Survey data analysis
Week 13:
“Inference for non-probability samples”

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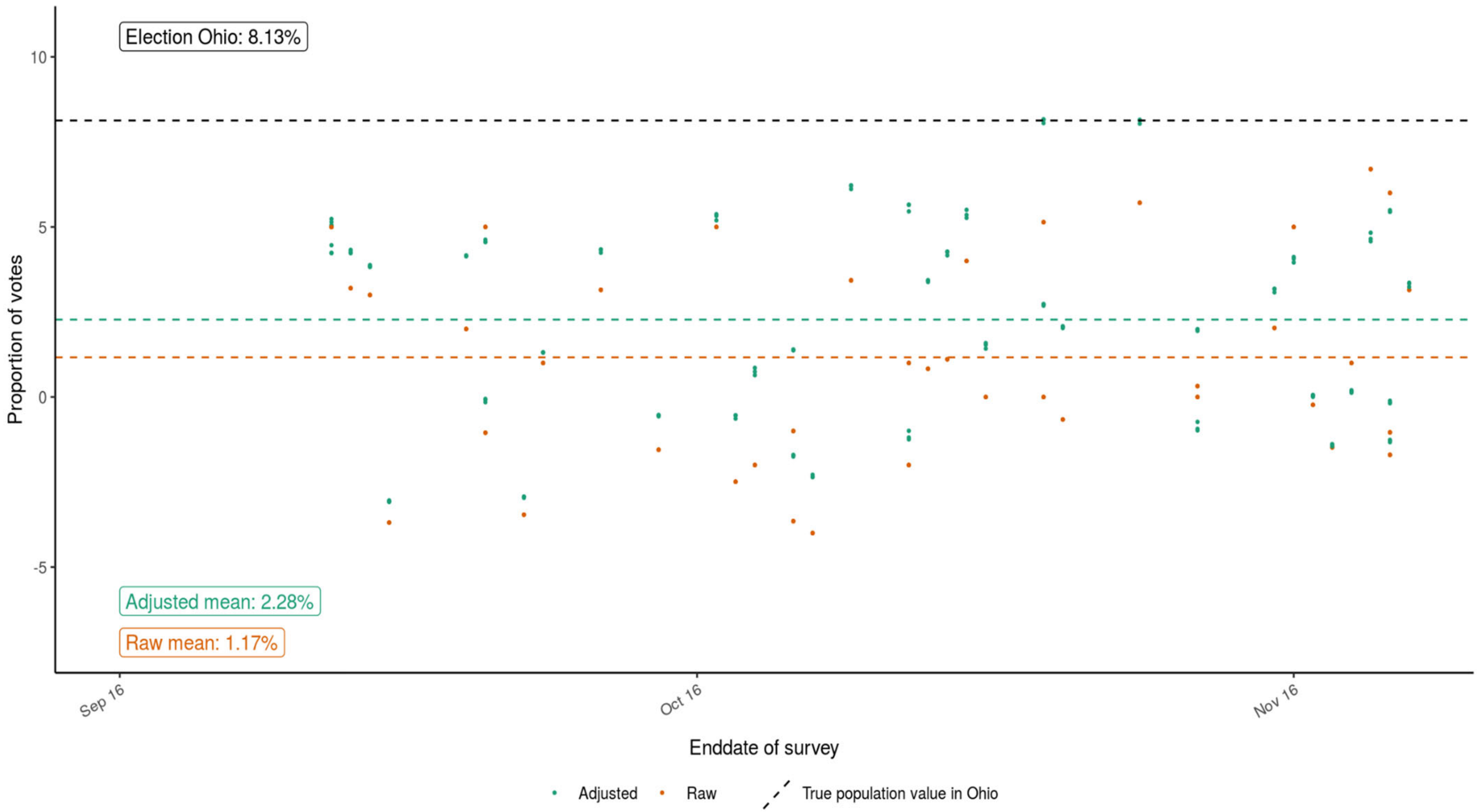
Today

- Group assignment

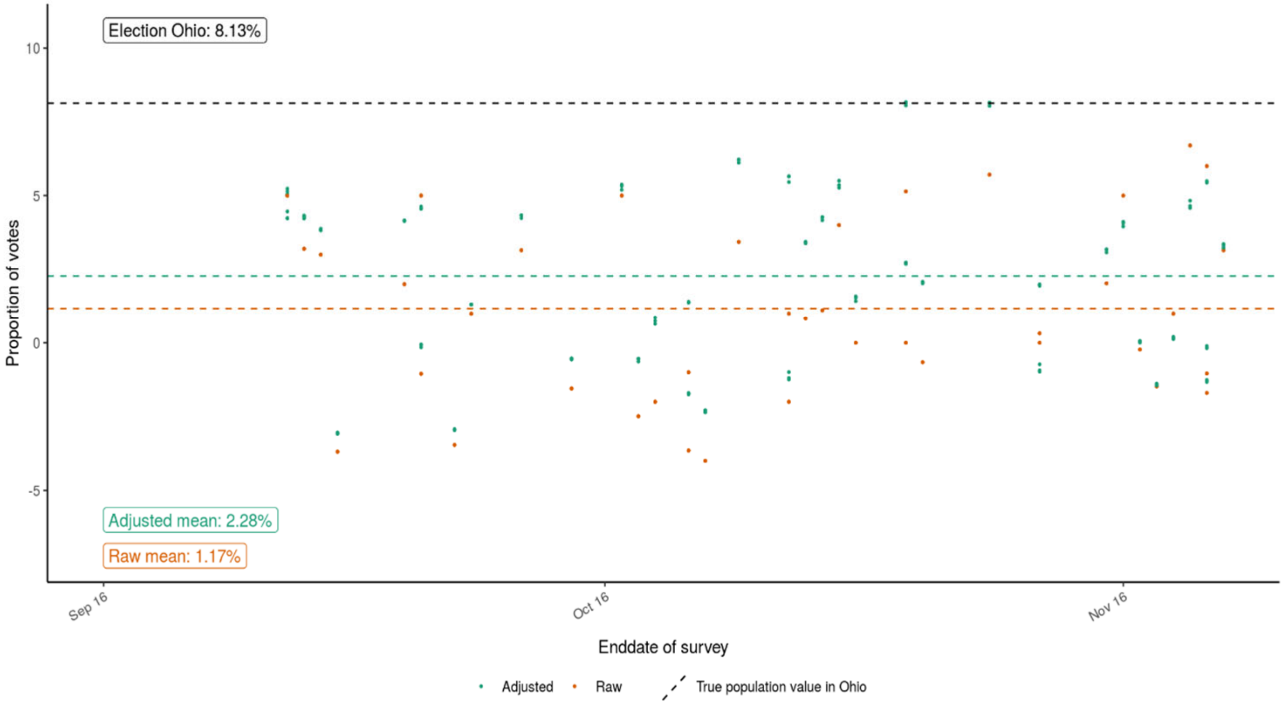
- Lecture
- Inference ‘competition’

Back to week 1



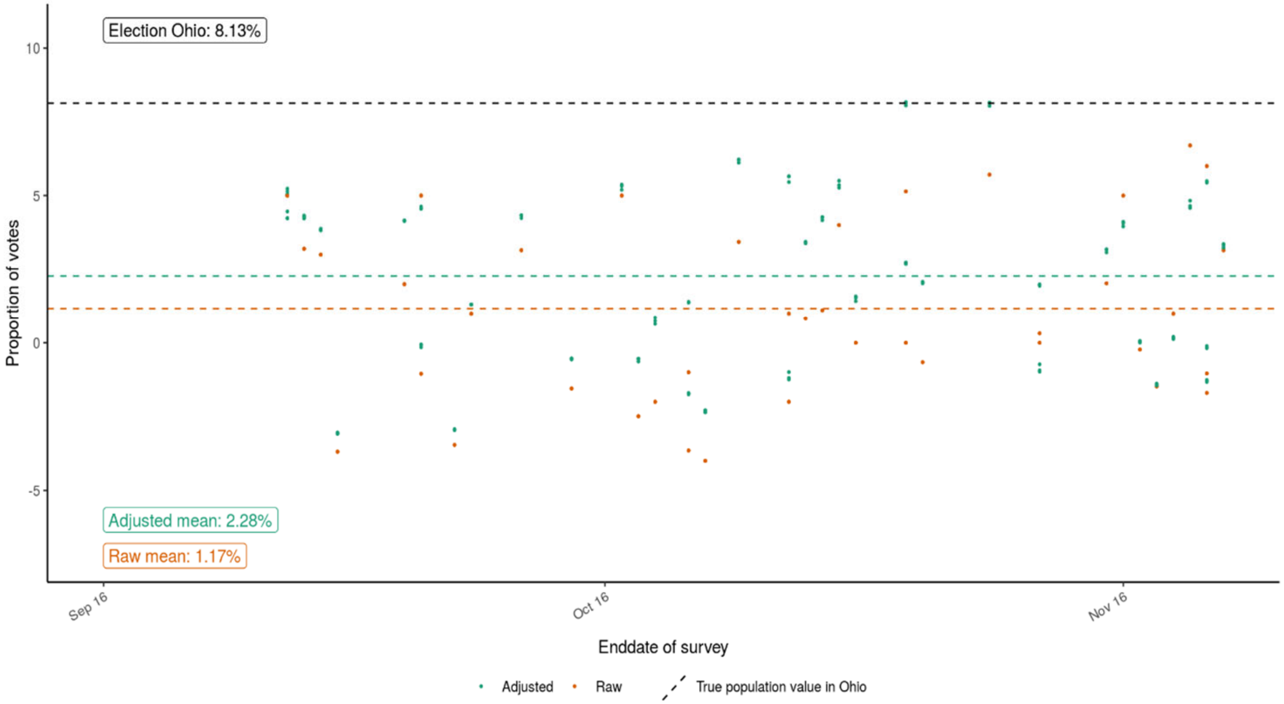
See: https://utrecht-university.shinyapps.io/SDA_shinyelectionbias/

Back to week 1



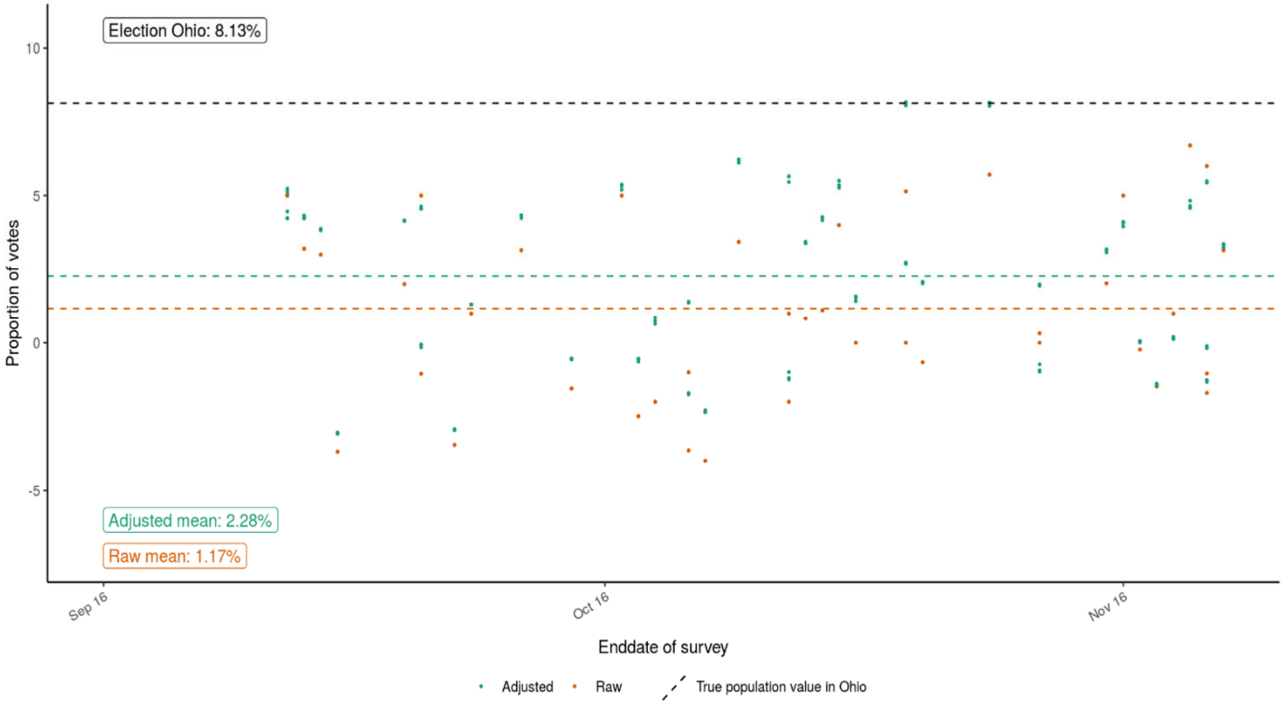
- Adjustments only help a bit on average
- For individual polls they sometimes make matters worse!

Back to week 1



- Adjustments only help a bit on average
- For individual polls they sometimes make matters worse!
- Grade of pollster/ sample size/ population dont make the difference

We have an inference problem



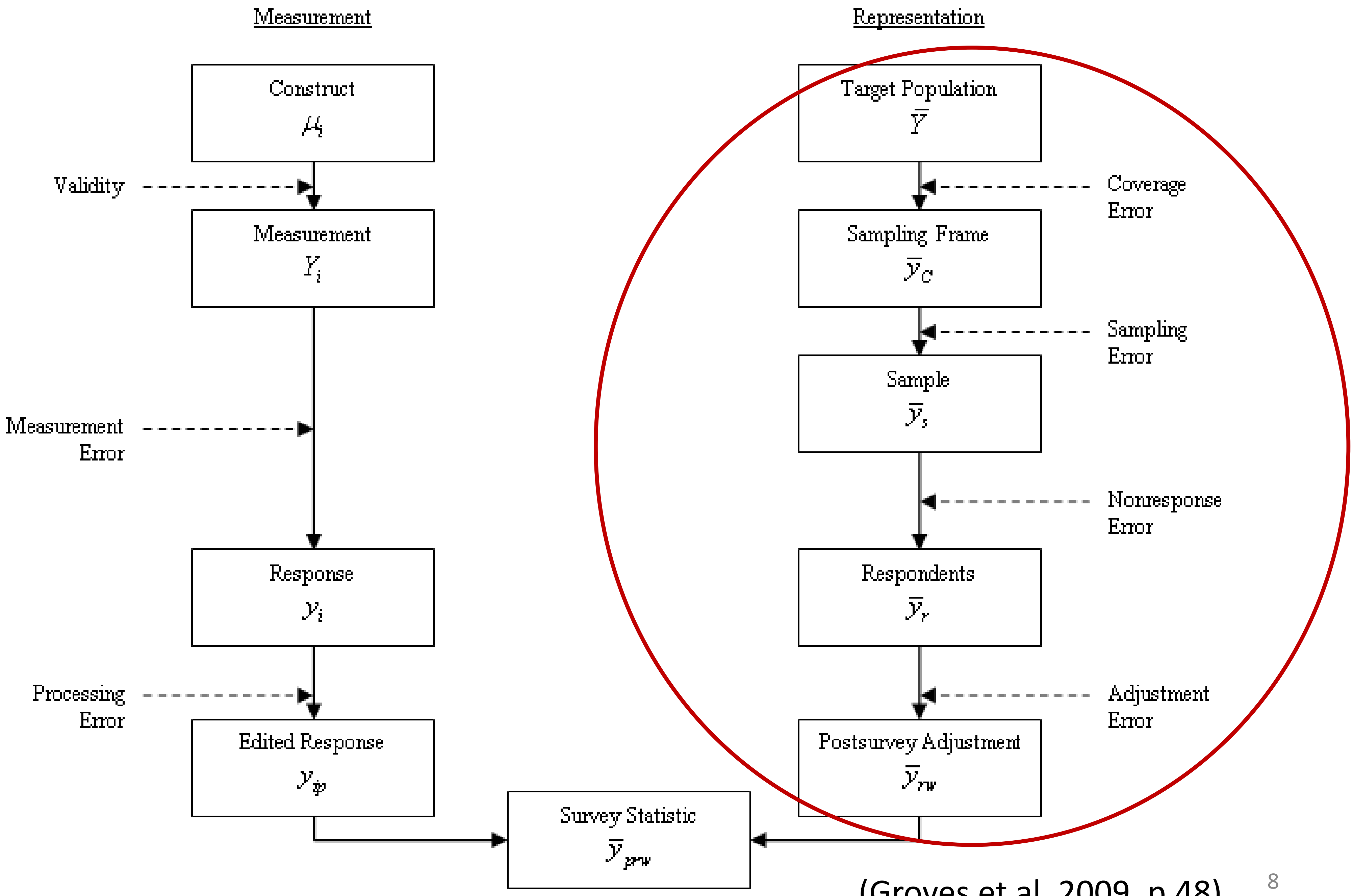
- Adjustments only help a bit on average
- For individual polls they sometimes make matters worse!
- Grade of pollster/ sample size/ population dont make the difference
- Problems with weighting
- A lot of polls are **not** probability based

Three articles today

- Mercer et al (2018)
- Meng (2018)
- Valliant (2020)
- (chapter of Lohr)

What are the differences between their views?

Selection bias vs. TSE



(Groves et al. 2009, p.48)

Mercer et al (2018)

- Three conditions for inference
- Which? Discuss in pairs….

Mercer et al (2018)

- Three conditions for inference (p. 252)
  - Exchangeability
    - Do we have all relevant X covariates that (could) explain selection bias?
  - Positivity
    - Do we have all subgroups?
  - Composition
    - Can we match sample to the population?
      - Calibration or other weighting techniques

Mercer et al (2018)

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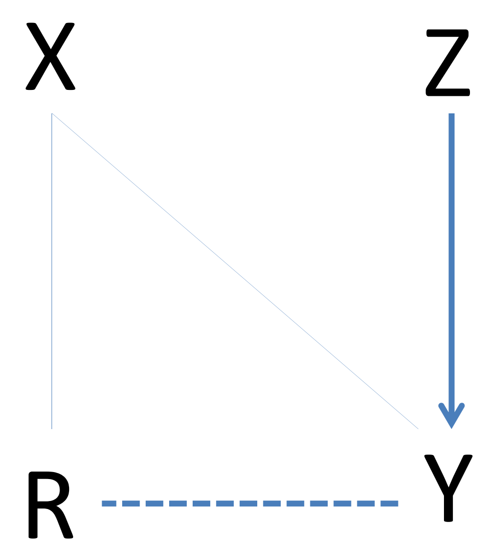

Can you apply these terms to the missing data diagrams? (2 min)

Mercer et al (2018)

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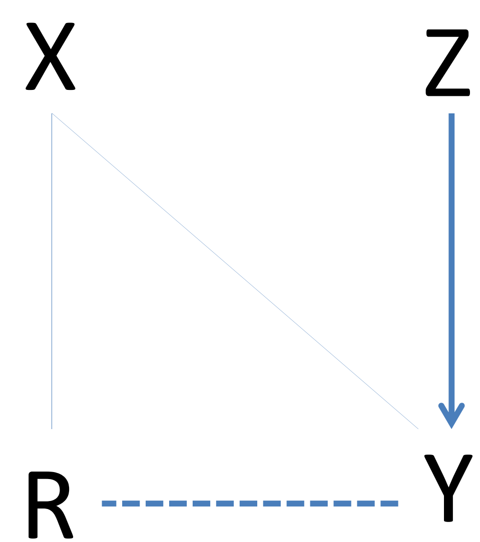
Can you apply these terms to the missing data diagrams? (2 min)



Inference: perspectives from other fields

- Natural sciences
  - Laws of nature: gravity works everywhere
  - Representation error not an issue
- 2 paradigms for inference in Social sciences:
  - We need descriptives about our population and models about the world
    - External validity
    - More sociological/epidemiological viewpoint
  - We want to test causal mechanisms
    - Internal validity
    - More psychological/medical viewpoint

Mercer et al (2018) on paradigm 1

- Causality: experiments
  - Strong ignorability (random assignment)
    - Causal effect (y) not dependent on X
      - Exchangeability and
      - Positivity
  - Transportability: composition of sample
    - Not considered an issue in inference
      - WEIRD samples

Mercer et al (2018) on paradigm 2

- Design-based surveys
  - Random samples leads to ignorability
    - Exchangeability and
    - Positivity
  - And to transportability
    - Only sampling error
- Nonresponse and coverage error
  - Weighting fixes exchangeabilty
  - Positivity assumed (subgroups are all there)

Mercer et al (2018)

- Non-prob surveys and what to do?
  - Exchangeability (we need the right X vars)
  - Positivity (we need to have all subgroups)
  - Composition
    - More a technical issue

Meng 2018 – linking data quality,quantity

- ρ(R,G): correlation between selection bias (R) and variable of interest
- **σ**(G): variation in population of variable of interest
  - E.g. If everyone votes for Clinton, no problem
- Data quantity: $\sqrt{\frac{1-f}{f}}$
  - f= sampling fraction from population.

$$\overline{G}_n - \overline{G}_N = \underbrace{\rho_{R,G}}_{\text{Data Quality}} \times \underbrace{\sqrt{\frac{1-f}{f}}}_{\text{Data Quantity}} \times \underbrace{\sigma_G}_{\text{Problem Difficulty}} .$$

  - P. 690 (eq 2.3)

Meng (2018) implications

$$\overline{G}_n - \overline{G}_N = \underbrace{\rho_{R,G}}_{\text{Data Quality}} \times \underbrace{\sqrt{\frac{1-f}{f}}}_{\text{Data Quantity}} \times \underbrace{\sigma_G}_{\text{Problem Difficulty}} .$$

- Problem difficulty is a given
- Data quantity: we never have full population
- Data quality: this matters. In Big data bias, is often larger than in small data, because data quality is a bigger problem

Meng 2018 – linking data quality,quantity

- R mechanism (response)
  - Design based
    - Sampling probabilities are known
    - Nonresponse propensities are modeled.
  - Non-probability: selection probabilities are unknown
- G: estimate of interest (e.g. a mean)
  - Y in missing data literature

$$\overline{G}_n - \overline{G}_N = \underbrace{\rho_{R,G}}_{\text{Data Quality}} \times \underbrace{\sqrt{\frac{1-f}{f}}}_{\text{Data Quantity}} \times \underbrace{\sigma_G}_{\text{Problem Difficulty}} .$$

- If correlation [R,G] = 0, no problem with any data
- If R does not vary over elements, no problem

Meng 2018 – valid inferences

When can we draw inferences for Big Data (non-probability samples)?

1. Data quality: ρ(R,G): 0
   - design based philosophy
   - Quality and quantity are independent (?)
2. Data quantity: f very large (close to 1)
   - Big data philosophy
   - Quality and quantity negatively correlated?
3. **σ**(G): very small

$$\overline{G}_n - \overline{G}_N = \underbrace{\rho_{R,G}}_{\text{Data Quality}} \times \underbrace{\sqrt{\frac{1-f}{f}}}_{\text{Data Quantity}} \times \underbrace{\sigma_G}_{\text{Problem Difficulty}} .$$

Valliant

Now to practice

- What matters in study design?
  - Exchangeability (Mercer), or $\rho(R,G)$: 0 (Meng)
    - Mercer: we need the right X variables that correct for biases between R <-> Y
    - Meng: we need to ensure the relation between R <-> is 0, and can do that by design (preferred) or having the right covariates.
  - Positivity is a design feature

Solutions - composition

- 1.Global correction methods
  - Quasi-randomisation (aka Pseudo design based estimation) (Elliott & Valliant 2017)
- 2. Estimate-specific methods
  - Superpopulation modeling (e.g. Elliott & Valliant, 2020)
    - Calibration (Little, 2004)
    - non-prob -> probability
  - Mass imputation (Yang and Kim, 2020)
- 3. Sensitivity analyses
  - Meng: for ρ(R,G)
  - Pattern mixture models for NMAR (e.g West 2020)

1. Quasi-randomisation example

non-probability survey

gender	age	education	health	Fav ice
0	34	1	5	vanilla
1	54	2	5	lemon
1	12	3	4	Choc
1	56	3	5	vanilla
0	87	4	2	strawb
1	45	5	3	zabaione
1	67	6	4	lemon
1	23	6	5	straccia
0	16	2	5	vanilla
1	24	4	4	straccia
1	56	2	4	straccia
1	78	3	2	vanilla

Taste	percentage
Vanilla	33%
Lemon	16%
Straccia	25%
Zabaione	8%
Strawberry	8%
Chocolate	8%

1. Quasi-randomisation

Large non-probability based

gender	age	education	health	Fav ice
0	34	1	5	vanilla
1	54	2	5	lemon
1	12	3	4	Choc
1	56	3	5	vanilla
0	87	4	2	strawb
1	45	5	3	zabaione
1	67	6	4	lemon
1	23	6	5	Banana
0	16	2	5	vanilla
1	24	4	4	pear
1	56	2	4	straccia
1	78	3	2	vanilla

Match on covariates

Other Probability based survey

gender	age	education	health	P(Response)
0	34	1	5	**,24**
1	54	2	5	**,44**
1	12	3	4	**.23**
1	56	3	5	**.56**
0	87	4	2	**,36**
1	45	5	3	**.56**
1	67	6	4	**.44**
1	23	6	5	**.33**
0	16	2	5	**,32**
1	24	4	4	**.43**
1	56	2	4	**.42**
1	78	3	2	**.43**

1. Quasi-randomisation

non-probability based

gender	age	education	health	P(Response)	Fav ice
0	34	1	5	,24	vanilla
1	54	2	5	,44	lemon
1	12	3	4	.23	Choc
1	56	3	5	.56	vanilla
0	87	4	2	,36	strawb
1	45	5	3	.56	zabaione
1	67	6	4	.44	lemon
1	23	6	5	.33	straccia
0	16	2	5	,32	vanilla
1	24	4	4	.43	straccia
1	56	2	4	.42	straccia
1	78	3	2	.43	vanilla

Taste	Raw percentage	Weight (1/p)
Vanilla	33%	1/.39
Lemon	16%	1/.44
Straccia	25%	1/.39
Zabaione	8%	1/.56
Strawberry	8%	1/.36
Chocolate	8%	1/.23

1. Quasi-randomisation

non-probability based

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1	24	4	4	.43	straccia
1	56	2	4	.42	straccia
1	78	3	2	.43	vanilla

Taste	Raw percentage	Weight (1/p)	Weighted %
Vanilla	33%	1/.39	33%
Lemon	16%	1/.44	14%
Straccia	25%	1/.39	24%
Zabaione	8%	1/.56	6%
Strawberry	8%	1/.36	9%
Chocolate	8%	1/.23	14%
Average		.40	

2. Estimate specific methods

2.1 Calibration (Little, 2004)

2.2 Superpopulation modeling (e.g. Elliott & Valliant, 2020)

2.3 Mass imputation (Yang and Kim, 2020)

2.1 traditional calibration

- Ask potential X variables in non-prob survey
- Weight to population characteristics
  - Every cell of cross-table: calibration
  - Margins of cross-table: raking
- Problem:
  - Lack of X variables
  - Small se., but still bias
  - Use same NR methods as earlier in course

2.1 Calibration for non-prob

- Conduct a large nonprobability sample
  - Small s.e., large bias(?)
- Conduct a small probability based sample
  - Large s.e., small bias
- Weight non-probabity based -> prob based
  - Small bias (?), small s.e.
  - Lots of X vars, because you have control
  - Use same NR methods as earlier in course
  - Expensive, time consuming

2.1 Little (2004) Calibrated bayes

- Model based (regression) vs. design based
- Solution:
  - Use a model that includes design-based features
    - E.g. A fixed-effects regression model to deal with clustering
  - Bayesian modeling for variance estimation
    - Priors (often uninformative)
    - Posteriors for variance estimation
    - Remember convergence, traceplots,, and how imputations are generated in Mice?

2.2 Superpopulation modeling

- Non-probability based surveys don't use sample frames
  - We can rake or calibrate to population statistics: gender, age, region, ethnicity, income, etc…
- Idea is to collect more population statistics X
  - Netflix subscriptions, voting Behavior, customer of a company, member of organization, ….

2.2 Superpopulation modeling

- Approach by Mercer (2018)
  - Netflix subscription? Voting Behavior, customer of a company, member of organization
- i.e. More elaborate weighting

Topics and corresponding benchmarks

Topic	Benchmark
Civic engagement	How often talks with neighbors
	Trusts neighbors
	Participated in a school group, neighborhood, or community association
	Volunteered in past year
Family	Marital status
	Presence of children in household
	Household size
Financial	Employment status
	Home ownership
	Family income
	Household member received food stamps
	Health insurance
Personal	Lived in house or apartment one year ago
	Active duty military service
	U.S. citizenship
	Gun ownership
	Smoking
	Food allergies
Political engagement	Voted in 2012
	Voted in 2014
	Contacted or visited a public official in past year
Technology	Tablet or e-reader use
	Texting or instant messaging
	Social networking

Note: See Appendix D for the source of each benchmark, the question text, the response categories, the benchmark estimate, and additional notes.
"For Weighting Online Opt-In Samples, What Matters Most?"
PEW RESEARCH CENTER

Source:https://www.pewresearch.org/methods/2018/01/26/reducing-bias-on-benchmarks/

2.3 Mass imputation

- We know the population distribution:
  - Gender, age, education, income, region, etc.
- In some cases we have frame data
- Why not impute **the whole population**?

Mass imputation

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  - Gender, age, education, income, region, etc.
- In some cases we have frame data
- Why not impute the whole population?

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0	16	2	5	vanilla
1	24	4	4	straccia
1	56	2	4	straccia
1	78	3	2	???
1	56	4	5	???
….	…	…	..	???
You have X million rows, only X thousand of thesehave Y				

Double-robust estimators

- Combine
- Example:
  - 1 quasi-randomization
    - Estimate response propensities
  - 2. Calibration (superpopulation)

Valliant (2020) simulation

- Tried out different estimation methods
  - Different methods
  - Variance estimation
    - Jackknife???

- Result:
  - no method works perfectly
  - Double robust methods generally best

3. Sensitivity analyses

- Cf Meng (2018)
- Pattern Mixture modeling
  - Enter an additional parameter in the model (e.g a selection bias parameter)
  - This parameter can take different forms
    - Covary with Y and all other parameters
  - Simulate
  - Similar to Heckman selection models.

See Andridge, R. R., & Little, R. J. (2011). Proxy pattern-mixture analysis for survey nonresponse. *Journal of Official Statistics*, *27*(2), 153.

See West, B. T., & Andridge, R. R. (2023). Evaluating Pre-Election Polling Estimates Using a New Measure of Non-Ignorable Selection Bias. *Public Opinion Quarterly*, nfad018.

Exercise (class + THE)

- Competition!
  - Three non-probability samples
  - Sample size 30.000
  - June/July 2016
  - You get 15.000 cases
  - And a superpopulation dataset (Mercer, Lau & Kennedy, 2018)
- Goal: adjust your sample:
  - Choose your variables
  - Calibrate, rake, impute?
- Prize: eternal fame and a survey related present

Next week

- Lecture on “designed big data”
- Keep working on your group assignments
- In two weeks -> final meeting
  - Prepare an online document that should be readable in 6 minutes
    - Video, wiki, website….
  - Send around by December 9, 17:00
  - Review 1 presentation of other group and prepare 3 questions.

More reading?

- Andridge, R. R., & Little, R. J. (2011). Proxy pattern-mixture analysis for survey nonresponse. *Journal of Official Statistics*, *27*(2), 153.
- Chen, S., Yang, S., & Kim, J. K. (2020). Nonparametric Mass Imputation for Data Integration. *Journal of Survey Statistics and Methodology*.
- Elliott, M. R., & Valliant, R. (2017). Inference for nonprobability samples. *Statistical Science*, *32*(2), 249-264.
- Kim, J. K., Park, S., Chen, Y., & Wu, C. (2018). Combining non-probability and probability survey samples through mass imputation. *arXiv preprint arXiv:1812.10694*.
- Rafei, A., Flannagan, C. A., & Elliott, M. R. (2020). Big Data for Finite Population Inference: Applying Quasi-Random Approaches to Naturalistic Driving Data Using Bayesian Additive Regression Trees. *Journal of Survey Statistics and Methodology*, *8*(1), 148-180.
- Valliant, R. (2020). Comparing alternatives for estimation from nonprobability samples. *Journal of Survey Statistics and Methodology*, *8*(2), 231-263.
- West, B. T., & Andridge, R. R. (2023). Evaluating Pre-Election Polling Estimates Using a New Measure of Non-Ignorable Selection Bias. *Public Opinion Quarterly*, nfad018.