Survey analysis week 6 "ratio and regression estimation"

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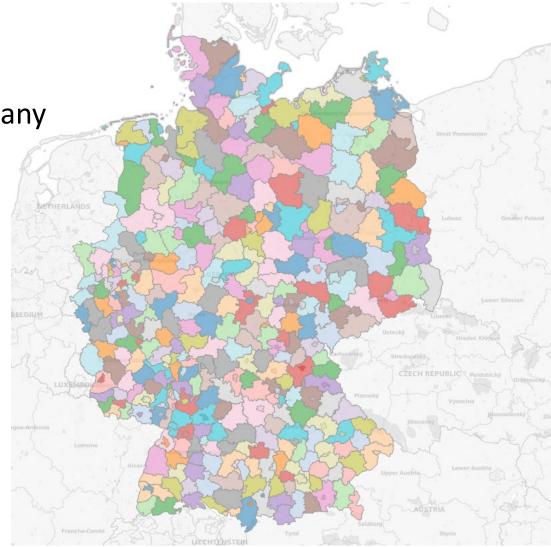
Today

- Why ratio estimation?
- Class exercise ratio estimation
 - New example: coffees at UU
- Lecture ratio and regression estimation
- Class exercise regression estimation

First rewind to cluster sampling....

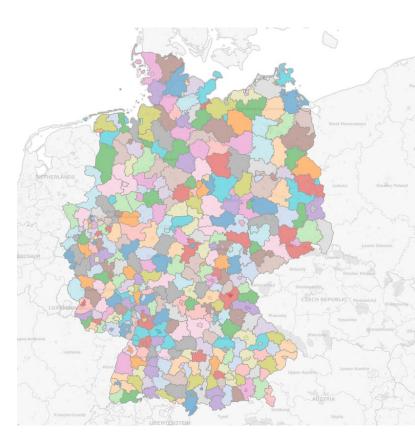
- You would like to estimate:
 - The number of "Whatsapp scams" in Germany

Mum, I've changed from prov my new number you ca old number ok xx 😁	
	Who are u 18:30 🗸
3 guesses mum 18:31	
	Why did u change.
EE 18:31	
Are you busy? 18:31	TA: 98. 8/5
Did u get nev busy.	v phone. No l'm r 📀 18:32 🗸
+	00



Cluster sampling in Germany

- 411 Kreise (in 2022)
- Sampling frames only available at level of Kreise
- Select k clusters (50)
 - Stratify?
- Select households in clusters
 - Size=1500 per cluster
- Two-stage cluster samples
- Can we do better?



Size of clusters is known

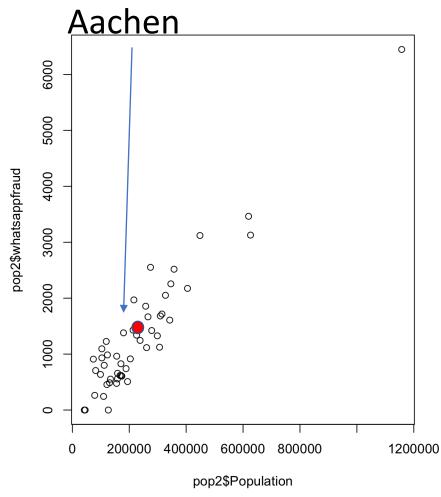
Wappen	Stadt ÷	Stadtkreis ID 🜩	BL ¢	Regierungsbezirk ^[5] ≎	UZ ÷	Fläche in ÷ km ²	tEW 1939 ≑ [6]	tEW 1950 ≑ [7]	tEW 1970 ≑ [8]	tEW 1990 ≑ [9]	tEW 2011 [10]	¢ EW jetzt ◆	di	ev :hte ≑ /km²)	Lagekarte
	Aachen ^[1] (δ 50° 47′ Ν, 6° 5′ Ο)	05334	🐼 NW	Köln	AC, MON	160,85	162,2	129,8	175,5	239,2	260	5 249.070 (2021))	1548	
	Amberg (ծ 49° 27' N, 11° 51' O)	09361	🚫 вү	Oberpfalz	АМ	50,13	31,8	37,9	41,3	42,9	43	5 41.994 (2021))	838	
	Ansbach (ծ 49° 18' N, 10° 34' O)	09561	🐯 вү	Mittelfranken	AN	99,91	26,0	33,2	33,2	37,6	40	3 41.662 (2021))	417	
	Aschaffenburg (≿ 49° 59' N, 9° 9' O)	09661	🐯 вү	Unterfranken	AB	62,45	45,4	45,5	55,1	63,6	68	8 71.381 (2021))	1143	
	Augsburg (ծ 48° 22' N, 10° 54' O)	09761	🚫 вү	Schwaben	A	146,85	185,4	185,2	213,2	254,3	266	6 296.478 (2021))	2019	
	Baden-Baden (ծ 48° 46' N, 8° 14' O)	08211	BW	Karlsruhe	BAD	140,19	33,2	36,6	37,2	51,5	54	5 55.527 (2021))	396	
(Bamberg (5 49° 54' N, 10° 54' O)	09461	🐯 вү	Oberfranken	BA	54,62	59,5	76,2	70,4	70,2	70	1 77.749 (2021))	1423	
	Bayreuth (ծ 49° 57′ N, 11° 35′ O)	09462	ВҮ	Oberfranken	BT	66,89	45,0	58,8	64,2	72,0	73	1 73.909 (2021))	1105	
X	Berlin (δ 52° 31′ Ν, 13° 24′ Ο)	11000	В	-	В	891,69	4338,8	3336,0	3200,7	3420,6	3501	9 3.677.472	2	3948	
	Bielefeld (5 52° 1′ N, 8° 32′ O)	05711	🐼 NW	Detmold	BI	258,83	129,5	153,6	168,6	317,2	323	4 334.002 (2021))	1290	

Estimate at individual cluster level

- Imagine we select the city Aachen as one cluster
 - We draw an SRS of 2.000 households
 - Conduct the survey: 1.000 households participate
 - We find that 12 people were victim of Whatsapp fraud last year
 - What is the total number of Whatsapp frauds in Aachen?
- Number of individuals in selected households: 2123
 - 12/2123 = .56% of individuals experiences Whatsapp fraud
- Number of whatsapp fraud in AAchen= .0056 * 249070 = 1394



Estimate at population level



Mean pop size of cluster = 235509 Mean whatsapp fraud = 1307

Ratio = 180/ 1

Or .00555 of population

Germany: population is 83 Million
 Whatapp fraud is 83M/180 = 461k

Why ratio estimation?

- We know:
 - The size of each farm in the USA
 - N_h and n_h
- Estimate from a sample:
 - What crops they produce
 - What is their yield per acre (or total production)

 USA wheat production = wheat production per acre * total # acres of wheat

Auxiliary information at level of farm

Why ratio estimation?

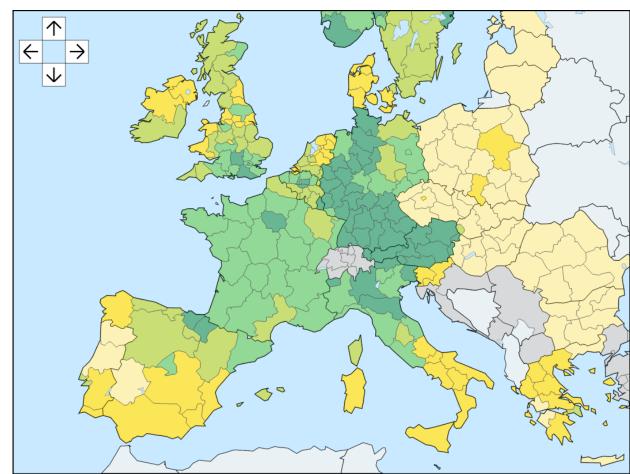
- We know:
 - How many schools there are: # schools
 - N_h (no. of clusters)
- Estimate from a sample:
 - The average number of children per school: n_h
 - the proportion with reading problems: p

• Total # children with learning diff = $n_h * N_h * p_{children with reading problems or}$

Auxiliary information at level of cluster

Why so often in cluster samples?

- We often don't know much about individuals
- But we do know about the clusters
 - Public sources:
 - Population size
 - income, employment
 - Gender, age distribution
 - Etc.
- Is Y strongly correlated with these?
 - And a ratio variable?
 - Ratio estimation
- E.g. No. of births, marriages, death

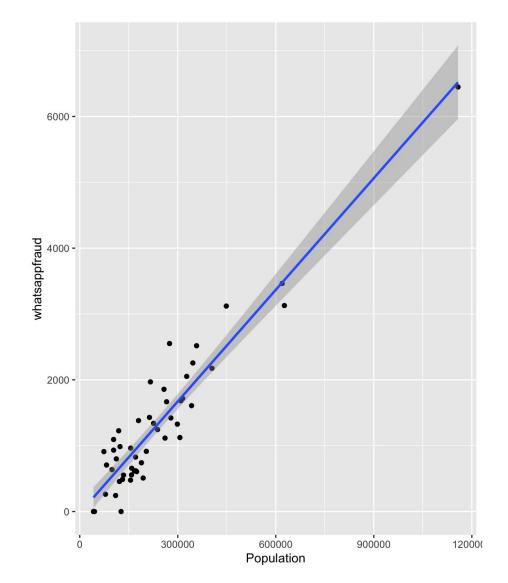


Class exercise 1

- 25 minutes
- 4 questions...

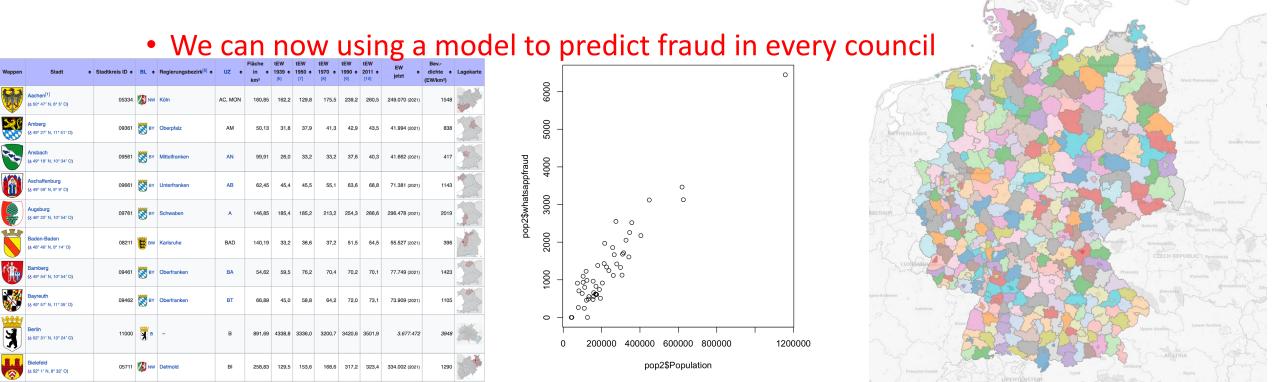
What is great in ratio estimation

- We can only sample some clusters
 BUT: we know the size of each cluster
 - Fatimenta francial in a prese alustaria
- Estimate fraud in some clusters
- The ratio <u>
 Population size</u> <u>
 Number of whatsapp fraud</u>
- Allows us to estimate with great precision
 - We know quite a lot about the clusters we didn't observe
 - Se = much lower than SRS
 - Design effect very small
 - We can lower sample size, and save \$\$\$



What more is there?

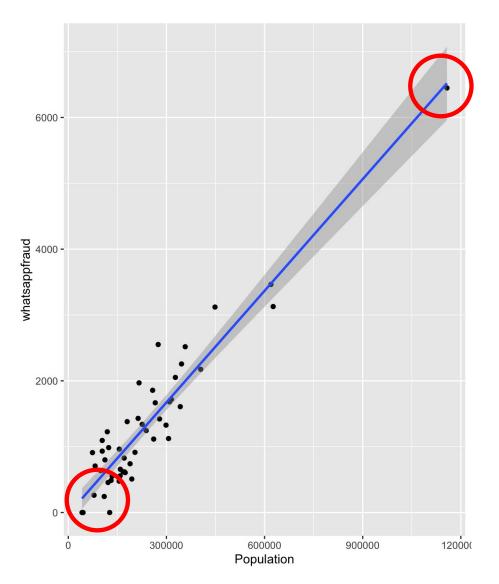
- Estimating fraud in every cluster
 - Berlin: population 3.7 million. Whatapp fraud 3.7M / 180 = 20558
 - Ansbach: population 41k. Whatsapp fraud 41k/180 = 228



What is a problem in ratio estimation

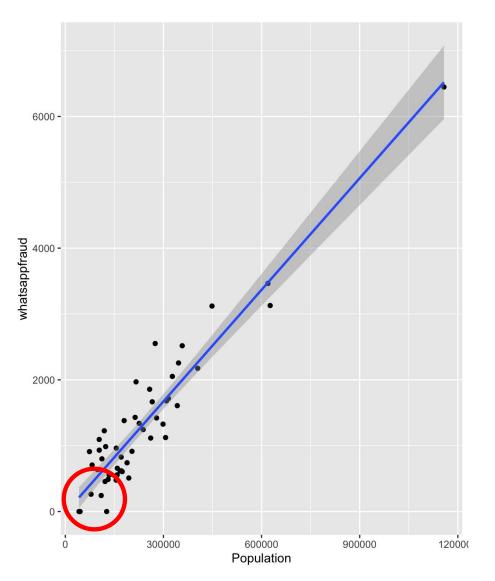
Question 4: class exercise

- There may be bias!
 - Outlier clusters
 - Large cities drive results
 - Whatsapp fraud may be local
 - Population size = 0 doesnt happen, but whatsapp fraud = 0 does!
 - The origin does not really exist



What about making the model more complex?

- What about including other covariates?
 - Urban/rural
 - Average income of cluster
 - State of the council
 - Etc.
- We build a regression model
 - More covariates
 - Why not an intercept?



Model-based estimation

- Using a survey from some clusters....
- We try to predict Fraud in other clusters
- And the sum of all predictions is the total

Wappen	Stadt ÷	Stadtkreis ID +	BL ¢	Regierungsbezirk ^[5] ≑	UZ ÷	Fläche in ¢ km²	tEW 1939 ≑ [6]	tEW 1950 ≑ [7]	tEW 1970 ≑ [8]	tEW 1990 ≑ [9]	tEW 2011 ≑ [10]	EW jetzt ÷	Bev dichte ÷ (EW/km²)	Lagekarte
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	Bielefeld (ծ 52° 1′ N, 8° 32′ O)	05711	🐼 NW	Detmold	BI	258,83	129,5	153,6	168,6	317,2	323,4	334.002 (2021)	1290	

Class exercise 2

- Regression estimation in practice
- 30 minutes

Design-based versus model-based

Variance of the estimator:

Design-based:

Average squared deviation of the estimate and the expected value, averaged over all possible samples under the sampling design (i.e. we repeat the sampling procedure 10000 times, and estimate variance in the total)

Model-based

Average squared deviation of the estimate and the expected value, averaged over all possible samples under the model (i.e. we assume the model is correct, and sample 10000 times new observations, fit the regression line, and estimate variance in total)

When ratio vs. regression?

Ratio

- Size of area/no. of buildings -> people in a certain area
- Turnover per company/no. of peppers -> total pepper production
 Often, good frame information, and a meaningful 0
 Regression
- Happiness <- grades:gender:income:sociallife
- Vote <- race:age:gender:education
- Fraud <-population:urban:incomes

Often, little good frame information, no meaningful 0

Implicationss of going model-based

- Sampling is not so important!
 - We just get data, and as long as we are confident that our model is correct **in the population**, we are fine...
- We need a good (regression) model for Y
- We need to worry about sample <-> population
 - On a more conceptual level, not about inclusion probabilities
 - Sample should capture variation
 - Selection bias, nonresponse
- From now on: more focus on model-based inference
 - Nonresponse model -> weights
 - Missing data model -> imputation
 - Selection bias model -> ???

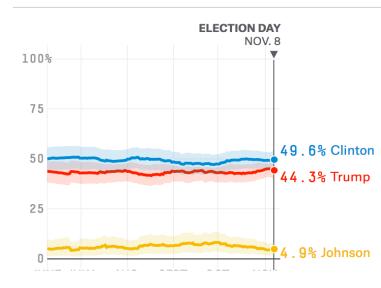
Model-based inference – an example

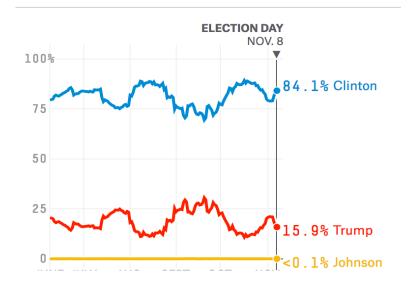
Chance of winning Wisconsin's 10 electoral votes



Projected vote share over time

Chances over time





Wisconsin – election outcome 2016

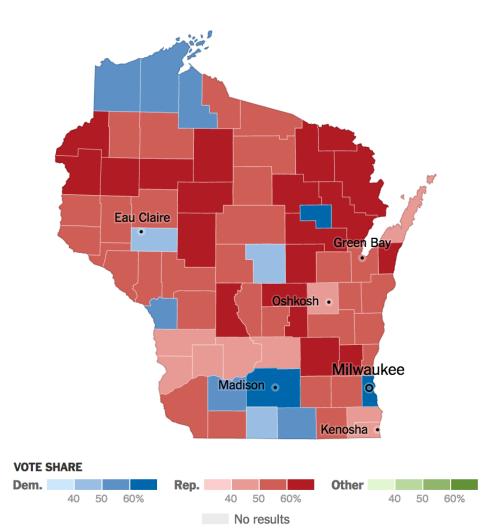
President

CANDIDATE	PARTY	VOTES	PCT.	E
Donald J. Trump	Republican	1,405,284	47.2%	10
Hillary Clinton	Democrat	1,382,530	46.5	-/
Gary Johnson	Libertarian	106,674	3.6	_
Others	Independent	35,150	1.2	
 Others 		46,506	1.6	_

100% reporting (3,620 of 3,620 precincts)

President Map »

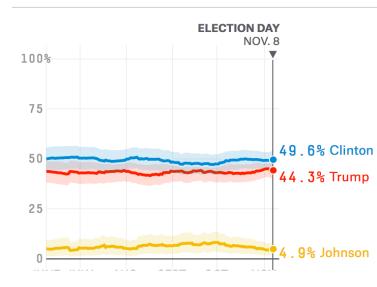
Race Preview: Wisconsin, a competitive state that leans Democratic, has 10 electoral votes. With a large population of white, working-class Democrats, it seemed promising for Mr. Trump, but he has struggled with Republican-leaning voters in the Milwaukee suburbs. <u>Barack Obama won Wisconsin in</u> 2012 by 6.9 percentage points.

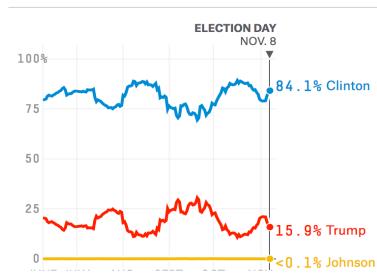


Model-based inference – an example

Chance of winning Wisconsin's 10 electoral votes







= sqrt(.496(1-.504)/10000) = .005

Clinton Vote CI: [.4904 - .5096]

How does political polling in the USA work?

DATES 🔶	POLLSTER 💂	GRADE	SAMPLE	WEIGHT 🔶	0	INTON	UMP 10	HNSON LEADER	ADJUSTED LEADER
OCT. 26-31	Marquette University	A	1,255 LV	 3.79	46%	40%	4%	Clinton +6	Clinton +5
NOV. 1-2	Remington		2,720 LV	3.26	49%	41%		Clinton +8	Clinton +9
NOV. 1-2	Clarity Campaign Labs	В	1,129 LV	2.99	47%	43%	4%	Clinton +4	Clinton +5
NOV. 3-6	Gravis Marketing	B-	1,184 RV	2.84	47%	44%	3%	Clinton +3	Clinton +4
OCT. 31- NOV. 1	Public Policy Polling	B+	891 LV	2.81	48%	41%		Clinton +7	Clinton +7
NOV. 1-7	SurveyMonkey	C -	2,246 LV	2.53	44%	42%	7%	Clinton +2	Clinton +1
OCT. 31- NOV. 1	Loras College	B-	500 LV	1.62	44%	38%	7%	Clinton +6	Clinton +5
OCT. 27-28	Emerson College	В	400 LV	1.23	48%	42%	9%	Clinton +6	Clinton +7
OCT. 13-16	St. Norbert College	A-	664 LV	1.20	47%	39%	1%	Clinton +8	Clinton +5
NOV. 1-7	Google Consumer Surveys	В	914 LV	1.03	43%	31%	4%	Clinton +12	Clinton +12
OCT. 15-18	Monmouth University	A+	403 LV	0.98	47%	40%	6%	Clinton +7	Clinton +4
OCT. 5-7	YouGov	В	993 LV	0.93	43%	39%	4%	Clinton +4	Clinton +2
OCT. 24- NOV. 6	lpsos	A-	625 LV	0.92	46%	40%		Clinton +6	Clinton +6
OCT. 18-20	McLaughlin & Associates	C -	600 LV	0.85	48%	43%	4%	Clinton +5	Clinton +3
OCT. 18-19	Public Policy Polling	B+	804 LV	0.73	50%	38%		Clinton +12	Clinton +9

Multiple polls Weighted by:

- Quality of organisation (grade)
- Recency

Results presented is aggregated total

But forecasters do not stop there...

	CLINTON	TRUMP	JOHNSON
1. Polling average	46.4%	40.5%	4.9%
Adjust for likely voters	+0.1	+0.2	-0.1
Adjust for convention bounce	-0.0	+0.0	+0.0
Adjust for vice-presidential selection	-0.0	+0.0	+0.0
Adjust for omitted third parties	-0.2	-0.2	+0.0
Adjust for trend line	+0.3	+1.0	-0.7
Adjust for house effects	-0.2	-0.5	+0.1
2. Adjusted polling average	46.4%	41.0%	4.2%
2. Adjusted polling average Allocate undecided and third-party voters	46.4% +3.3	41.0% +3.3	4.2% +0.5
Allocate undecided and third-party voters			
Allocate undecided and third-party voters	+3.3	+3.3	+0.5
3. Polls-based vote share	+3.3 49.6%	+3.3 44.2%	+0.5 4.8%
Allocate undecided and third-party voters 3. Polls-based vote share Calculate demographic regression 4. Polls- and demographics-based projection	+3.3 49.6% 49.6%	+3.3 44.2% 44.2%	+0.5 4.8% 5.5%

Adjustments for:

- Likely voters
 - Not all people are likely to go and vote
- Omitted third parties
 - Not all polls ask for all parties
- Adjust for trend line
 - A smoothing adjustment to avoid large fluctuations
- House effects
 - Some pollsters are known to have a bias

But forecasters do not stop there...

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Allocate undecided and third-party voters	+3.3	+3.3	+0.5
3. Polls-based vote share	49.6%	44.2%	4.8%
Calculate demographic regression	49.6%	44.2%	5.5%
4. Polls- and demographics-based projection Weighted average 91% polls-based, 9% demographics	49.6%	44.2%	4.9%
Calculate fundamentals forecast	47.6%	46.3%	4.9%
5. Projected vote share for Nov. 8 Weighted average 99% polls/demographics, 1% fundamentals	49.6%	44.3%	4.9%

Adjustments for:

- Undecideds
 - Assumption about how "don't know" answers will vote

But forecasters do not stop there...

	CLINTON	TRUMP	JOHNSON
1. Polling average	46.4%	40.5%	4.9%
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	(7.0)	46.3%	4.9%
Calculate fundamentals forecast	47.6%	40.J%	4.00

Demographic regression Use data from other states:

- Fit a model with demographics (ethnicity, age, college degree, income)
- 2. What is predicted vote in Wisconsin?
- 3. Mix the poll outcome with model-based outcome

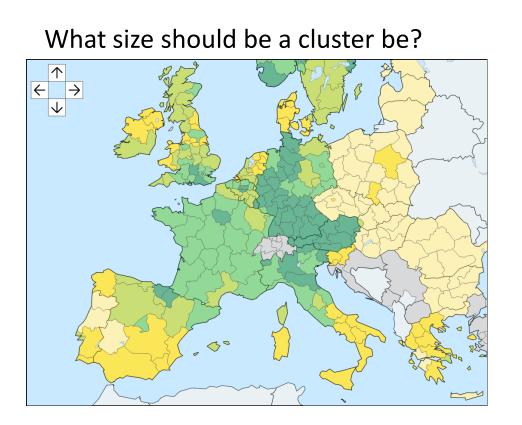
Why were the polls wrong?

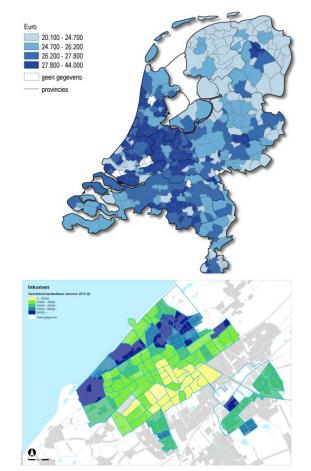
- It wasn't all the modeling.....
 - Polls only: 46 vs. 40 result: 46.5 vs. 47.2
 - + modeling: 49 vs. 44
- AAPOR report (Kennedy et al, 2017) week 1
- Shy Trump vote
- Low turnout
- Late swing to Trump
- Failure to correct for overrepresentation of highly educated

Why were the polls wrong?

- Model based estimation depends on quality of model!
 - In design based, we can estimate error
 - In model-based -> much more difficult
- Why not do design-based inference?
 - Costs
 - Time
 - Problems with coverage, nonresponse
 - -> still needs modeling
 - There are too many people who want to do a a poll
 - 100s in Wisconsin alone

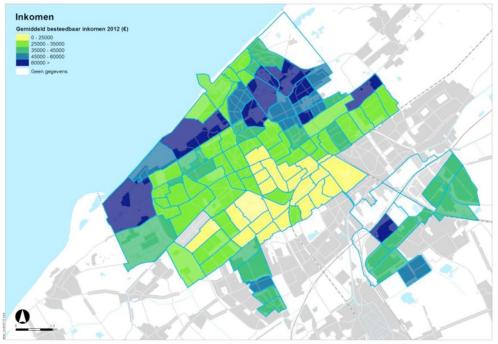
What is a cluster?





Small Area Estimation

- Desire for detailed statistics at low geographical level.
- Would result in 1000s clusters in Netherlands, even more in Europe
- Solution: Small area estimation
 - Analogue to coffee machines example
 - There are 100s of machines at UU
 - Build an elaborate model with many auxiliary variables
- Predict Y in every cluster by using a model

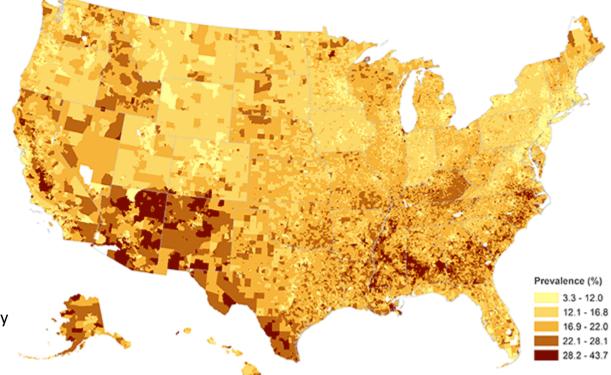


Example

Childhood obesity

Used 91,642 completed interviews from NCSH survey:

- Model for every county:
- NSCH child obesity status (yes or no) = sex + age + race (individual level)
- + median household income + lifestyle classifications + urbanization levels (zip-code level)
- + median household income + urban-rural (county-level)
- + random effects (state- and county levels)



Next week(s)

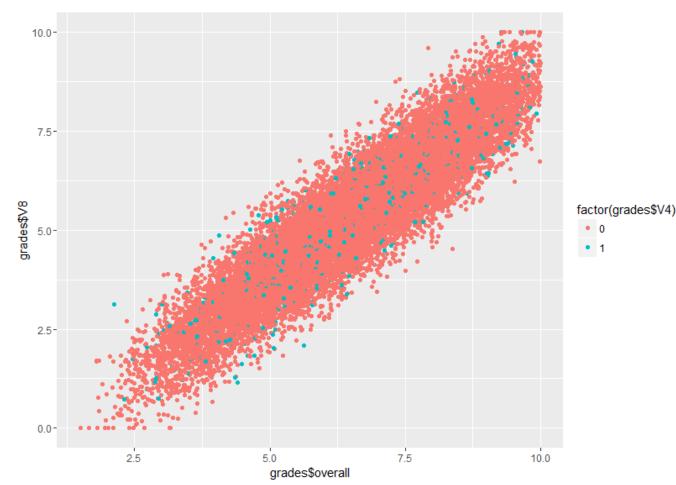
- Next week: class free
 - Finish regression exercise
 - Catch up on reading
- In two weeks: nonresponse Readings: several articles
- During class-free week: assignment 1 (!)

Extra slides

• What goes right and wrong?

Model based sampling

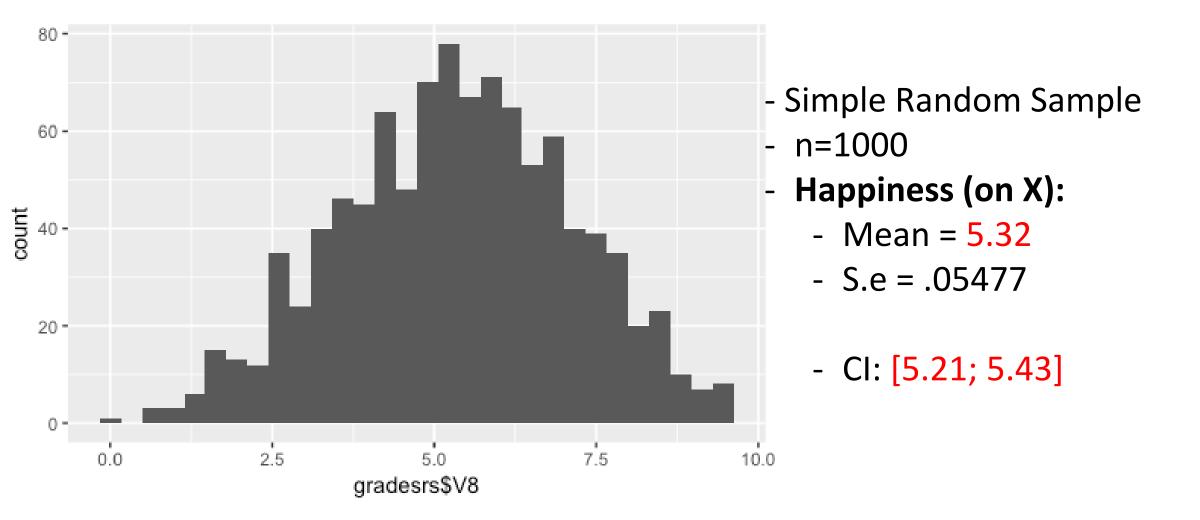
• Let's bring student happiness in!



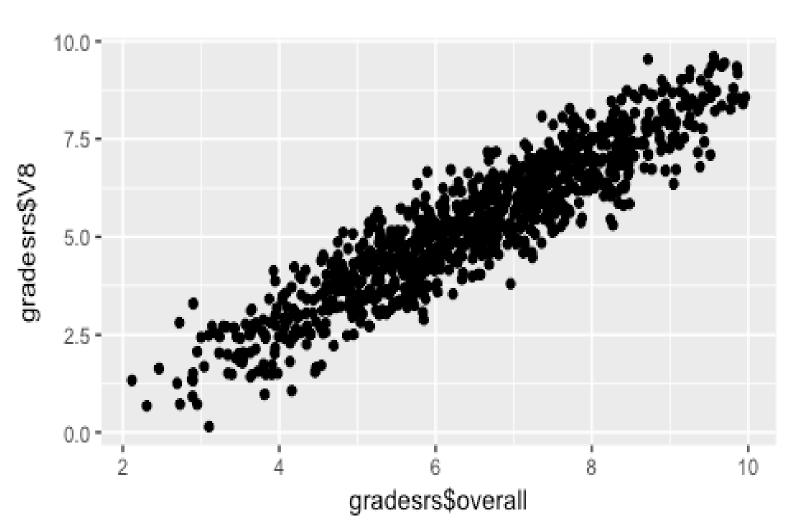
Population data:

- N=20000
- X = grades
- Y = student happiness (also 0-10 scale)
- Mean happiness = 5.37

Simple Random Sampling



Ratio estimation under SRS



Svyratio(~happiness, ~grades, design = ratio.design)

- B= .8231
- s.e. = .0024
- Predicted mean= 5.34

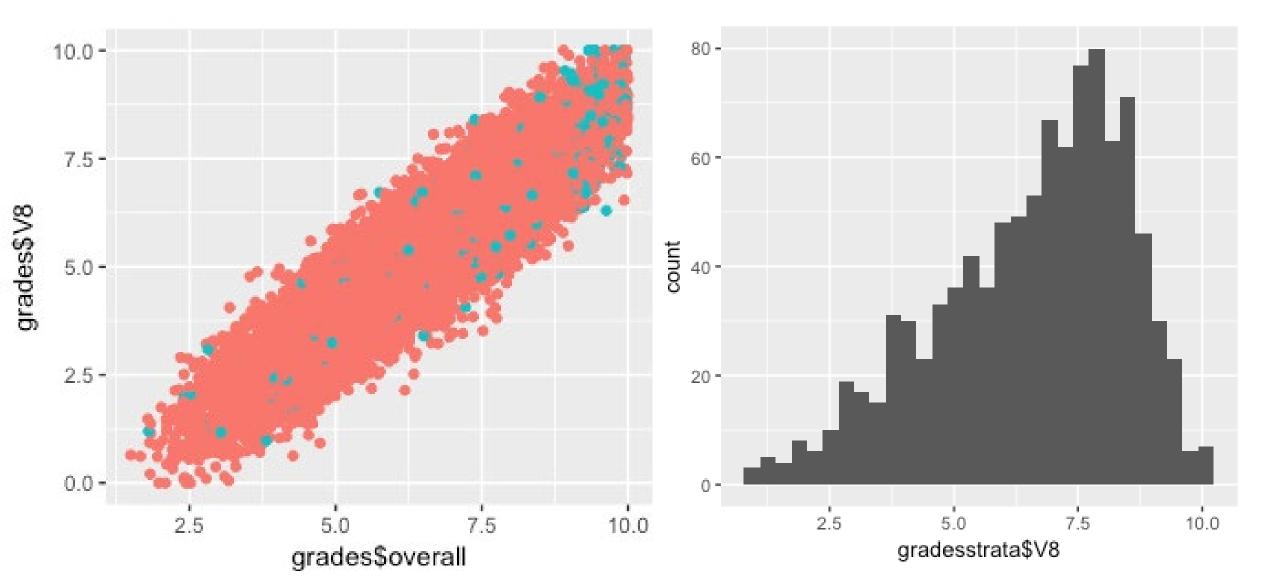
Or:

summary(Im(happiness~0+grades,data =gradesrs, subset=(V4==1)))

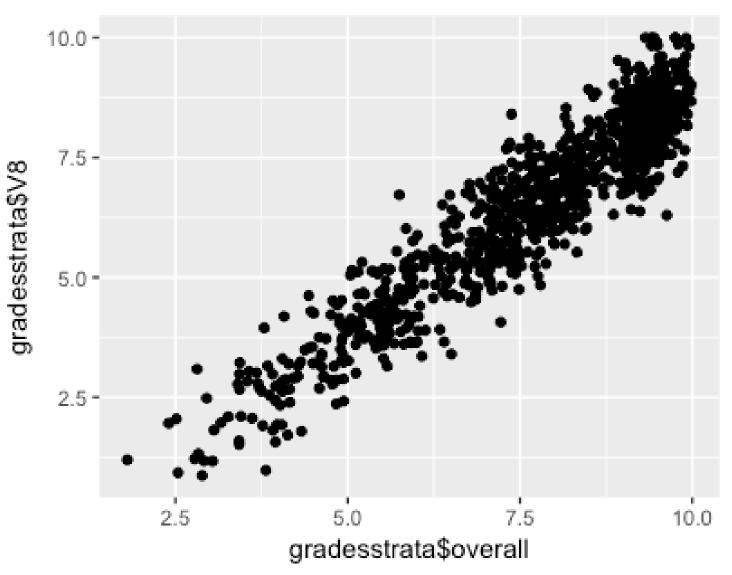
Mean(data\$fittedvalues)

- B = .83
- s.e. =.0036
- Predicted mean = 5.42

Oversample students who get good grades

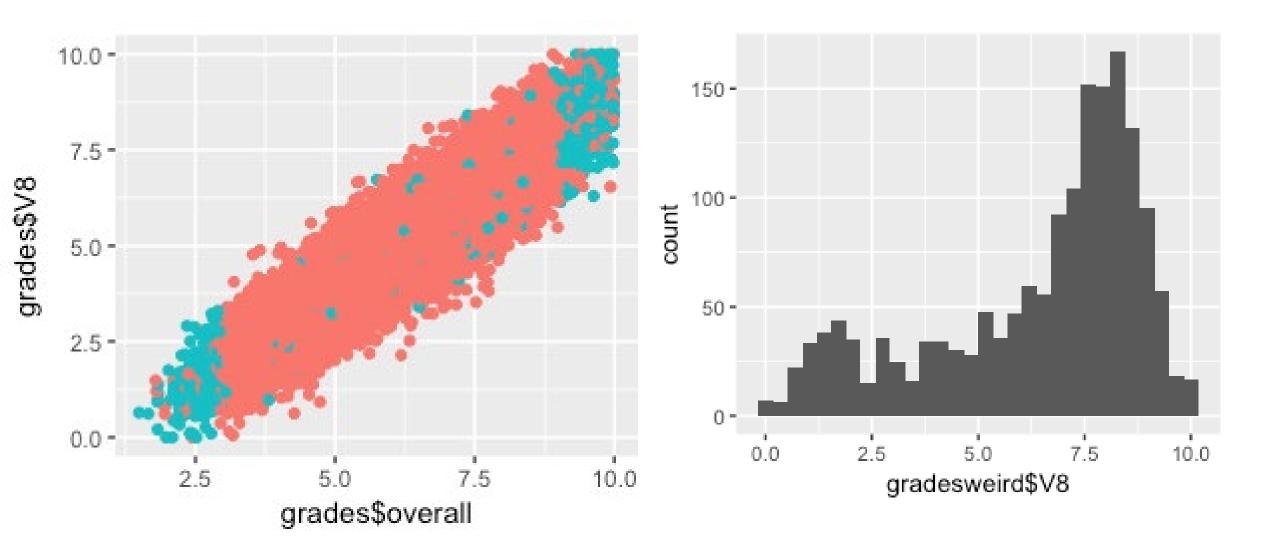


Oversampling students with good grades

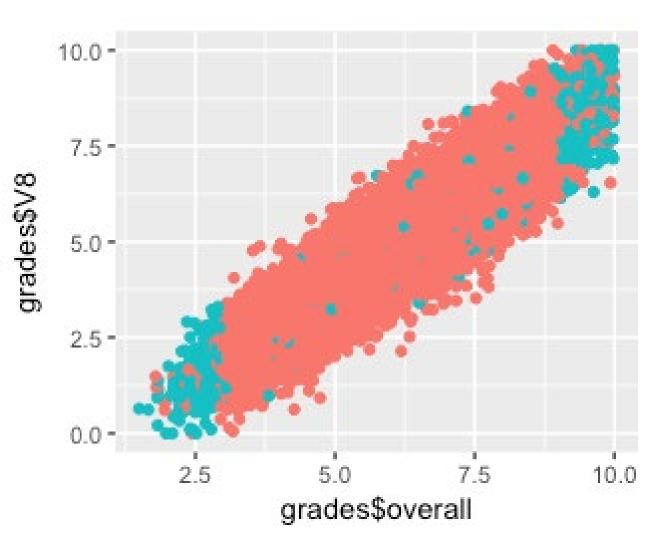


- Design based:
 - Mean = 5.33
 - S.e. = .0337
- Ratio estimation
 - B=.87
 - S.e. = .0026
 - Mean= 5.335
- Regression estimation
 - B = .83
 - S.e. = .0036
 - Mean=5.45

Truly model based – extreme cases



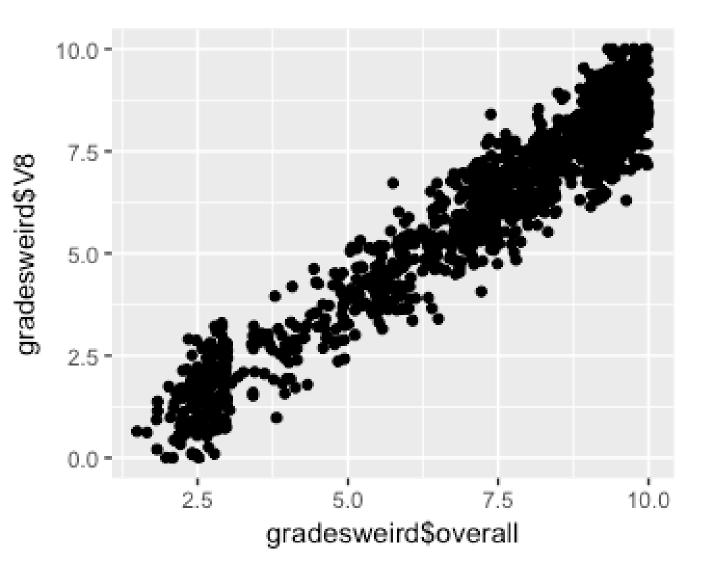
Truly model based – regression



• Regression model: Happiness <- grades + programme

(+ age, gender, etc.)

Truly model based



- Design based
 - Mean = 5.33
 - S.e. = .0335
- Ratio estimation
 - B=.87
 - S.e. = .0026
 - Mean= 5.33
- Regression estimation
 - B = .87
 - S.e. = .0027
 - Mean=6.28

What works?

	Type of sample	Mean	Precision	Mean square error
Design Based	SRS	5.32	.0548	$.05^2 + .05 = .0525$
	Oversample good students	5.33	.0337	.04 ² + .03= .0353
	Extreme cases	5.33	0.335	$.04^2 + .03 = .0351$
Ratio-estimation	SRS	5.34	.0027	$.03^2 + .0027 = .0036$
	Oversample good students	5.335	.0026	.035 ² + .0026 = .0037
	Extreme cases	5.335	.0026	035 ² + .0026 = . <mark>0037</mark>
Regression estimation	SRS	5.42	.0036	$.05^2 + .0036 = .0061$
	Oversample good students	5.45	.0027	.08 ² + .0027= .0091
	Extreme cases	6.28	.0036	.93 ² + .0036 = .8685

Notes: Population mean = 5.37. MSE = bias + se^2