Probability and non-probability sampling

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	Sampling	Interviews	Data environment
1st era	Area probability	Face-to-face	Stand-alone
2nd era	Random digital dial probability	Telephone	Stand-alone
3rd era	Non-probability	Computer-administered	Linked

Probability Samples

$$P(u_i) = \frac{p_i}{(N-1)\cdots(N-n+1)}\binom{N-1}{n-1}(n-1)!$$
$$+ \sum_{j\neq i}^{N} \frac{p_j}{(N-1)\cdots(N-n+1)}\binom{N-1}{n-1}(n-1)!\,\frac{n-1}{N-1},$$

which upon simplification becomes

$$(19) \qquad P(u_i) = \frac{N-n}{N-1}p_i + \frac{n-1}{N-1}, \qquad (i = 1, 2, \cdots, N).$$

Similarly, it may be shown that for this case

$$(20) \qquad P(u_iu_j) = \frac{n-1}{N-1}\left[\frac{N-n}{N-2}(p_i+p_j) + \frac{n-2}{N-2}\right],$$
$$(i \neq j: i, j = 1, 2, \cdots, N).$$

Non-Probability Samples

http://www.chicagotribune.com/news/nationworld/politics/chi-chicagodays-deweydefeats-story-story.html

Probability Samples	Non-Probability Samples
unknown sampling process weighting based on unverifiable assumptions	unknown sampling process weighting based on unverifiable assumptions

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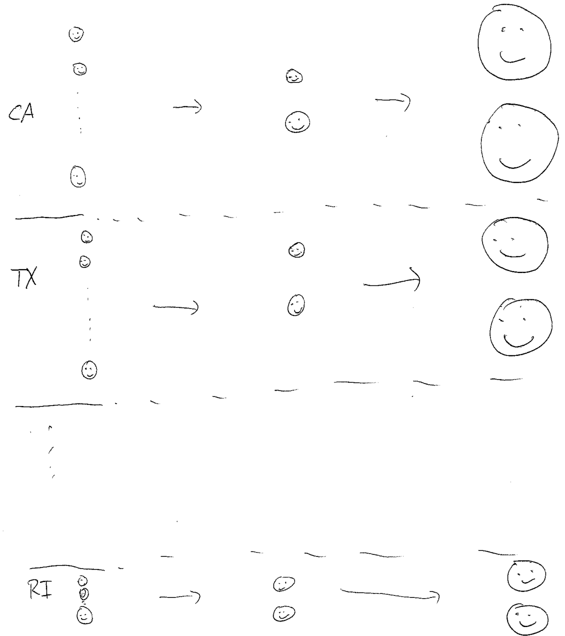
- Not all probability samples look like miniature versions of the population
- But, with appropriate weighting, probability samples can yield unbiased estimates of the frame population

Main insight from probability samples:

- How you collect your data impacts how you make inference
- Focus on properties of estimators not properties samples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$$\hat{\bar{y}} = \frac{\sum_{i \in s} y_i / \pi_i}{N}$$

where π_i is person i's probability of inclusion

Sometimes called:

- Horvitz-Thompson estimator
- π estimator

Inference from probability samples in theory

$$\left.\begin{array}{r}\text{respondents}\\ \text{known information about sampling}\end{array}\right\}\ \text{estimates}$$

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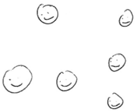

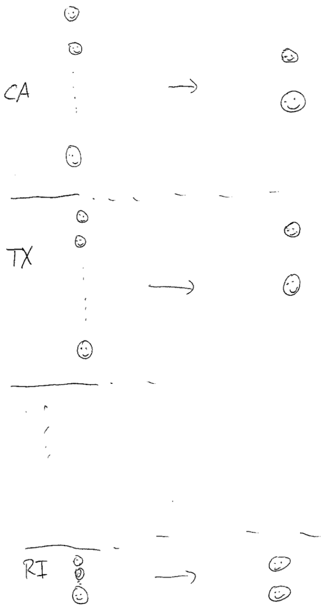
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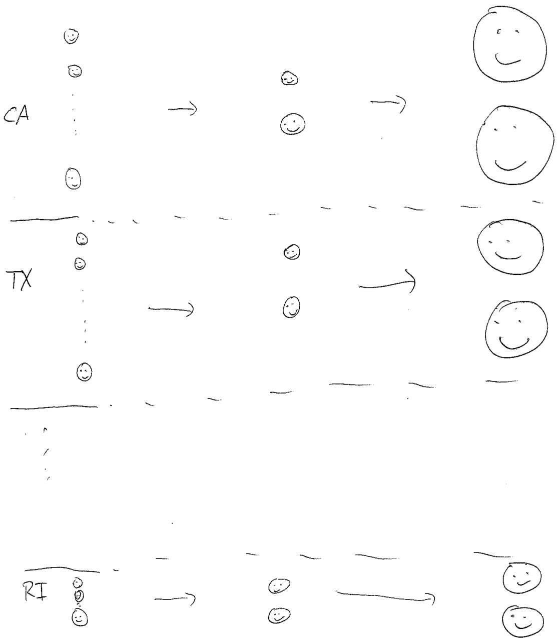
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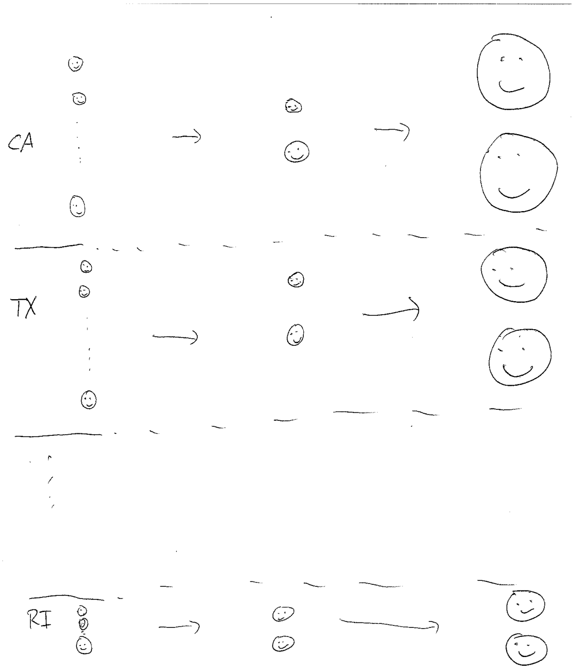
$$\hat{\bar{y}} = \frac{\sum_{i \in s} y_i / \hat{\pi}_i}{N}$$

where $\hat{\pi}_i = \frac{n_g}{N_g} \quad \forall \quad i \in g$ (estimated probability of inclusion)

Requires:

- auxiliary information (N_g)
- ability to place respondents in groups
- assumptions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- If external information is incorrect or used improperly then you can make things worse (but it usually seems to make things better)

Imagine that you want to estimate the average height of Princeton students.

- Assume 50% are male and 50% are female
- You stand outside Peretsman Scully Hall and recruit 60 Princeton students
- Males (n= 20): Average height: 180cm
- Females (n=40): Average heigh: 170cm

What is your estimate of the average height? (think-pair-share)

- sample mean $= 173.3$cm $\left(\frac{180*20+170*40}{20+40}\right)$

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How could this go wrong?

Imagine that you want to estimate the average height of Princeton students.

- Assume 50% male and 50% female; assume 25% first-year; 25% sophomore; 25% junior; 25% senior; assume gender and class year are independent
- Your (relatively) sample does not include any female seniors. How could you use the same trick?

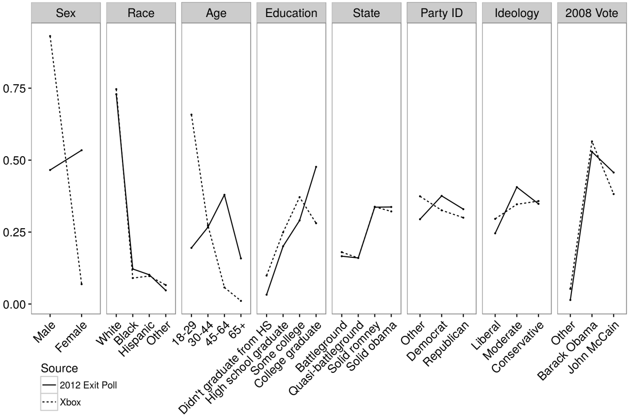
Forecasting elections with non-representative polls

Wei Wang[a,*], David Rothschild[b], Sharad Goel[b], Andrew Gelman[a,c]

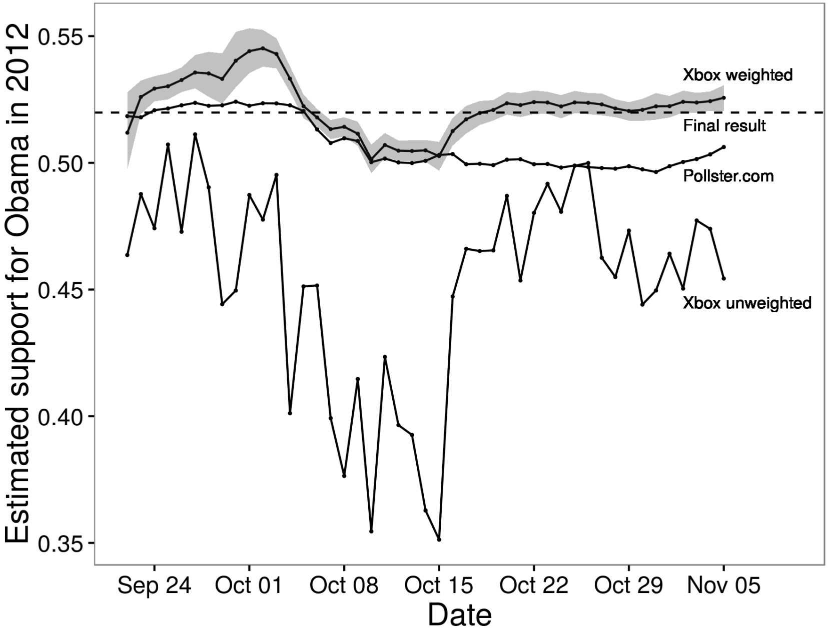
[a] *Department of Statistics, Columbia University, New York, NY, USA*

[b] *Microsoft Research, New York, NY, USA*

[c] *Department of Political Science, Columbia University, New York, NY, USA*



- about 750,000 interviews
- about 350,000 unique respondents



Estimated support for Obama in 2012
0.55
0.50
0.45
0.40
0.35
Xbox weighted
Final result
Pollster.com
Xbox unweighted
Sep 24
Oct 01
Oct 08
Oct 15
Oct 22
Oct 29
Nov 05
Date

Statistical Modeling, Causal Inference, and Social Science

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Nate Silver's website »

President of American Association of Buggy-Whip Manufacturers takes a strong stand against internal combustion engine, argues that the so-called "automobile" has "little grounding in theory" and that "results can vary widely based on the particular fuel that is used"

Posted by Andrew on 6 August 2014, 2:45 pm

http://andrewgelman.com/2014/08/06/president-american-association-buggy-whip-manufacturers-takes-strong-stand-internal-combustion-engine-argues-called-automobile-little-grounding-theory/

Online, Opt-in Surveys: Fast and Cheap, but are they Accurate?

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- there are also non-probability sampling methods that focus on sampling rather than weighting (e.g., quota-sampling, sample matching)

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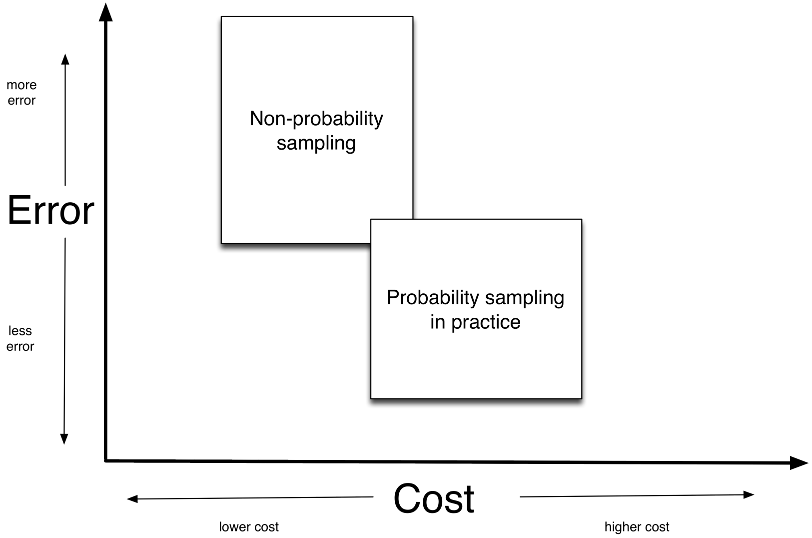
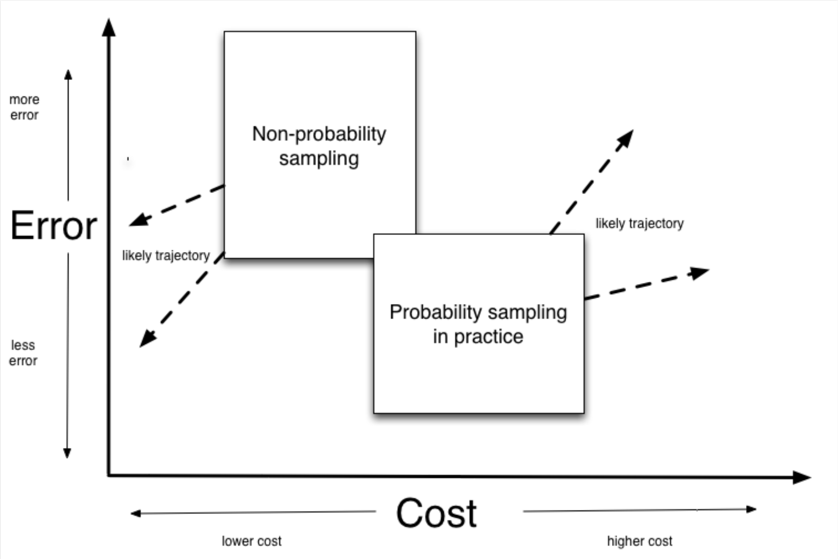
- the performance of Mr. P. (and related methods) is an empirical question
- related methods can be applied to big data and experiments
- there are also non-probability sampling methods that focus on sampling rather than weighting (e.g., quota-sampling, sample matching)
- we should not let what happened in 1948 prevent us from trying new things today


Error
more
error
less
error
Non-probability
sampling
Probability sampling
in practice
Cost
lower cost
higher cost



more error
Error
less error
Non-probability sampling
likely trajectory
likely trajectory
Probability sampling in practice
Cost
lower cost
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Wrap-up:

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- Key to making good estimates is for estimation process to account for the sampling process
- There is not a bright-line difference between probability sampling in practice and non-probability sampling
- To learn more: Lohr (2009) or Sandal et al (2013)