IPTW Causal Project

```
library(tidyverse)
## -- Attaching packages ------ tidyverse 1.3.0 --
## v ggplot2 3.3.3 v purrr 0.3.4
## v tibble 3.1.0 v dplyr 1.0.5
## v tidyr 1.1.3 v stringr 1.4.0
## v readr 1.4.0 v forcats 0.5.1
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag() masks stats::lag()
library(readxl)
library(pander)
IPTW estimand:
\Psi(\mathbb{P}_0)=\mathbb{E}_0[\frac{\mathbb{I}(A=1)}{\mathbb{P}_{\nu}(A=1|W)}Y] - \mathbb{E}_0[\frac{\mathbb{I}(A=0)}{\mathbb{P}_{\nu}(A=0|W)}Y]
set.seed(252)
ObsData <- read.csv("slpexcov1517.csv")</pre>
ObsData <- ObsData %>% dplyr::select(-SEQN, -exminwk, -slphrs, -household, -income, -snoring,
                               -apnea, -bmicat, -smoke, -alcohol, -phq9)
ObsData <- ObsData %>% mutate(A = targetex) %>% mutate(Y = targetslp) %>%
  dplyr::select(-targetex, -targetslp)
ObsData <- na.omit(ObsData)</pre>
names(ObsData)
## [1] "age"
                    "raceeth"
                              "educ"
                                             "marital"
                                                          "bmi"
                                                                      "waist"
## [7] "depressed" "A"
                                "Y"
summary(ObsData)
                                                        marital
                      {\tt raceeth}
                                           educ
         age
## Min. :20.00 Min. :1.000 Min. :1.000 Min. :1.000
## 1st Qu.:31.00 1st Qu.:1.000 1st Qu.:2.000 1st Qu.:1.000
## Median: 43.00 Median: 2.000 Median: 3.000 Median: 2.000
## Mean :42.94 Mean :2.299 Mean :2.574 Mean :1.644
```

```
3rd Qu.:55.00
                   3rd Qu.:3.000
                                   3rd Qu.:3.000
                                                   3rd Qu.:2.000
##
   Max.
          :64.00
                          :4.000
                                         :4.000
                                                         :2.000
                  Max.
                                   Max.
                                                  Max.
                                      depressed
##
        bmi
                       waist
                          : 62.30
##
  Min.
          :15.50
                                   Min.
                                           :0.00000
                                                             :0.0000
                   Min.
                                                     Min.
##
   1st Qu.:24.82
                   1st Qu.: 89.83
                                    1st Qu.:0.00000
                                                      1st Qu.:0.0000
  Median :28.35
                  Median : 99.30
                                    Median :0.00000
                                                      Median :0.0000
##
         :29.32
                   Mean :101.28
                                    Mean :0.07017
                                                      Mean :0.4163
   3rd Qu.:32.80
                   3rd Qu.:110.60
                                    3rd Qu.:0.00000
                                                      3rd Qu.:1.0000
##
##
   Max.
          :61.90
                   Max.
                          :169.60
                                    Max.
                                         :1.00000
                                                     Max.
                                                            :1.0000
##
          :0.0000
##
  Min.
##
   1st Qu.:1.0000
## Median :1.0000
## Mean
          :0.7783
## 3rd Qu.:1.0000
## Max.
          :1.0000
```

1) Create the propensity scores

First fit the logistic regression model:

Get propensity scores:

```
prob.1W <- predict(fit, type= "response") #prediced probability of getting the exercise
prob.0W <- 1 - prob.1W #prediced probability of not getting the exercise</pre>
```

look at distribution of propensity scores:

```
\hat{\mathbb{P}}(A=1|W_i)
```

```
summary(prob.1W) %>% pander
```

| Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|---------|---------|--------|--------|---------|--------|
| 0.05052 | 0.2721 | 0.3997 | 0.4163 | 0.5506 | 0.8722 |

```
\hat{\mathbb{P}}(A=0|W_i)
```

```
summary(prob.0W) %>% pander
```

| Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|--------|---------|--------|--------|---------|--------|
| 0.1278 | 0.4494 | 0.6003 | 0.5837 | 0.7279 | 0.9495 |

2) Create the weights:

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

Look at weights:

```
\frac{\mathbb{I}(A_i = 1)}{\hat{\mathbb{P}}(A = 1 | W_i)}
```

summary(wt1) %>% pander

| Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|------|---------|--------|-------|---------|-------|
| 0 | 0 | 0 | 1.007 | 1.83 | 19.79 |

```
\frac{\mathbb{I}(A_i=0)}{\hat{\mathbb{P}}(A=0|W_i)}
```

summary(wt0) %>% pander

| Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|------|---------|--------|-------|---------|-------|
| 0 | 0 | 1.229 | 0.997 | 1.586 | 5.409 |

3) Estimate:

```
IPTW<- mean( wt1*ObsData$Y) - mean( wt0*ObsData$Y)</pre>
IPTW
```

[1] 0.05629606

```
unadj<-mean(ObsData$Y[ObsData$A==1])-mean(ObsData$Y[ObsData$A==0])
unadj</pre>
```

[1] 0.06442889

4) Arbitrarily truncate weights at 10, to see what happens:

First see how many weights are greater than 10:

```
sum(wt1>10)
```

[1] 3

```
sum(wt0>10)
## [1] 0
wt1.trunc<- wt1
wt1.trunc[ wt1.trunc>10] <-10
wt0.trunc<- wt0
wt0.trunc[ wt0.trunc>10] <-10
IPTW with truncated weights at 10:
mean(wt1.trunc*ObsData$Y) - mean( wt0.trunc*ObsData$Y)
## [1] 0.05262378
What about truncated at 5?
sum(wt1>5)
## [1] 71
sum(wt0>5)
## [1] 5
wt1.trunc5<- wt1
wt1.trunc5[ wt1.trunc5>5] <-5
wt0.trunc5<- wt0
wt0.trunc5[ wt0.trunc>5] <-5
IPTW with truncated weights at 5:
mean(wt1.trunc5*ObsData$Y) - mean( wt0.trunc5*ObsData$Y)
## [1] 0.03135125
```

5) Stabilized IPTW estimator - Modified Horwitz Thompson estimator

```
mean( wt1*ObsData$Y)/mean( wt1) - mean( wt0*ObsData$Y)/mean( wt0)
## [1] 0.04822426
```