Introduction to group activity

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Summer Institute in Computational Social Science
June 21, 2018

The Summer Institute in Computational Social Science is supported by grants from the Russell Sage Foundation and the Alfred P. Sloan Foundation.

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

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https://5harad.com/papers/dirtysurveys.pdf

ABSTRACT

It is increasingly common for government and industry organizations to conduct online, opt-in surveys, in part because they are typically fast, inexpensive, and convenient. Online polls, however, attract a non-representative set of respondents, and so it is unclear whether results from such surveys generalize to the broader population. These non-representative surveys stand in contrast to probability-based sampling methods, such as random-digit dialing (RDD) of phones, which are a staple of traditional survey research. Here we investigate the accuracy of non-representative data by administering an online, fully opt-in poll of social and political attitudes. Our survey consisted of 49 multiple-choice attitudinal questions drawn from the probability-based, in-person 2012 General Social Survey (GSS) and select RDD phone surveys by the Pew Research Center. To correct for the inherent biases of non-representative data, we statistically adjust estimates via model-based poststratification, a classic statistical tool but one that is only infrequently used for bias correction. Our online survey took less than one-twentieth the time and money of traditional RDD polling, and less than one-hundredth the time and money of GSS polling. After statistical correction, we find the median absolute difference between the non-probability-based online survey and the probability-based GSS and Pew studies is 7 percentage points. This difference is considerably larger than if the surveys were all perfect simple random samples drawn from the same population; the gap, however, is comparable to that between the GSS and Pew estimates themselves. Our results suggest that with proper statistical adjustment, online, non-representative surveys are a valuable tool for practitioners in varied domains.

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- De-identify and open-source data

This activity will give you practice:

- Designing questionnaires

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- Collecting survey data
- Analyzing survey data (data wrangling and post-stratification)
- Working with Amazon Mechanical Turk
- Archiving data for other researchers

Remember: This is a learning activity so try whatever you want.

Our recommended work flow:

- Create survey on Google Forms (we have a template)
- Deploy to MTurk
- Take a break

Allison Morgan
@alliecmorgan

Following

Just wrapped up the first week of #SICSS2017! On Thursday, we got 50+ online survey responses, all while frolicking in a fountain.

3:24 PM - 24 Jun 2017

Our recommended work flow:

- Create survey on Google Forms
- Deploy to MTurk
- Take a break
- Validate and pay workers
- Analyze the much larger sample that we have collected for you

A quick and dirty tour of the post-stratification methods we will use

Cell-based Poststratification

Let's split the sample into H mutually exclusive and exhaustive groups.

$$\hat{\bar{y}}_{post} = \sum_{h=1}^{H} \frac{N_h}{N} \hat{\bar{y}}_h$$

where

- N: size of the population
- N_h: size of group h
- $\hat{\bar{y}}_h$: estimated average outcome for group h

Roughly, we are producing estimates for each group and then putting them together in the right way.

Cell-based Poststratification

Assumptions:

- The realized sample s is partitioned into H groups, $s_1, s_2, \ldots s_H$
- Given s, all elements in s_k are assumed to have the same response probability; different groups can have different response probabilities
- Equivalent to data is missing completely at random (MCAR) within each group
- "Response Homogeneity Group Model" (RHG Model), see Sarndal et al. (1992) Sec 15.6.2 ("A Useful Response Model")

If RHG model holds (and some other minor technical conditions), then the poststratification estimator is unbiased. See Sarndal et al. (1992) Result 15.6.1

Bias of cell-based poststratification estimator from non-response

If RHG does not hold and if the original sample is simple random sampling without replacement, then (Bethlehem, Cobben, and Schouten 2011, sec. 8.2.1):

$$bias(\hat{\bar{y}}_{post}) = \frac{1}{N}\sum_{h=1}^{H} \frac{cor(\phi_i, y_i)^{(h)} S(\phi_i)^{(h)} S(y_i)^{(h)}}{\bar{\phi}^{(h)}}$$

So, how should we create the H groups?

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So, how should we create the H groups?

- form homogeneous groups where there is little variation in response propensity ($S(\phi_i)^{(h)} \approx 0$) and the outcome ($S(y_i)^{(h)} \approx 0$)
- form groups where the people that you see are like the people that you don't see ($cor(\phi_i, y_i)^{(h)} \approx 0$)

In practice this can be difficult because you want to form many groups, but then you have noisy estimates for each group.

$$\hat{\hat{y}}_{post} = \sum_{h=1}^{H} \frac{N_h}{N} \hat{\hat{y}}_h$$

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Use this estimator in three steps:

1. Chop up the sample into groups

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Use this estimator in three steps:

1. Chop up the sample into groups
2. Estimate the mean in each group
3. Combine the estimates for each group into an overall estimate

Note:

- Horvitz-Thompson estimation is individual-based weight
- Poststratification can better be understood as a group-based weight

Three increasingly sophisticated ways to make group estimate $\hat{\bar{y}}_h$

- cell-based poststratification
- model-based poststratification
- multilevel regression postratification (Mr. P)

Data

- Our survey data comes from a survey of 684 people on MTurk collected in less than a week ago
- We will compare to high-quality telephone surveys from the Pew Research Center
- To poststratify our survey data, we will use data from the Census Bureau about the population of the US

Data

Example questions (after question wrangling):

- If you were making up the budget for the federal government this year would you increase funding for scientific research?

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- If you were making up the budget for the federal government this year would you increase funding for scientific research?
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- All in all, are you satisfied with the way that things are going in this country today?

Data

Example questions (after question wrangling):

- If you were making up the budget for the federal government this year would you increase funding for scientific research?
- Do you not smoke cigarettes at all?
- All in all, are you satisfied with the way that things are going in this country today?

We use multiple questions because estimates are also a property of a question not just a sample.

Simple cell-based poststratification

Let's do lots of groups.

- gender (2 groups)
- age (4 groups)
- race (5 groups)
- region (4 groups)
- Makes 160 ($2 \times 4 \times 5 \times 4$) groups

Simple cell-based poststratification

$$\hat{\bar{y}}_h = \frac{\sum_{i \in h} y_i}{n_h}$$

h is a group described by a unique combination of gender (2 groups) $\times$ age (4 groups) $\times$ race (5 groups) $\times$ region (4 groups)

Cell-based poststratification

- We can't make an estimate for each group. For example, we don't have any female, 65+, Hispanic living in the South.

Cell-based poststratification

- We can't make an estimate for each group. For example, we don't have any female, 65+, Hispanic living in the South.
- This problem can arise if you have too many cell. We have a crude work-around in the code we provide.

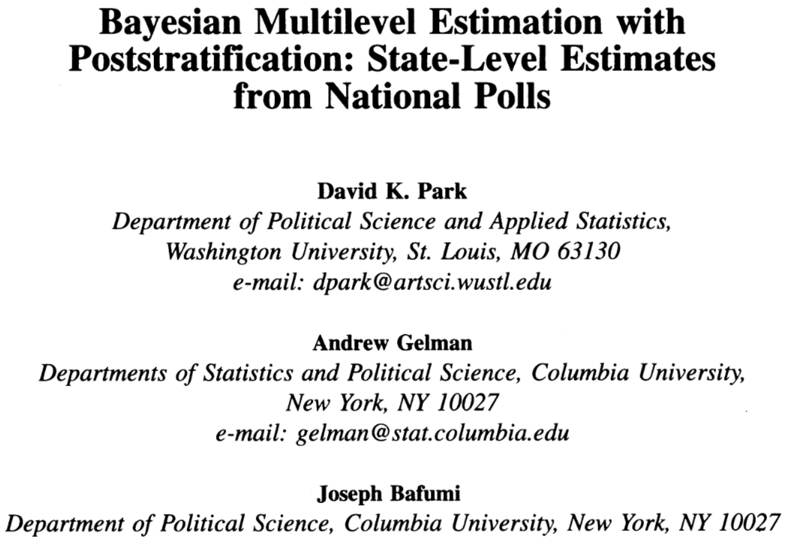
Model-based poststratification

$$\hat{\hat{y}}_{post} = \sum_{h=1}^{H} \frac{N_h}{N} \hat{\hat{y}}_h$$

where $\hat{\hat{y}}_h$ comes from

$$\begin{aligned}
Pr(y_i = 1) = logit^{-1}(\beta_0 + \\
\beta_{male} \cdot male_i + \\
\beta_{30-49} \cdot 30-49_i + \beta_{50-64} \cdot 50-64_i + \beta_{65+} \cdot 65_i + \\
\beta_{afr-am} \cdot afam_i + \beta_{as-am} \cdot asam_i + \beta_{hispanic} \cdot hisp_i + \beta_{other} \cdot other_i + \\
\beta_{midwest} \cdot midwest_i + \beta_{south} \cdot south_i + \beta_{west} \cdot west_i)
\end{aligned}$$

Mr. P


Bayesian Multilevel Estimation with Poststratification: State-Level Estimates from National Polls

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Mr. P

We fit a multilevel logistic regression model for the mean of a binary response variable conditional on poststratification cells. This approach combines the modeling approach often used in small-area estimation with the population information used in poststratification (see Gelman and Little 1997, *Survey Methodology* 23:127–135). To validate the method, we apply it to U.S. preelection polls for 1988 and 1992, poststratified by state, region, and the usual demographic variables. We evaluate the model by comparing it to state-level election outcomes. The multilevel model outperforms more commonly used models in political science. We envision the most important usage of this method to be not forecasting elections but estimating public opinion on a variety of issues at the state level.

`https://www.jstor.org/stable/25791784`
See also Gelman and Hill (2007), Chapter 14 ("Multilevel logistic regression")

Mr. P.

$\hat{\bar{y}}_h$ comes from

$$
\begin{aligned}
Pr(y_i = 1) = logit^{-1}(\beta_0 + \\
\beta_{male} \cdot male_i + \\
\alpha^{age}_{k[i]} + \\
\alpha^{race}_{k[i]} + \\
\alpha^{region}_{k[i]})
\end{aligned}
$$

$$
\begin{aligned}
\alpha^{age}_k &\sim N(0, \sigma^2_{age}) \text{ for } k = 1, \dots, 4 \\
\alpha^{race}_k &\sim N(0, \sigma^2_{race}) \text{ for } k = 1, \dots, 5 \\
\alpha^{region}_k &\sim N(0, \sigma^2_{region}) \text{ for } k = 1, \dots, 4
\end{aligned}
$$

Priors determined by RStanarm (`https://cran.r-project.org/web/packages/rstanarm/vignettes/priors.html`)

Notes

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- These techniques is widely used by modern pollsters (e.g., YouGov) and political scientists
- These same techniques can be for small-area estimation

To learn more about Mr. P.

Generally optimistic:

- Park, Gelman, and Bafumi. 2004. "Bayesian Multilevel Estimation with Poststratification: State-Level Estimates from National Polls." *Political Analysis*.
- Lax and Phillips. 2009. "How should we estimate public opinion in the states?" *American Journal of Political Science*.
- Ghitza and Gelman. 2013. "Deep Interactions with MRP: Election Turnout and Voting Patterns Among Small Electoral Subgroups." *American Journal of Political Science*.
- Warshaw and Rodden. 2012. "How should we measure district-level public opinion on individual issues?" *Journal of Politics*.
- Downs et al. 2018. "Multilevel Regression and Poststratification: A Modelling Approach to Estimating Population Quantities From Highly Selected Survey Samples." *American Journal of Epidemiology*.

Generally cautious:

- Buttice and Highton. 2013. "How Does Multilevel Regression and Poststratification Perform with Conventional National Surveys?" *Political Analysis*.

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