Survey weighting and hierarchical regression

Andrew Gelman

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- State-level opinions from national polls
- Our struggle with the Social Indicators Survey
- Weighting from a hierarchical Bayes perspective

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Survey weighting is a mess

- Using weights
  - Weighted mean: $\bar{y}_w = \sum_{i=1}^{n} w_i y_i \Big/ \sum_{i=1}^{n} w_i$
  - Estimating a ratio: $r_w = \sum_{i=1}^{n} w_i y_i \Big/ \sum_{i=1}^{n} w_i x_i$
  - Estimating anything more complicated: ???
- Regression modeling as an alternative

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Where do weights come from?

- Survey weights are not inverse probabilities of selection
- Simple theoretical example
- CBS/New York Times pre-election polls
- NYC Social Indicators Survey

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Simple theoretical example

- Survey of a population with 52% women, 48% men
- Simple random sampling, $n = 100$
  - SRS 1: 52 women, 48 men. Weights are $w_i = 1$ for everyone
  - SRS 2: 60 women, 40 men. Weights are $w_i = \frac{52}{60}$ for women, $\frac{48}{40}$ for men
- We know the population proportions, so the selection probabilities are irrelevant
- Weights depend on the entire survey; the (y_i, w_i) paradigm is inappropriate

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6140	cbsnyt	NA	7	3	1	2	923
6141	cbsnyt	1	39	4	2	2	558
6142	cbsnyt	0	31	2	4	1	448
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- Telephone survey every 2 years of NYC families
- Administered by Columbia Univ School of Social Work
- Questions such as, "Do you rate the schools as poor, fair, good, or very good?"
- Weighting to match Current Population Survey: #adults and children in family, marital status, ethnicity, age, education
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Estimating national opinion trends

Estimating state-by-state opinion trends

- Goal: estimating time series within each state
- One poll at a time: small-area estimation
- It works! Validated for pre-election polls
- Combining surveys: hierarchical model for parallel time series
- Straightforward hierarchical modeling + poststratification

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Poststratification for the CBS polls

- We don't actually use the "weights"
- We model y conditional on the variables used in the weighting
- These define poststratification cells $j = 1, \ldots, J = 3264$
- $2 \times 2 \times 4 \times 4 \times 51$: sex $\times$ ethnicity $\times$ age $\times$ education $\times$ state
- Poststratified average, $\theta = \frac{\sum_{j=1}^{J} N_j \theta_j}{\sum_{j=1}^{J} N_j}$
- N_j = population in cell j (from Census)
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- Hierarchical model for the data
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- Goal is to estimate $\bar{Y}^{2001} - \bar{Y}^{1999}$, for various survey responses y
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  - Fit regression, look at coefficient for the "2001" indicator

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- Illustration with a sequence of regressions:
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  - also black/white
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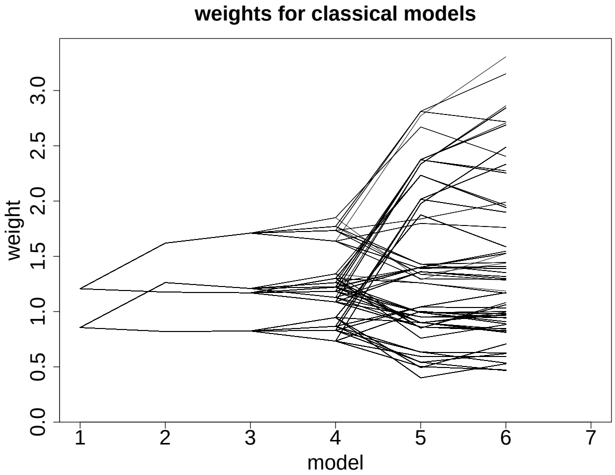

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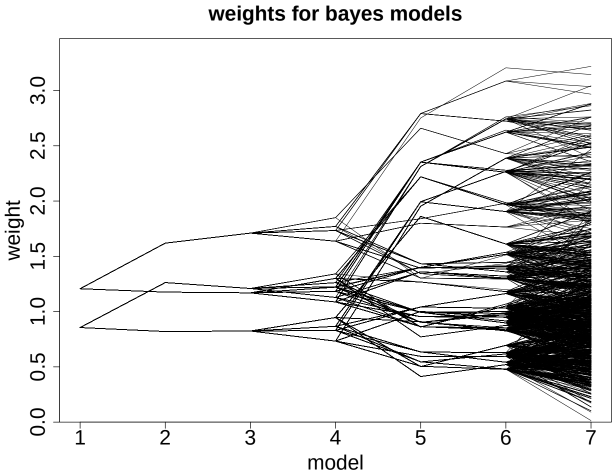

Hierarchical models and smoothing of weights

- Exchangeable normal model on J categories
  - Raw weights $w_i \propto N_j/n_j$ in cell j
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