>
  colnames(predictions) <- c('givenAW', 'given1W', 'given0W')</pre>
  list(estimates=estimates, predictions=predictions, H.AW=H.AW, probA1.givenW=probA1.givenW, probA0.giv
set.seed(123)
out <- run.tmle(ObsData = ObsData, SL.library = SL.library)</pre>
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: algorithm did not converge

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

est <- out$estimates
est

## PsiHat.SS PsiHat.IPTW PsiHat.TMLE

## 1 -0.01154755 0.007405697 -0.001736849</pre>
```

CV Superlearner

```
X<- subset(ObsData, select= -Y )</pre>
CV.SL.out<- CV.SuperLearner(Y=ObsData$Y, X=X,
                            SL.library=SL.library, family='binomial',
                            cvControl = list(V = 5),
                            innerCvControl = list(list(V =20)))
summary(CV.SL.out)
##
## Call:
## CV.SuperLearner(Y = ObsData$Y, X = X, family = "binomial", SL.library = SL.library,
       cvControl = list(V = 5), innerCvControl = list(list(V = 20)))
##
## Risk is based on: Mean Squared Error
## All risk estimates are based on V = 5
##
##
                 Algorithm
                               Ave
                                          se
                                                  Min
##
             Super Learner 0.10442 0.023248 0.070131 0.12935
##
               Discrete SL 0.11212 0.025168 0.083258 0.12891
                SL.glm_All 0.12693 0.026052 0.097734 0.16780
##
##
   SL.glm.interaction_All 0.29806 0.045259 0.198018 0.36518
               SL.step_All 0.11065 0.024642 0.067470 0.13037
##
##
       SL.randomForest_All 0.10702 0.023984 0.083258 0.13574
##
       SL.step.forward_All 0.10927 0.025401 0.067470 0.13037
            SL.stepAIC_All 0.10650 0.025014 0.055156 0.12891
##
##
               SL.mean_All 0.10650 0.025014 0.055156 0.12891
```

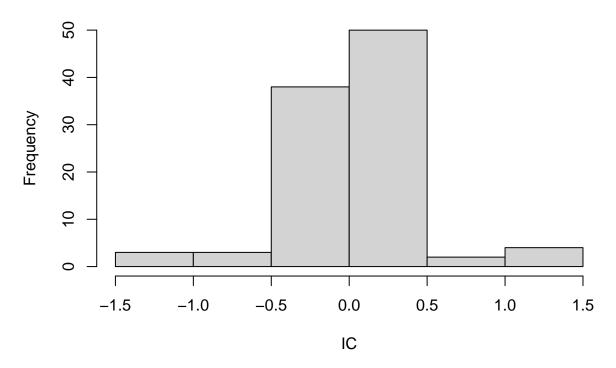
Influence Curve

```
n <- nrow(ObsData)
# clever covariate
H.AW <- out$H.AW
# targeted predictions
expY.AW.star <- out$predictions[,'givenAW']
expY.1W.star <- out$predictions[,'given1W']
expY.0W.star <- out$predictions[,'givenOW']
# point estimate
PsiHat.TMLE <- est$PsiHat.TMLE
# plug-in
IC <- H.AW*(ObsData$Y - expY.AW.star) + expY.1W.star - expY.OW.star - PsiHat.TMLE
summary(IC)</pre>
```

```
## V1
## Min. :-1.31959
## 1st Qu.:-0.16434
## Median : 0.08188
## Mean : 0.00000
## 3rd Qu.: 0.12865
## Max. : 1.28855
```

hist(IC)

Histogram of IC



```
\# estimate sigma @ with the variance of the IC divided by n
varHat.IC <- var(IC)/n</pre>
varHat.IC
##
               [,1]
## [1,] 0.001566286
# standard error estimate
se <- sqrt(varHat.IC)</pre>
##
              [,1]
## [1,] 0.03957634
##### TMLE
# obtain 95% two-sided confidence intervals TMLE:
alpha \leftarrow 0.05
c(PsiHat.TMLE+qnorm(alpha/2, lower.tail=T)*se,
 PsiHat.TMLE+qnorm(alpha/2, lower.tail=F)*se)
## [1] -0.07930504 0.07583135
# calculate the pvalue tmle
2* pnorm( abs(PsiHat.TMLE /se), lower.tail=F )
             [,1]
## [1,] 0.9649952
###### IPTW
PsiHat.IPTW <- est$PsiHat.IPTW
# obtain 95% two-sided confidence intervals TMLE:
alpha \leftarrow 0.05
c(PsiHat.IPTW+qnorm(alpha/2, lower.tail=T)*se,
 PsiHat.IPTW+qnorm(alpha/2, lower.tail=F)*se)
## [1] -0.07016250 0.08497389
# calculate the pvalue tmle
2* pnorm( abs(PsiHat.IPTW /se), lower.tail=F )
             [,1]
## [1,] 0.8515631
```

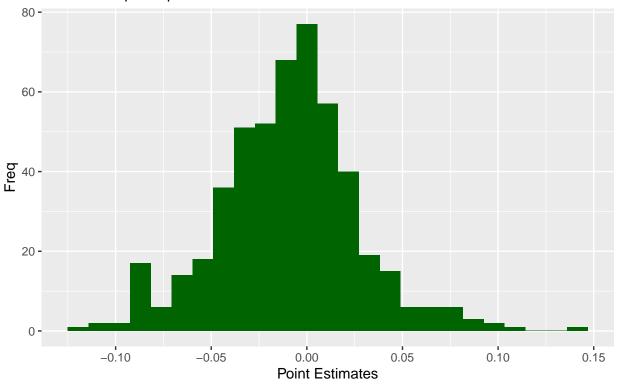
Non-parametric bootstrap

```
load('boot_par.Rdata')
colnames(estimates)<-c("SimpSubs", "IPTW", "TMLE")
summary(estimates)</pre>
```

```
##
      SimpSubs
                            IPTW
                                               TMLE
##
          :-0.121058
                              :-0.110710
                                                 :-0.35724
                       Min.
                       1st Qu.:-0.022379
                                          1st Qu.:-0.12376
   1st Qu.:-0.031503
   Median :-0.007640
                      Median : 0.003216
                                          Median :-0.02707
##
  Mean
         :-0.009831
                      Mean : 0.002566
                                          Mean : 0.01231
   3rd Qu.: 0.010143
                       3rd Qu.: 0.026642
                                          3rd Qu.: 0.15362
  Max. : 0.140009
                             : 0.118716
                                          Max. : 0.52217
##
                      Max.
##
                                          NA's
                                                 :2
```

Simple Substitution Estimator

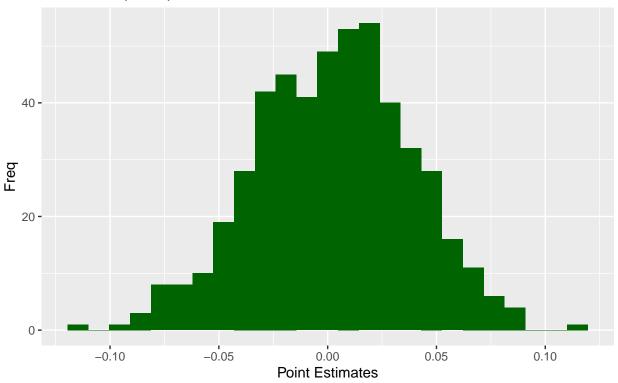
500 Bootstrap Samples



```
ggplot(mapping = aes(estimates[,2]))+
  geom_histogram(fill="dark green",bins = 25)+
  xlab("Point Estimates")+
  ylab("Freq")+
  labs(title="IPTW Estimator",
      subtitle = "500 Bootstrap Samples")+
  theme(plot.title = element_text(colour = "red"))
```

IPTW Estimator

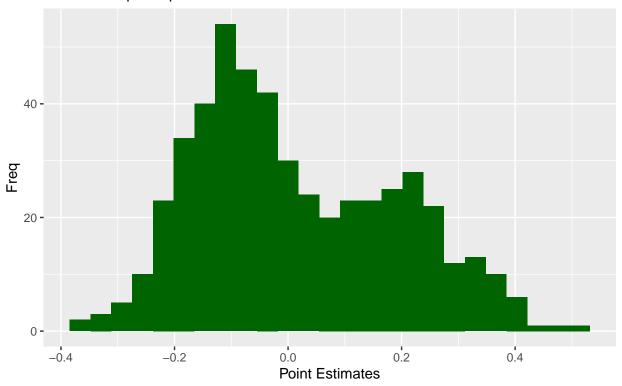
500 Bootstrap Samples



Warning: Removed 2 rows containing non-finite values (stat_bin).

TMLE Estimator

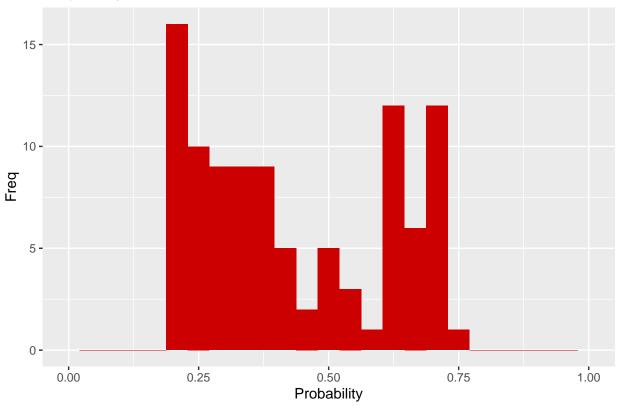
500 Bootstrap Samples



```
ggplot(mapping = aes(out$probA1.givenW))+
  geom_histogram(fill="red3",bins = 25)+
  xlab("Probability")+
  ylab("Freq")+
  labs(title="Propensity Score A=1")+
  theme(plot.title = element_text(colour = "dark green"))+
  xlim(0,1)
```

Warning: Removed 2 rows containing missing values (geom_bar).

Propensity Score A=1



```
# 95% Confidence intervals assuming a normal dist & via quantiles
create.CI <- function(pt, boot, alpha=0.05){</pre>
 Zquant <- qnorm(alpha/2, lower.tail=F)</pre>
 CI.normal <- c(pt - Zquant*sd(boot,na.rm = TRUE),</pre>
                 pt + Zquant*sd(boot,na.rm = TRUE) )
 CI.quant <- quantile(boot, prob=c(0.025,0.975), na.rm=TRUE)
 out <- data.frame(rbind(CI.normal, CI.quant))</pre>
  colnames(out) <- c('CI.lo', 'CI.hi')</pre>
  out
# IMPORTANT - POINT OF CONFUSION FOR PAST STUDENTS
# The point estimate 'pt' is from the original dataset
# Simple Subs - note the bias because of misspecified regression? Will it converge fast enough?
est$PsiHat.SS
## [1] -0.01154755
create.CI(pt=est$PsiHat.SS, boot=estimates[,"SimpSubs"])
##
                   CI.lo
                               CI.hi
## CI.normal -0.08264802 0.05955292
## CI.quant -0.08675253 0.06975379
```

```
# IPTW
est$PsiHat.IPTW
## [1] 0.007405697
create.CI(pt=est$PsiHat.IPTW, boot=estimates[,"IPTW"])
                   CI.lo
##
## CI.normal -0.06291296 0.07772436
## CI.quant -0.07220831 0.06989418
# TMLE
est$PsiHat.TMLE
## [1] -0.001736849
create.CI(pt=est$PsiHat.TMLE, boot=estimates[,"TMLE"])
                 CI.lo
                            CI.hi
## CI.normal -0.3484276 0.3449539
## CI.quant -0.2599113 0.3679674
# Compare to IC estimate
c(PsiHat.TMLE+qnorm(alpha/2, lower.tail=T)*se,
PsiHat.TMLE+qnorm(alpha/2, lower.tail=F)*se)
## [1] -0.07930504 0.07583135
```