What to do about Biases in Survey Research

Gary King

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September 6, 2007

Readings

- Gary King and Jonathan Wand. "Comparing Incomparable Survey Responses: Evaluating and Selecting Anchoring Vignettes," *Political Analysis*, 15, 1 (Winter, 2007): 46–66.

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- Gary King; Christopher J.L. Murray; Joshua A. Salomon; and Ajay Tandon. "Enhancing the Validity and Cross-cultural Comparability of Measurement in Survey Research," *American Political Science Review*, Vol. 98, No. 1 (February, 2004): 191–207.

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- Gary King; Christopher J.L. Murray; Joshua A. Salomon; and Ajay Tandon. "Enhancing the Validity and Cross-cultural Comparability of Measurement in Survey Research," *American Political Science Review*, Vol. 98, No. 1 (February, 2004): 191–207.
- Papers, FAQ, examples, software, conferences, videos: http://GKing.Harvard.edu/vign

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Examples of the Problem

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Presidential Approval: the longest public opinion time series

- On 9/10/2001, 55% of Americans approved of the way George W. Bush was "handling his job as president".
- The next day — which the president spent in hiding — 90% approved.
- Was this massive opinion change, or was the same question interpreted differently?

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- The facts of the case seemed clear
- Did he do it? Whites: 62% say "yes". Blacks: 14% say "yes".
- Did black and white Americans have genuinely opposing views about whether Simpson committed murder, or did the two groups interpret the same survey question differently?

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- Is the young woman less healthy or are the two interpreting the same question differently?
- In some countries, responses to this survey question correlate negatively with objective measures of health status (Sen, 2002).

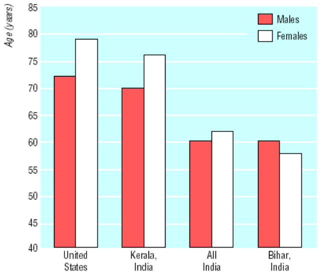

Fig 1 Life expectancy among males and females in India compared with United States, mid-1990s[7 8]

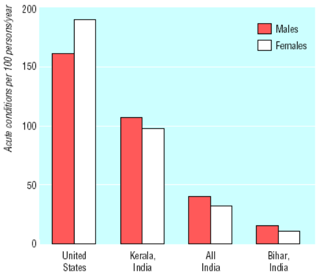

Fig 2 Incidence of reported morbidity in India, mid-1970s, compared with United States, mid-1980s[8 9]

Anchoring Vignettes & Self-Assessments: Political Efficacy (about voting)

How much say [does 'name' / do you] have in getting the government to address issues that interest [him / her / you]?

(a) Unlimited say, (b) A lot of say, (c) Some say, (d) Little say, (e) No say at all

Anchoring Vignettes & Self-Assessments: Political Efficacy (about voting)

- "[Alison] lacks clean drinking water. She and her neighbors are supporting an opposition candidate in the forthcoming elections that has promised to address the issue. It appears that so many people in her area feel the same way that the opposition candidate will defeat the incumbent representative."

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- "[Moses] lacks clean drinking water. He would like to change this, but he can't vote, and feels that no one in the government cares about this issue. So he suffers in silence, hoping something will be done in the future."

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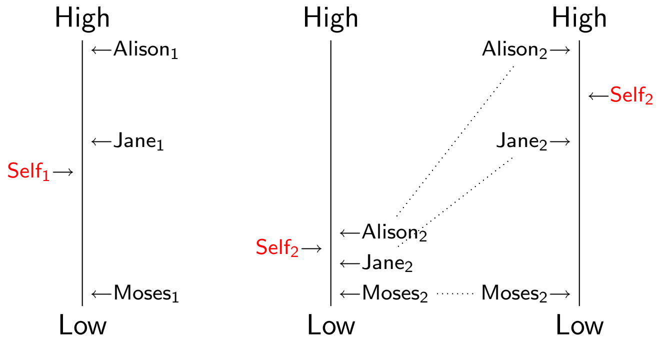
Does R_1 or R_2 have More Political Efficacy?



- The only reason for vignette assessments to change over respondents is DIF
- Assumption holds because investigator creates the anchors (Alison, Jane, Moses)
- Our simple (nonparametric) method works this way.

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- (Our parametric method doesn't)

Comparing China and Mexico

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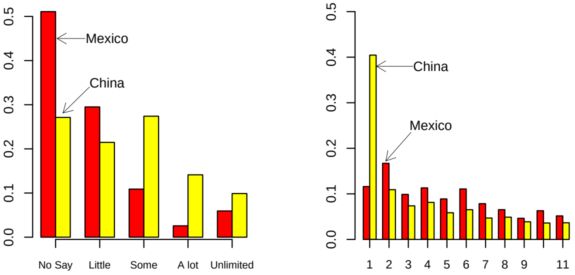
Mexico

Opposition leader Vicente Fox elected President.
71-year rule of PRI party ends.
Peaceful transition of power begins.

Plenty of political efficacy

China: How much say do you have in getting the government to address issues that interest you?

Nonparametric Estimates of Political Efficacy



- The left graph is a histogram of the observed categorical self-assessments.
- The right graph is a histogram of C, our nonparametric DIF-corrected estimate of the same distribution.

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3. In other words: we allow response-category DIF but assume stem question equivalence.

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Example	Survey Responses	1: $y < z_1$	2: $y = z_1$	3: $z_1 < y < z_2$	4: $y = z_2$	5: $y > z_2$	C

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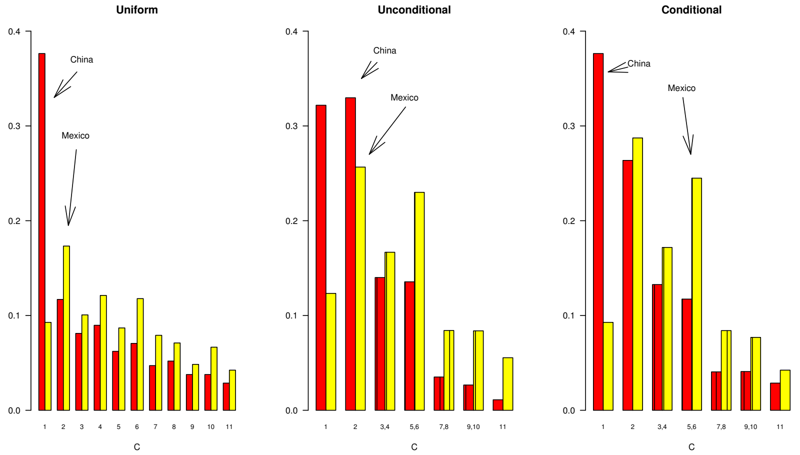
- Useful for vignettes; also useful for survey questions that allow ranges of responses

Improved Efficiency in Practice



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    - Choose vignettes for the main survey based on H and cost of survey questions.

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- Only question remaining: How do we calculate entropy when C is not a scalar?

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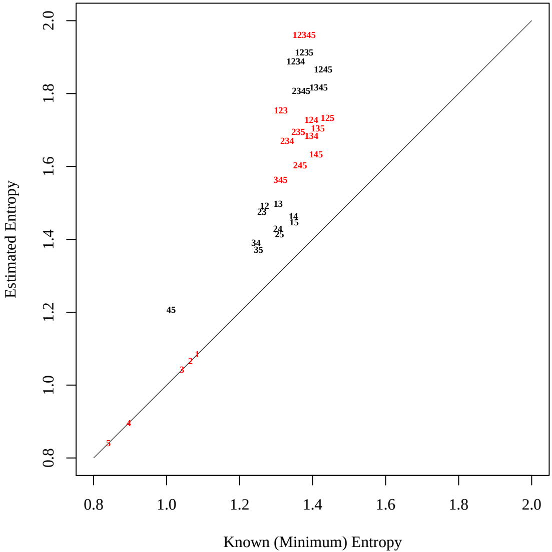
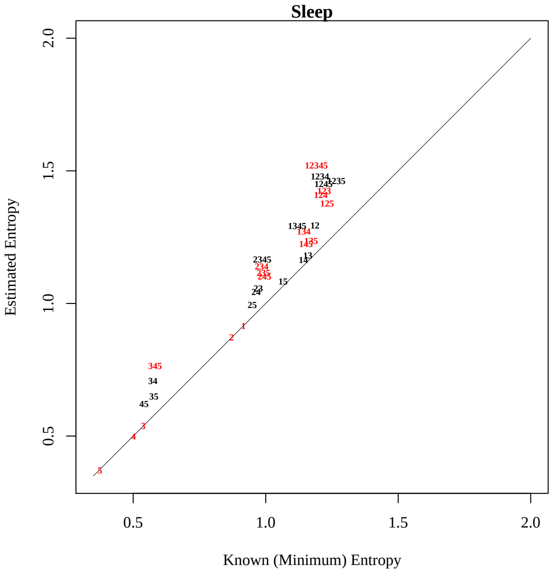
- Result is easy to use: one measure indicating information in survey question and vignettes

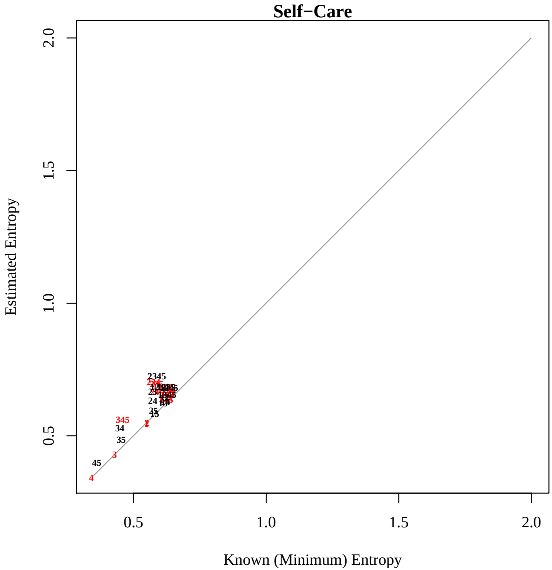
Political Efficacy (Mex & China)



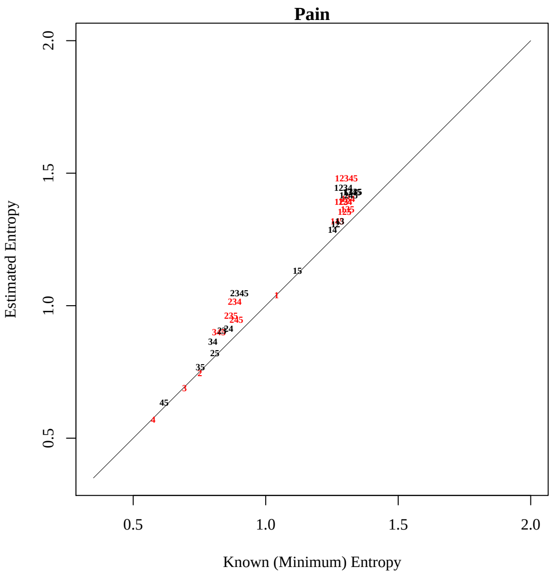
One vignette can be better than three: Sleep (China)



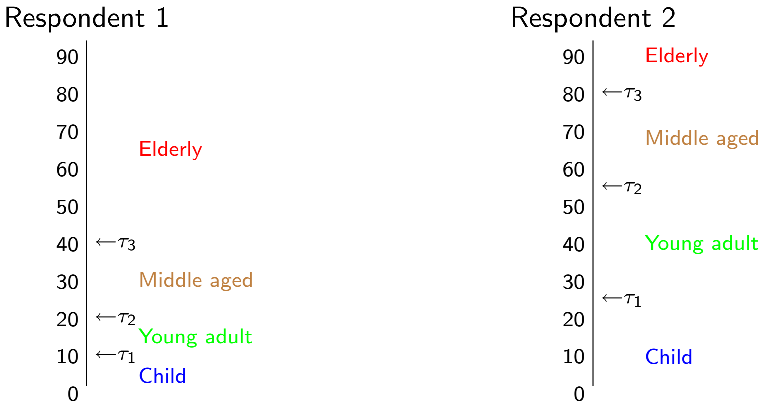
Some vignette sets are uninformative: Self-Care (China)



Some covariates are unhelpful: Pain (China)



Categorizing Years of Age



- If thresholds vary, categorical answers are meaningless.
- Our parametric model works by estimating the thresholds.
- Vignettes provide identifying information for the τ's.

Self-Assessments v. Medical Tests

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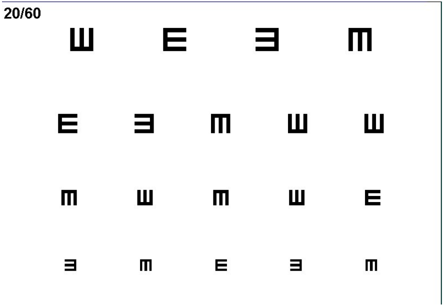
The Snellen Eye Chart Test:



Fixing DIF in Self-Assessments of Visual (Non)acuity

	Snellen Eye Chart		Ordinal Probit		Chopit	
	Mean	(s.e.)	μ	(s.e.)	μ	(s.e.)
Slovakia	8.006	(.272)	.660	(.127)	.286	(.129)
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For More Information

http://GKing.Harvard.edu/vign

Includes:

- Academic papers
- Anchoring vignette examples by researchers in many fields,
- Frequently asked questions,
- Videos
- Conferences
- Statistical software

Anchoring Vignettes Measure DIF, not Vision: A Heuristic

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   - Vignettes estimate: D_v (which may differ from D_s)
   - Vignette-corrected self-assessments: $(\mu + D_s) - D_v = \mu + (D_s - D_v)$
   - Which is larger?
     (a) Self-assessment bias: D_s
     (b) Vignette-corrected self-assessment bias: $(D_s - D_v)$
   - Since the same person generates both D_s and D_v, (b) will usually be smaller.
3. Conclusion: Anchoring vignettes will usually help reduce bias. They will sometimes not make a difference. They will almost never exacerbate bias.

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The Likelihood Function: Self-Assessment Component

If η_i were observed:

$$\mathrm{P}(y_i|\eta_i) = \prod_{i=1}^{n}\prod_{s=1}^{S}\prod_{k=1}^{K_s}\left[F(\tau_{is}^{k}|X_i\beta+\eta_i,1) - F(\tau_{is}^{k-1}|X_i\beta+\eta_i,1)\right]^{\mathbf{1}(y_{is}=k)}$$

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$$L_s(\beta,\omega^2,\gamma|y) \propto \prod_{i=1}^{n}\int_{-\infty}^{\infty}\prod_{s=1}^{S}\prod_{k=1}^{K_s}\left[F(\tau_{is}^{k}|X_i\beta+\eta,\,1) - F(\tau_{is}^{k-1}|X_i\beta+\eta,\,1)\right]^{\mathbf{1}(y_{is}=k)} N(\eta|0,\omega^2)d\eta$$

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In the special case where $S = 1$, this simplifies to

$$L_s(\beta, \omega^2, \gamma|y) = \prod_{i=1}^{n} \prod_{k=1}^{K_1} \left[F(\tau_{i1}^{k}|X_i\beta,\ 1+\omega^2) - F(\tau_{i1}^{k-1}|X_i\beta,\ 1+\omega^2)\right]^{\mathbf{1}(y_{i1}=k)}$$

The Likelihood Function: Adding the Vignette Component

The *vignette component* is a J-variate ordinal probit with varying thresholds:

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The *joint likelihood* shares parameter γ:

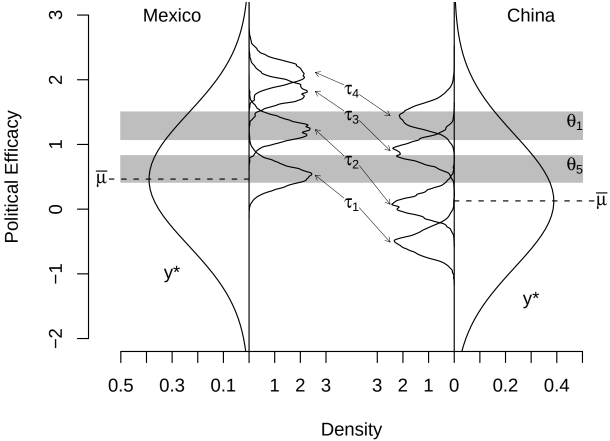
$$L(\beta, \sigma^2, \omega^2, \theta, \gamma | y, z) = L_s(\beta, \sigma^2, \omega^2, \gamma | y) \times L_v(\theta, \gamma | z).$$

and nests the ordinal probit model as a special case.

Fixing DIF in China and Mexico

		Ordinal Probit		Chopit	
Eqn.	Variable	Coeff.	(s.e.)	Coeff.	(s.e.)
μ	China	.670	(.081)	$-.362$	(.090)
	age	.004	(.003)	.006	(.003)
	male	.087	(.076)	.113	(.081)
	education	.020	(.008)	.019	(.008)
Vignettes	θ_1			1.393	(.190)
	θ_2			1.304	(.190)
	θ_3			.953	(.189)
	θ_4			.902	(.188)
	θ_5			.729	(.188)
	$\ln \sigma$			$-.238$	(.042)

The Source of DIF in China and Mexico: Threshold Variation



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   - E.g., we can use the mean, $X_c\hat{\beta}$ as a point estimate of the actual level when $X = X_c$.

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   - So the new method takes roughly the weighted average of the model prediction $\hat{\mu}_E$ and the observed y_E, with weights determined by the how good a prediction it is.

More formally, we use Bayes theorem

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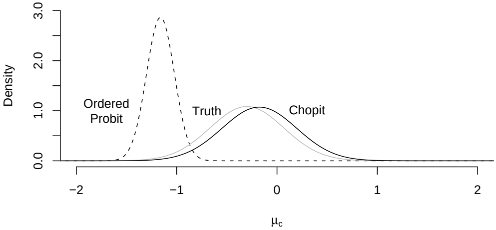
Key Difference:

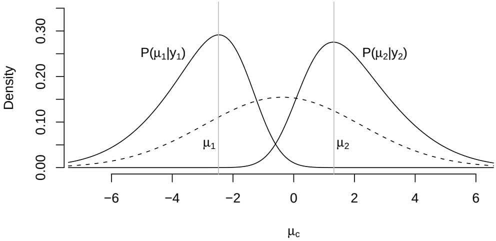
$P(\mu_i\|y)$	works for out-of-sample prediction
$P(\mu_i\|y, y_i)$	works better when y_i is available

Unconditional Posterior



Unconditional posterior for a hypothetical 65-year-old respondent in country 1, based on one simulated data set.

Conditional Posteriors



Conditional posteriors for two different 21 year old respondents. Person 1 gave responses (1,1) on the two self-evaluation questions; Person 2 gave responses (4,3). The unconditional posterior, drawn with a dashed line, gives less specific predictions. Each curve was computed from one simulated data set.

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- Thus, we also want "known entropy".

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We now compute *estimated entropy* and *known entropy* for all possible subsets of vignettes.

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$$\Pr(C = c|x_0, c_i) = \begin{cases} \frac{\Pr(C=c|x_0)}{\sum_{a \in c_i} \Pr(C=a|x_0)} & \text{for } c \in c_i \\ 0 & \text{otherwise} \end{cases}$$

- Advantages compared to unconditional probabilities:
  - Conditions on c_i by normalizing the probability to sum to one within the set c_i and zero outside that set.
  - For scalar values of c_i, this expression simply returns the observed category: $\Pr(C = c|x_i, c_i) = 1$ for category c and 0 otherwise.
  - For vector valued c_i, it puts probability density over categories within c_i, which in total sum to one.
  - Probabilities can be interpreted for causal effects or summed to produce a histogram.
  - Result:
    - highly robust to model mispecification,

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    - highly robust to model mispecification,
    - extracts considerably more information from anchoring vignette data.