

# Survey Analysis week 41

“R practical – putting it all together”

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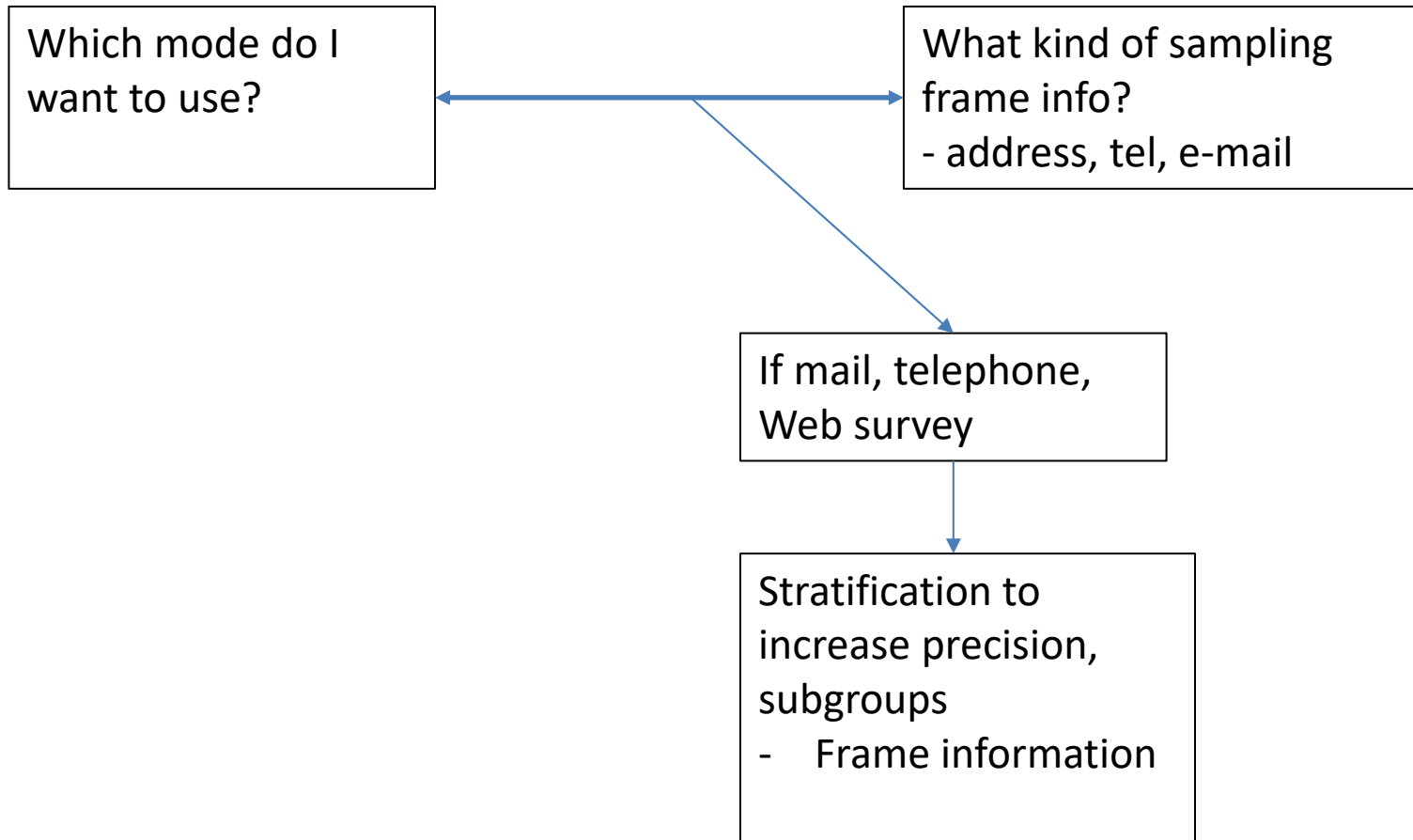
# Today

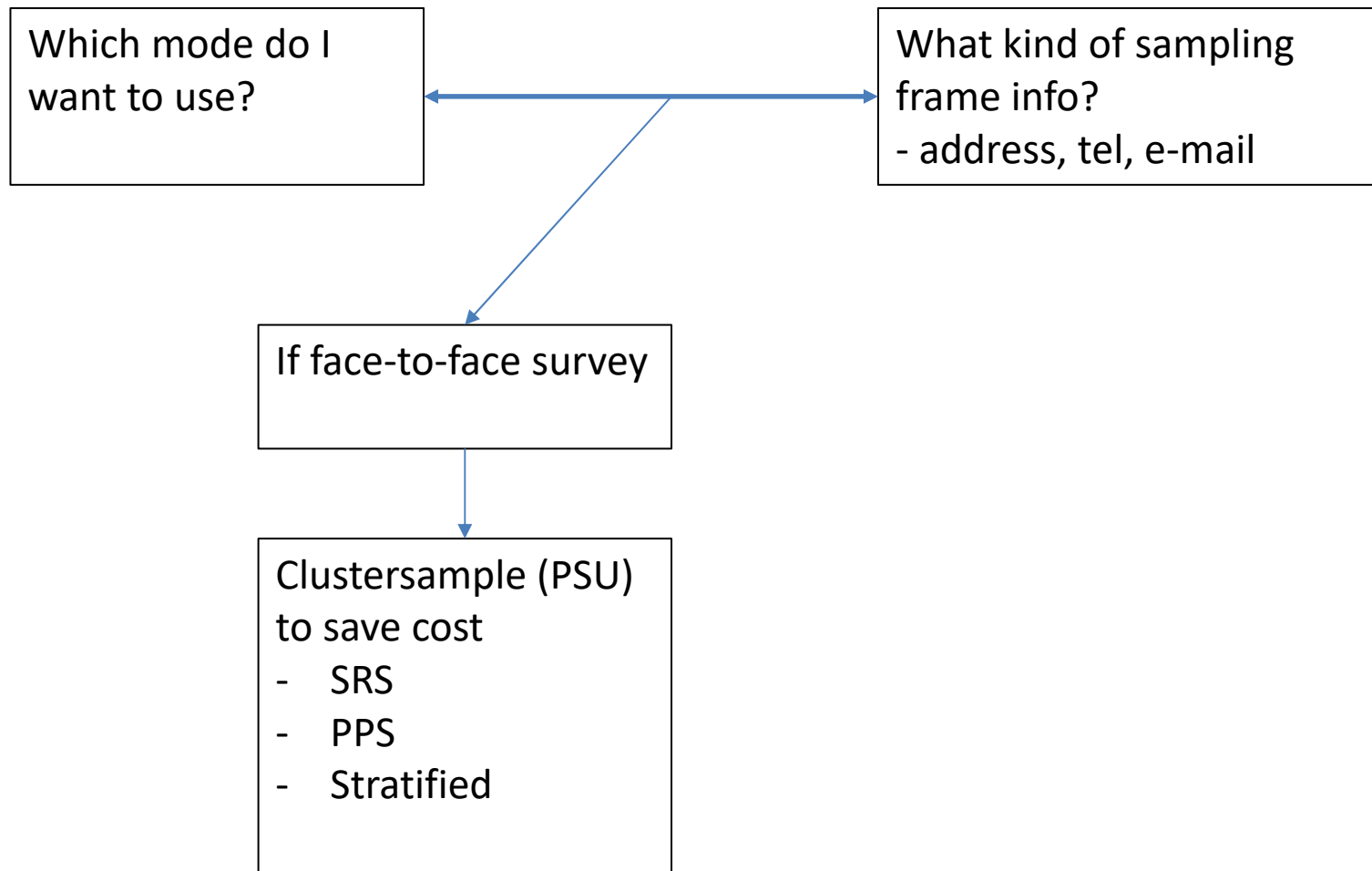
- Discuss take home exercise
  - Your adopted survey
  - How to stratify?
  - How to cluster?
- Set of class exercises

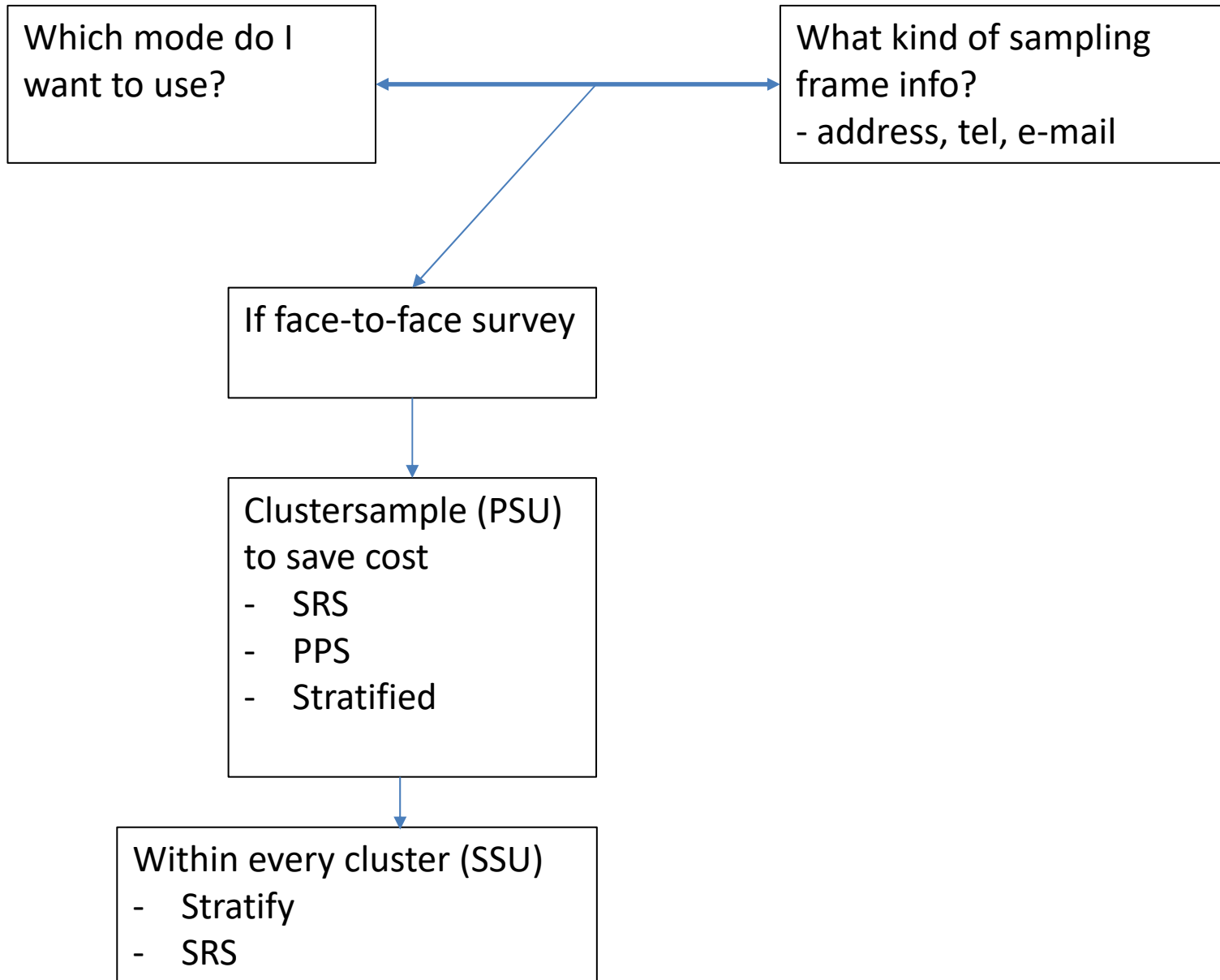
Which mode do I  
want to use?

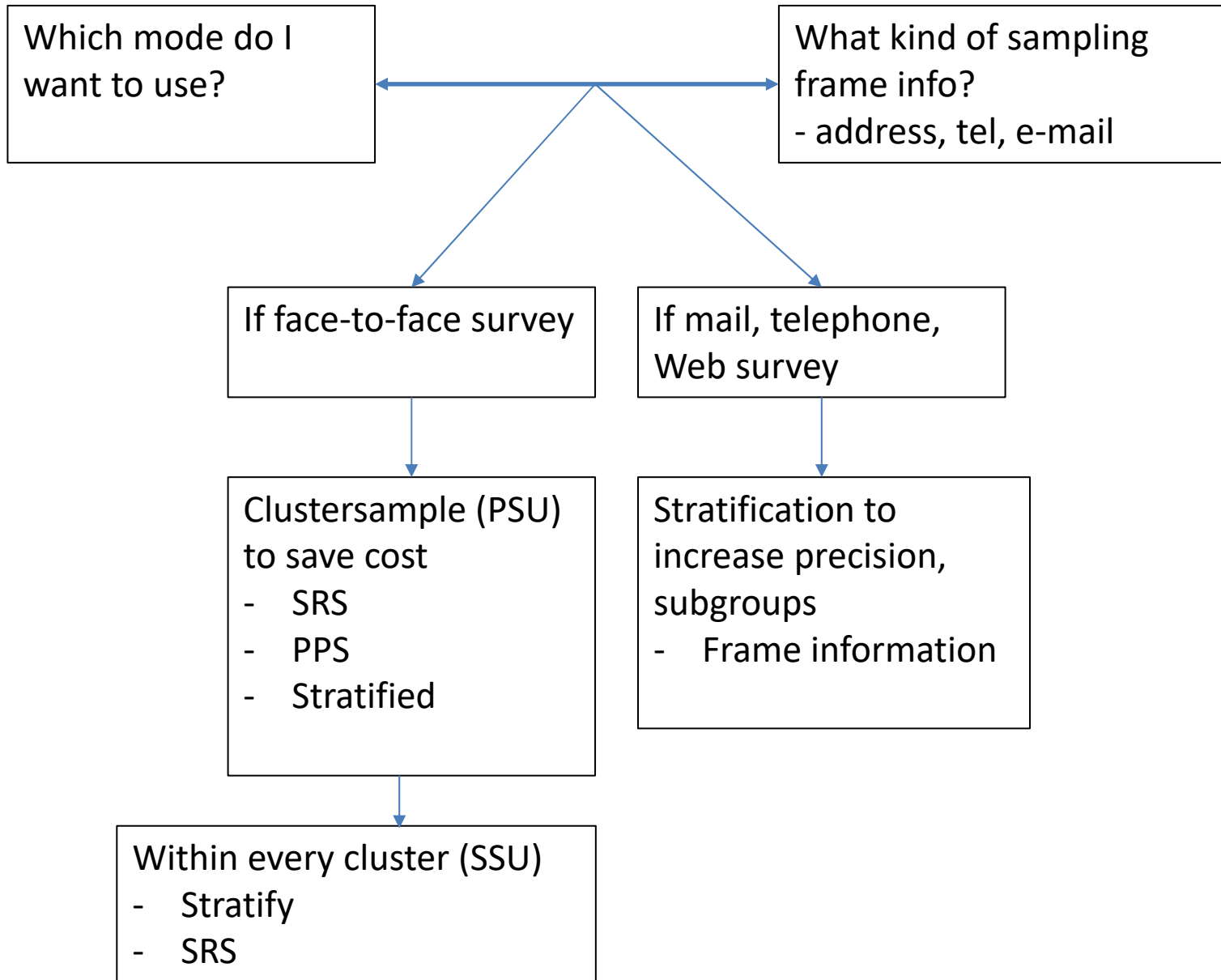


What kind of sampling  
frame info?  
- address, tel, e-mail









# Class exercises

1. Other statistics
2. Hurvitz-Thompson estimator
  - Design weights
  - Inclusion probabilities
3. Stratified cluster samples



# Extra slides

*Not discussed in class, but in case you want to know the end of the story of the “student” sample...*

# Horvitz-Thompson estimation

- We discussed SRS, stratified and cluster sampling
  - With and without replacement
  - Equal + unequal probabilities
  - All with slightly different formulas
- Horvitz and Thompson (1952) designed a general framework for inference for random (probability surveys)

- For me:  $\hat{y}_{HT} = \frac{1}{N} \sum_{i \in S} \frac{y_i}{\pi_i} = \frac{1}{N} \sum_{i=1}^N a_i \frac{Y_i}{\pi_i}$

- $\pi_i$  = inclusion probability of individual  $i$ ,
    - $a_i=1$ : in sample.  $a_i=0$ , not selected
    - $S$ : all individuals in sample

# HT-estimation – a unifying framework...

$$\hat{y}_{HT} = \frac{1}{N} \sum_{i \in S} \frac{y_i}{\pi_i} = \frac{1}{N} \sum_{i=1}^N a_i \frac{Y_i}{\pi_i} \quad \text{design-based sampling}$$

methods

- SRS equal probabilities:  $\pi_i$  = equal
- Stratified:  $\pi_i$  depends on strata selection
- One-stage cluster:  $\pi_i$  depends on cluster selection
- Two-stage (and more complex): cluster and within-cluster

All you need is  $\pi_i$  , for every individual on your sampling frame

# Horvitz Thompson: stratified

- Sample  $n_1$  out of  $N_1$ ,  $n_2$  out of  $N_2$

$$\hat{y}_{HT} = \frac{\sum_{i=1}^n w_i y_i}{\sum_{i=1}^n w_i} = \frac{\sum_{i=1}^{n_1} \frac{N_1}{n_1} y_{1i} + \sum_{i=1}^{n_2} \frac{N_2}{n_2} y_{2i}}{\sum_{i=1}^{n_1} \frac{N_1}{n_1} + \sum_{i=1}^{n_2} \frac{N_2}{n_2}}$$

$$\hat{y}_{HT} = \frac{N_1 \bar{y}_1 + N_2 \bar{y}_2}{N_1 + N_2} = \frac{N_1}{N} \bar{y}_1 + \frac{N_2}{N} \bar{y}_2$$

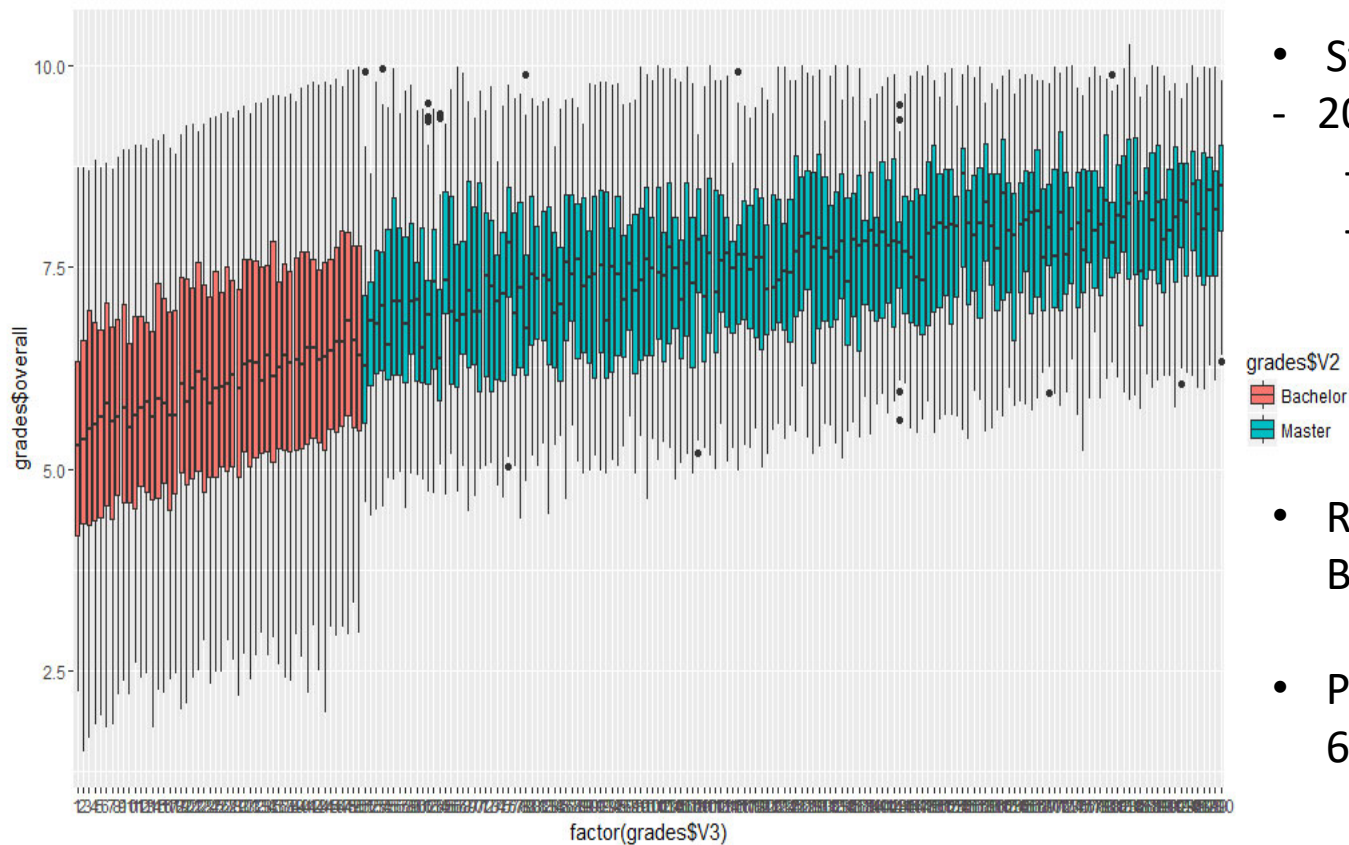
# Our recurring example

- We would like to do a survey among all students at Utrecht University
  - Population = 20.000
  - RQ: Interested in differences in **grades** and **student happiness** between programmes
  - approx. 49 BA programmes and 150 MA programmes
  - Limited budget (cannot do census) for about  $n=1000$
- This week:

What if we combine clustering and stratification?

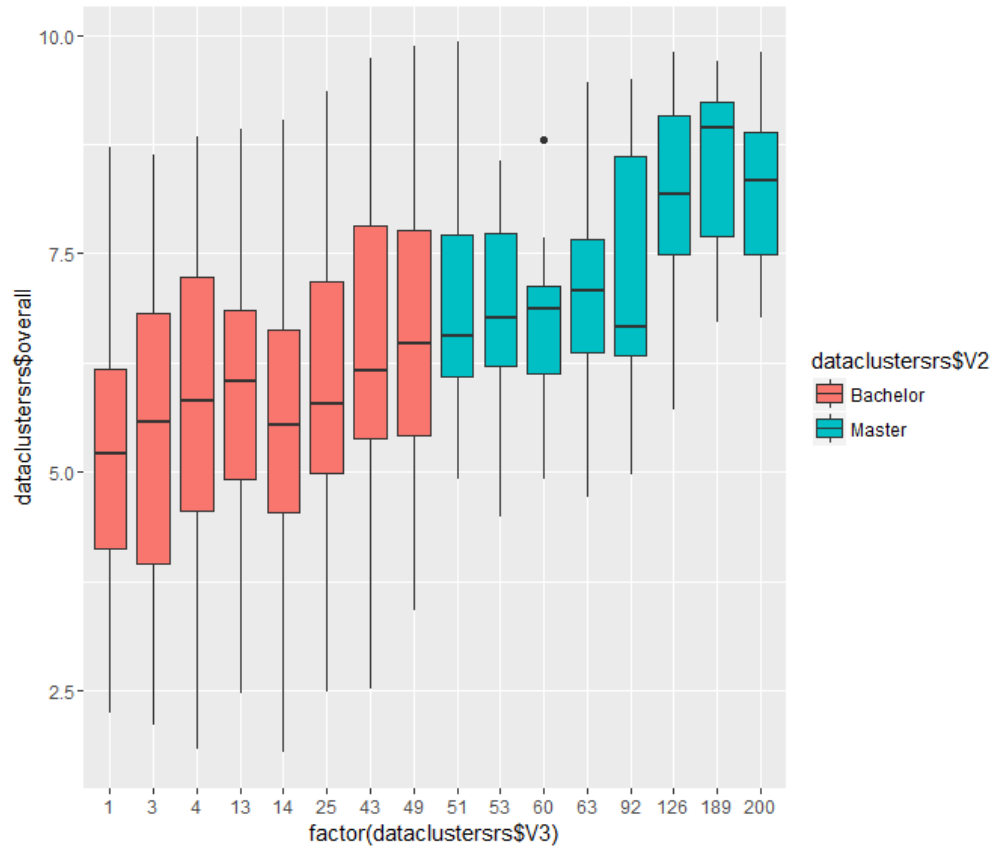
# Example – 150 programmes (Ba/MA)

simulated data



- Student grades (y)
  - 200 programmes (x)
    - 50 BA, n=280 each
    - 150 MA, n=40 each
- R-code is available on Blackboard
- Population mean: 6.52

# Stratified cluster sample



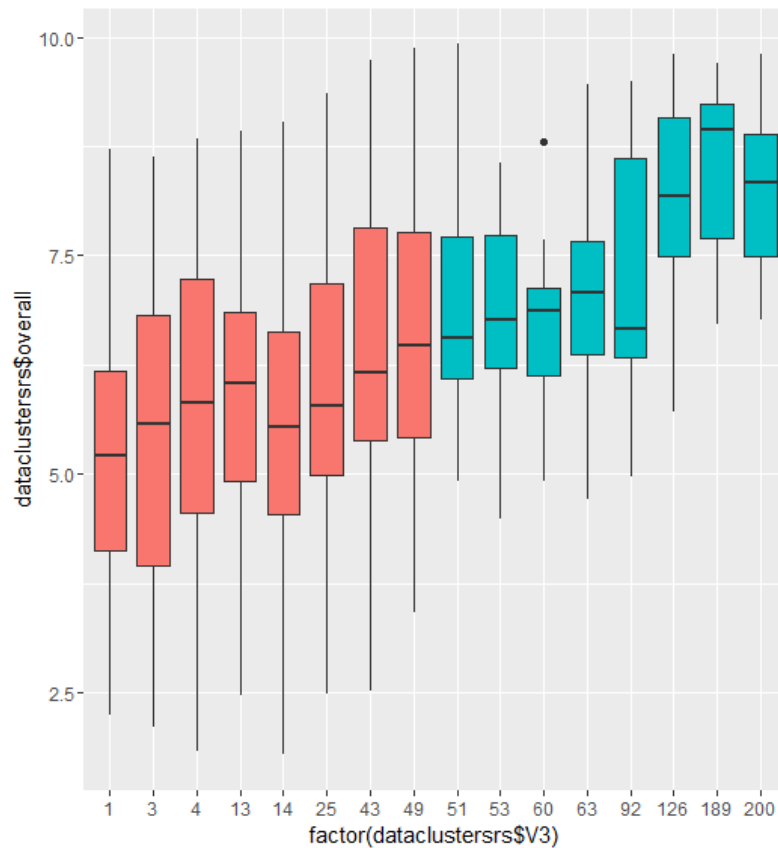
Stratify on programme (2)  
8 clusters in each (can also vary)  
Random sample per cluster PPS:  
• sample with  $p=.4$

16 clusters

For BA:

Total  $n=1000$  out of population 20000

# Variance estimation



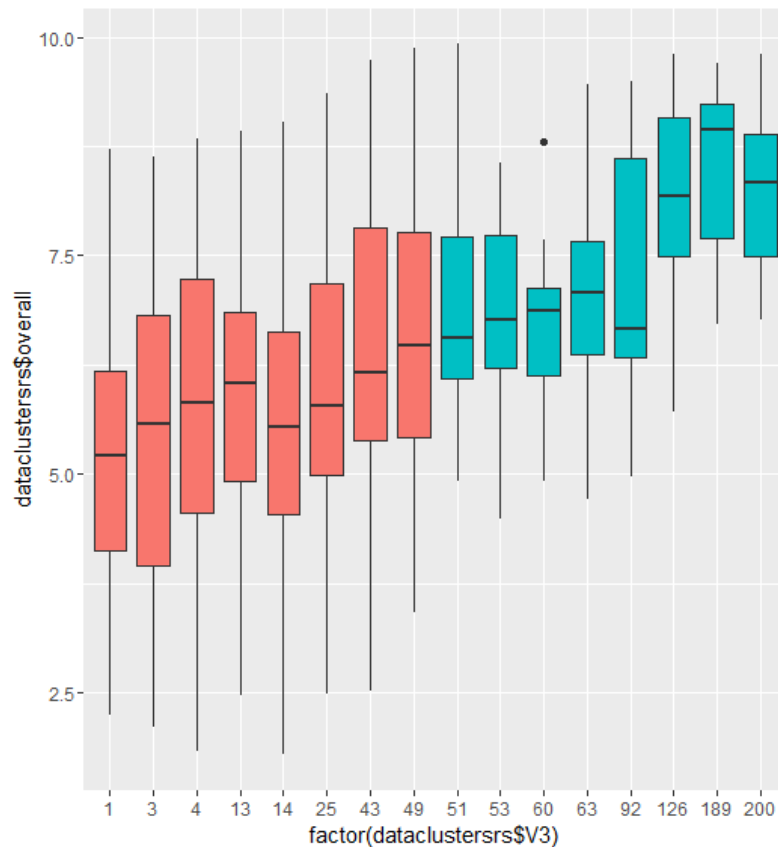
- How do we calculate variances.
- Alternative: Horvitz-Thompson estimator
  - Stage 1: stratify
  - Stage 1: cluster
  - Stage 2: Select individuals



- Weights:
- Stage 2: per cluster:
  - $Wt|s, master = 15 \text{ out of } 40 \rightarrow 2.5$
  - $Wt|s, Bachelor = 112 \text{ out of } 280 \rightarrow 2.5$

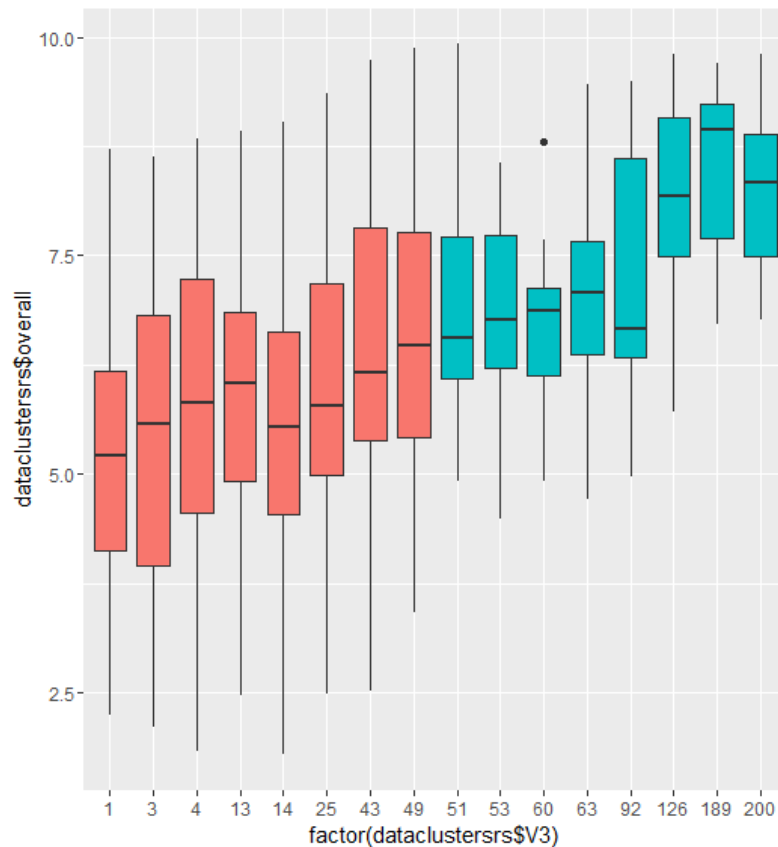


# Variance estimation using weights



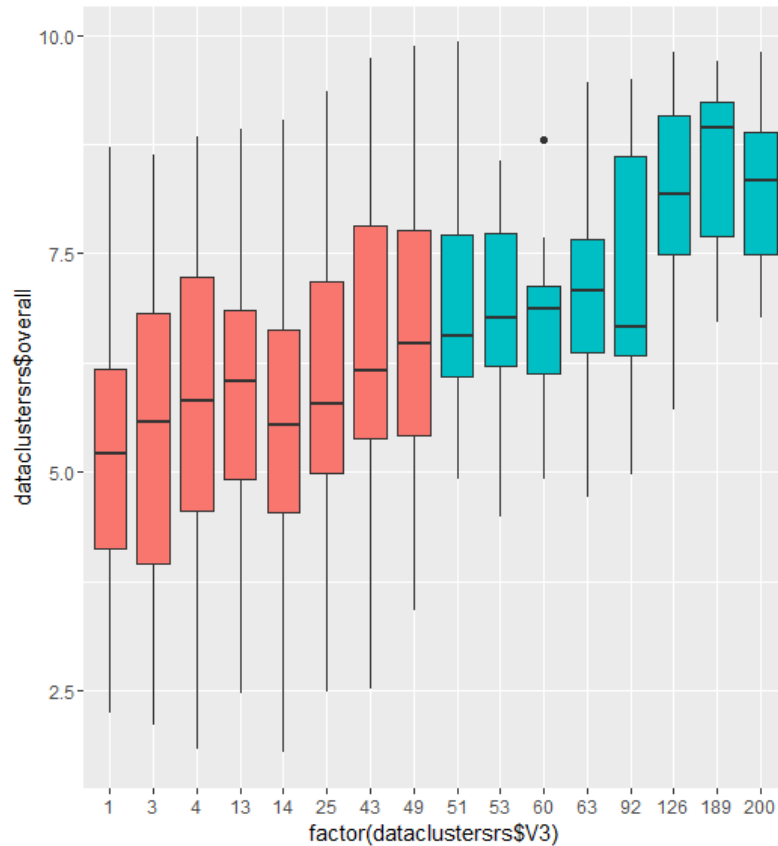
- Weights:
- Stage 2: per cluster:
  - $Wt|s, master = 15$  out of 40  $\rightarrow 2.5$
  - $Wt|s, Bachelor = 112$  out of 280  $\rightarrow 2.5$
- Stage 1: clusters out of strata
  - $Wt|s, master = 8$  out of 150  $\rightarrow 18.75$
  - $Wt|s, Bachelor = 8$  out of 50  $\rightarrow 6.25$

# Variance estimation – constructing weights



- Weights:
- Stage 2: per cluster:
  - $Wt|s, master = 15 \text{ out of } 40 \rightarrow 2.5$
  - $Wt|s, Bachelor = 112 \text{ out of } 280 \rightarrow 2.5$
- Stage 1: clusters out of population
  - $Wt|s, master = 8 \text{ out of } 150 \rightarrow 18.75$
  - $Wt|s, Bachelor = 8 \text{ out of } 50 \rightarrow 6.25$
- Total weight
  - $Wt|s, master = 2.5 * 18.75 \rightarrow 46.875$
  - $Wt|s, Bachelor = 2.5 * 6.25 \rightarrow 15.625$
- Rescaled weight
  - $Wt|s, master = 46.875 / \text{mean}(Wt) = 2.42$
  - $Wt|s, Bachelor = 15.625 / \text{mean}(Wt) = 0.81$

# Variance estimation in R – identical results



```
clus2a <- svydesign(ids=~cluster+id, strata=~programme,  
# weights=~weights, fpc = ~fpc1+fpc2, data=dataclustersrs)
```



dataclustersrs\$V2

Bachelor  
Master

```
Clus2b <- svydesign(ids=~cluster+id, #strata=~dataclustersrs$V2,  
weights=~weights,# fpc = ~fpc1+ffpc2,data=dataclustersrs)
```

Mean: 6.04

s.e. = .15275

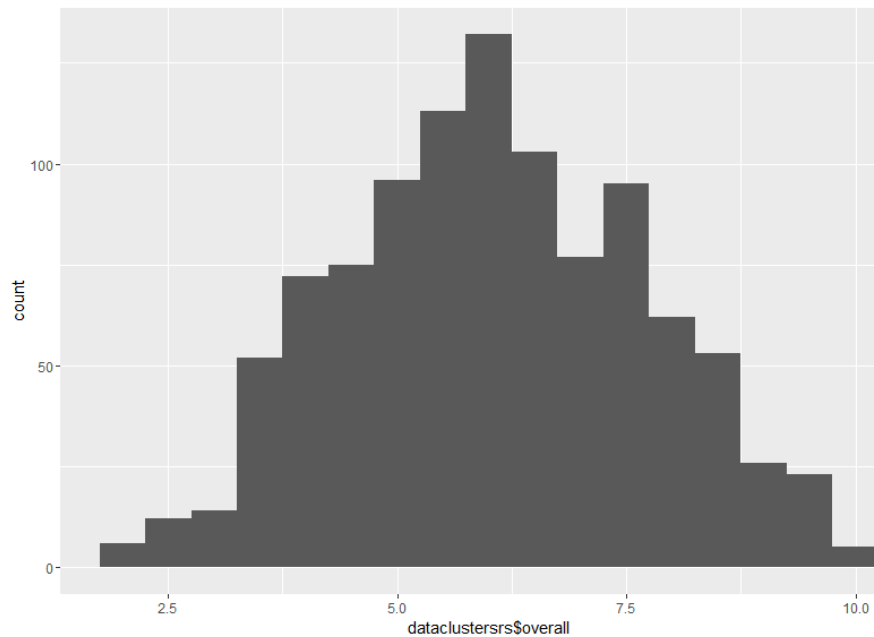
Deff= 8.86

# Weights

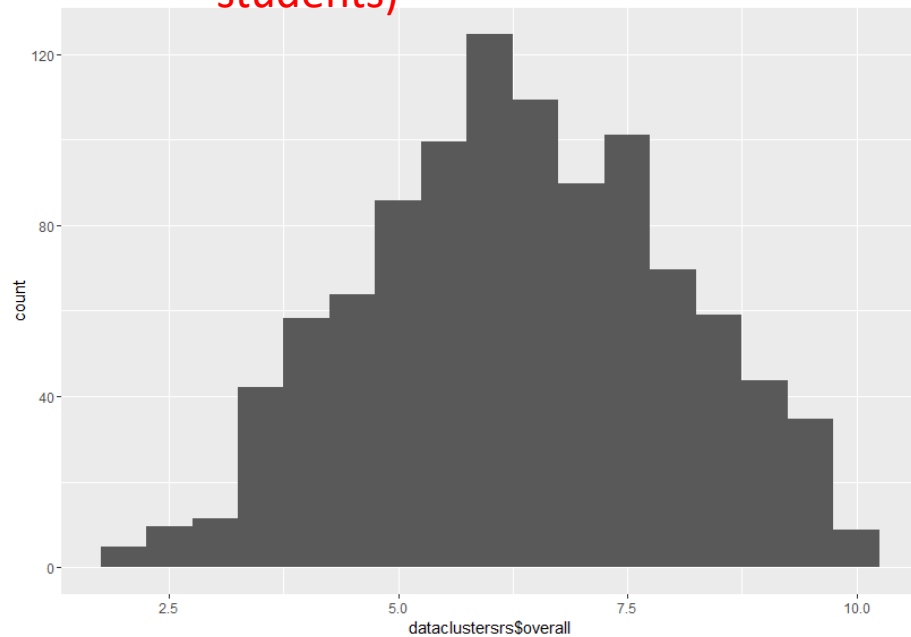
- The study doesn't stop at sampling
  - nonresponse weights (see week 44,45)
- Variance in weights indication of difference with perfect SRS design without nonresponse
  - In SRS  $\rightarrow W_i=1$ ,  $\text{Var}(\text{weights})=0$ .
  - In our design  $\rightarrow \text{Var}(\text{weights})=.27$
  - Likely in our design with NR:  $\text{Var}(\text{weights}) > .27$ 
    - Variance inflation
- Can trim weights if they are large (rescaled weights  $>3$  or  $5$ )
  - Bias becomes larger
  - Variance lower  $\rightarrow$  precision higher
  - Goal is to Minimize Mean Square Error ( $\text{bias}^2 + \text{variance}$ )

# Weighted graphs (using ggplot2)

- Without weights



- With weights
  - Heavier mass in upper tail  
(high weights for MA students)



# Next weeks:

- Next week:
  - Last week about sampling: **model assisted estimation**
    - Design based ----- model-based
    - Ratio and regression estimation
  - Stuart 71-90
  - Finish class exercises today
  - Take home exercise:
    - Specify your survey design in R
  - In two weeks: class-free week
  - Assignment 1 online tonight
    - **Deadline: 20 October 17:00**