

# Class exercise week 10 - Designing weights

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## Question 1: diagnostics

Consider that you succeeded to draw a relatively large and perfectly random sample from your target population. This means that with fully observed data (the 1517 cases in the file “unit non response information.RDS”), the sample would be representative for the population (no worries about coverage and sampling errors for now). However, not every respondent that was addressed was willing to fill in your questionnaire, so unfortunately there is ‘unit non-response’. This possibly creates bias. Luckily, we still have some basic information about the non-responders, so it is possible to weight back to the full sample (representing the target population).

The first part of the exercise is about checking for the potential bias (a). In the second part (b), you are asked to answer some research-questions correcting for this possible bias. a. Open the data file “unit non response information.RDS”. In this file you find all available information about both responders and non-responders. Examine if there are any large differences between respondents and non-respondents with regard to region, gender, education, race, and age. In other words: are there strong predictor of response. The following variables are available:

id - Respondent id

region - 1= Northeast USA, 2= Southern US, 3= West sex - 1 = male, 2= female educ - higher number mean higher levels race - 1 = white, 2 = black, 3 = other (hispanic) age - Age in years response - 0 = nonresponse, 1 = response

## Question 2: Creating a weight

Two variables were selected for the subsequent weighting exercises: sex and race. Consider the sample to be unbiased with respect to all other variables. Compute the Nonresponse weight for the variable sex and race. Compute two weights (for each variable one), and then multiply both weights to achieve one nonresponse weights in your dataset. The easiest way to do this is to run a glm() with a logit link function, and then add the fitted.values (these are the propensity scores) to your dataset. The inverse of these propensity scores is your weight.

We now want to add the weights not to the dataset that contains respondents and nonrespondents, but only to the dataset with respondents. The code below loads the datafile “responders\_data.RDS”, recodes missing values and then adds the weights you created in the previous question to the respondent dataset.

```
# now merge with substantive data
respdata <- readRDS("responders_data.RDS") # read data in as data frame
respdata$income[respdata$income==999999] <- NA

# and merge to the respondent data
finaldata <-merge(respdata,data)
```

### Question 3: explore other ways to create weights.

There are different ways to produce weights. Last week we discussed the following four methods:

1. Using poststratification (use the lecture slides about nonresponse). The basic idea is here that you compute a weight for every cell in the multi-way crosstable of your weight-variables.
2. Using linear weighting using population totals
3. Using a propensity based model using the population distribution (easiest if you have good sampling frame data)
4. Using Raking

The general syntax for these methods look like this: Poststratification:

```
- postStratify(design= svy.unweighted, strata = sexrace, population=sexrace.dist)
```

Linear weighting:

```
- calibrate(design=svy.unweighted,formula=~sex+race, population=c(sex.dist,race.dist), calfun=c("linear"))
```

Propensity score weighting (using population totals) - calibrate(design=svy.unweighted,formula=~sex+race, population=c(sex.dist,race.dist), calfun=c("logit"))

Raking:

```
- rake(design=svy.unweighted,sample.margins=list(sex,race), population.margins=list(sex.dist,race.dist))
```

Explore each of the weighting methods. Adjust the code below so you also include the variable "region". You may also add other variables, just to try out how these methods work.

```
# create sexrace crosstable
```

```
svy.unweighted <-svydesign(ids=~id, data=respdata)
```

```
## Warning in svydesign.default(ids = ~id, data = respdata): No weights or  
## probabilities supplied, assuming equal probability
```

```
sexrace<- as.data.frame(table(respdata$sex,respdata$race))
```

```
sexrace.dist <-xtabs(~sex+race, data=data)
```

```
poststratdesign <- postStratify(design= svy.unweighted, strata =~sex+race, population=sexrace.dist)
```

```
# for Calibration (linear weighting)
```

```
sex.dist <- as.data.frame(table(data$sex))
```

```
colnames(sex.dist) <- c("sex", "Freq")
```

```
race.dist <- as.data.frame(table(data$race))
```

```
colnames(race.dist) <- c("race", "Freq")
```

```
# check whether table looks good
```

```
table(data$sex,data$race)
```

```
pop.totals<-c('(Intercept)'=1517,sexFemale=719+133+29,raceBlack=133+71,raceOther=20+29)
```

```
# you need to get the totals from rows and columns as numbers
```

```
# the first column is the intercept
```

```
linearweightdesign <- calibrate(design=svy.unweighted,formula=~sex+race,
```

```
population=pop.totals, calfun=c("linear")) #linear weighting
```

```
# a useful check to see if weighting went correctly is to make a table of the covariates in the respond
```

```
# the probabilities should be similar, but not the same, due to use of population totals, rather than c
```

```
# calculate probabilities manually
```

```

manualprob <- table(finaldata$race,finaldata$sex)/table(data$race,data$sex)
manualprob
# and compare
table(linearweightdesign$prob,linearweightdesign$variables$race)

propweightdesign <- calibrate(design=svy.unweighted,formula=~sex+race,
                             population=pop.totals, calfun=c("logit"), bounds=c(0.3,3))
#inverse probability (propensity)
# a note about the bounds here -> they are needed to make sure the model converges.
# I trimmed at 3, but you can choose other values
# remember bias/variance trade-off?

rakeddesign <- rake(design=svy.unweighted,sample.margins=list(~sex,~race),
                  population.margins=list(sex.dist,race.dist))

```

#### Question 4: does it matter?.

Compute the mean and variance in ‘income’ for the respondents without weights and then using the (three) weights that you created in the previous question. Do you find any differences between the weighted and unweighted estimates? And does the weighting method make a difference? Do you think that variance inflation due to weighting is a problem here?

#### Question 5 (optional)

How large is the difference in income between men and women under all weightingscenarios?

```

t.test(finaldata$income~ finaldata$sex)
svyttest(income~sex, design=poststratdesign,family=gaussian)
# etc.

```

#### Question 6 (optional):

To get a more real-life situation, I looked up some employment statistics in the USA. The variable ‘employm’ indicates for respondents whether they have a job (1) or not (0). The population distribution for employment is as follows:

Employed: 48,2% Not employed: 51.8%

Use raking to correct for nonresponse using this additional variable . Use employm + the variables you used earlier in this exercise. Inspect the effects of using the additional variables on the mean and variance of ‘income’.

Example code:

```

rake(design = svy.unweighted,(sample.margins = list(~sex, ~race, ~employm),(population.margins =
list(sex.dist, race.dist, employ.dist))

```

– End of document –