# A method for eliciting and integrating prior information into psychological studies

J.S. Chrabaszcz J.W. Tidwell M.R. Dougherty

University of Maryland, College Park

## Abstract

Though Bayesian methods are being used more frequently, many still struggle with the best method for setting priors with novel measures or task environments. We propose a method for setting priors by eliciting continuous probability distributions from naive participants. This allows us to include any relevant information participants have for a given effect. Even when prior means are near-zero, this method provides a principle way to estimate dispersion and produce shrinkage, reducing the occurrence of overestimated effect sizes. We demonstrate this method with a number of published studies and compare the effect of different prior elicitation methods.

## Methods

- Experimenters selected studies that tested the substantive theory by comparing two group means.
- 48 undergraduates gave estimates of the outcome for each group on the scale of the measured variable.
- Aggregated responses to produce priors for the studies.

## Elicitation

- Elicit lowest and highest possible estimates for each control and experimental condition (added language for experimental condition in parentheses)

| | |
|---|---|
| 1 | How far away would the average person (who had just eaten pretzels) estimate a bottle of water that is truly three feet away? |
| 2 | On a range of 0 to 20, how depressed is the average person (after viewing pictures of a luxury good)? |
| 3 | Out of 10 attempts, how many putts at a distance of 3 feet would the average person sink (after hearing that they are using a lucky ball)? |
| 4 | One a scale of 0 to 200 cents, how much would an average person say 100 units of a randomly selected foreign currency is worth (while holding a heavy clipboard)? |

- Calculate cutpoints based on interval widths $\boldsymbol{H}, \boldsymbol{L}$

$$c_1 = L + \frac{H-L}{6},\; c_2 = \frac{H-L}{2},\; c_3 = H - \frac{H-L}{6}$$

- Elicit probability that observed effect is lower than $c_1$, $c_2$, and $c_3$.

## Aggregation

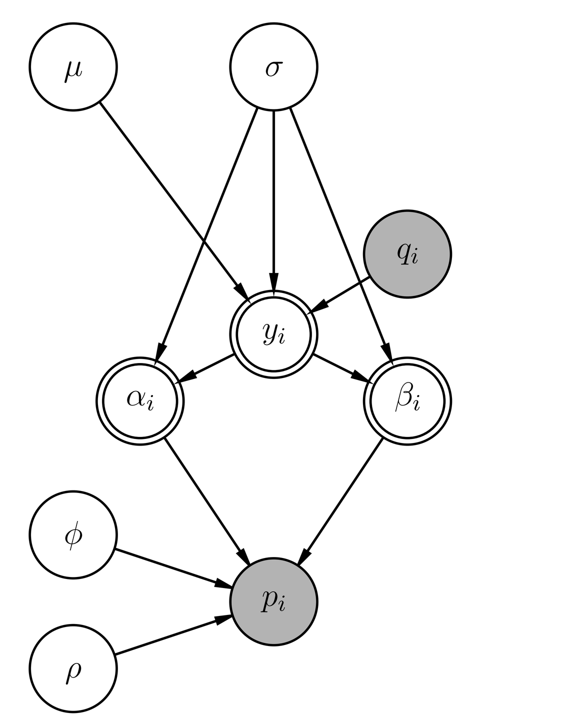
Median aggregation Estimate each participant's location and scale parameters independently for each experimental condition. The estimated prior values are the median of the subject location and scale parameter values.

Full Pooling Bayesian Implements graphical model to the immediate right to independently estimate control and experimental parameters. This method ignores individual differences, only produces group prior estimates.

Partial Pooling Bayesian Implements graphical model to the far right to independently estimate control and experimental parameters while varying all parameters by participant (and shrinking those estimates toward the group means using a normal hyperprior).

| Effect Size | Study | Uniform Prior | Max. Lik. | No Pool | Part Pool |
|---|---|---|---|---|---|
| | 1 | -0.30 | 0.17 | 0.19 | 0.18 |
| | 2 | 0.40 | 0.16 | 0.21 | 0.18 |
| | 3 | 0.65 | 0.09 | 0.10 | 0.09 |
| | 4 | 0.13 | 0.00 | 0.06 | 0.05 |
| Observed ***t*** | | | | | |
| | 1 | 2.00 | 2.79 | 2.79 | 2.79 |
| | 2 | 2.00 | 2.73 | 2.74 | 2.73 |
| | 3 | 2.14 | 3.21 | 3.21 | 3.20 |
| | 4 | 8.00 | 0.96 | 0.97 | 0.97 |

## Full Pooling Bayesian

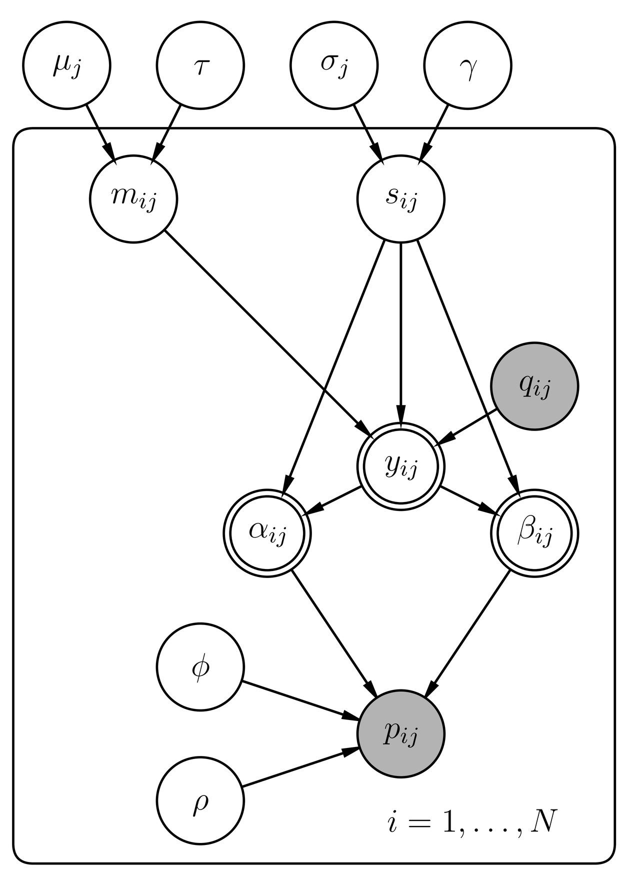


$$\mu \sim N(0, 1e^4)$$
$$\sigma \sim \chi^{-2}(2)$$

$$y = \Phi(\tfrac{q-\mu}{\sigma})$$
$$\alpha = \sigma y$$
$$\beta = \sigma(1-y)$$

$$\rho \sim U(0,1)$$
$$\phi \sim U(0,1)$$
$$p \sim \begin{cases} \phi\rho & \text{if } y = 1 \\ \phi(1-\rho) & \text{if } y = 0 \\ (1-\phi)\text{Beta}(\alpha,\beta) & \text{if } 0 < y < 1 \end{cases}$$

## Partial Pooling Bayesian

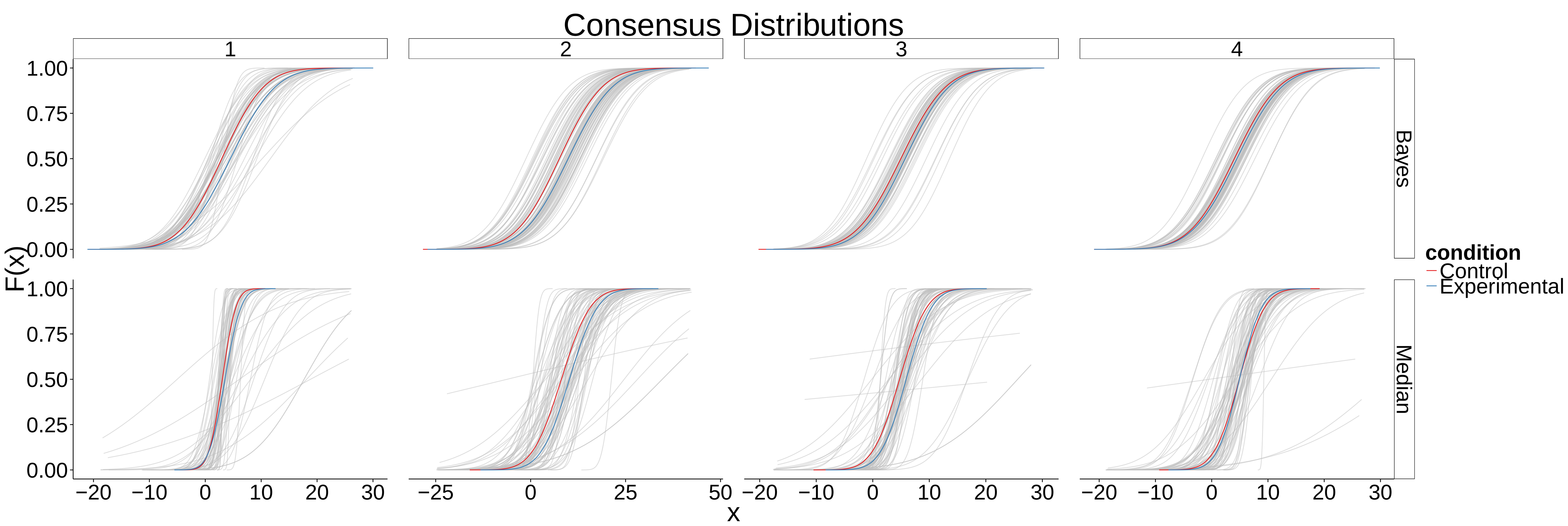



$$\mu_j \sim N(0, 1e^4)$$
$$\sigma_j \sim \chi^{-2}(2)$$
$$\tau \sim U(0, \infty)$$
$$\gamma \sim U(0, \infty)$$
$$m_{ij} \sim N(\mu_j, \tau)$$
$$s_{ij} \sim N(\sigma_j, \gamma)$$

$$y_{ij} = \Phi(\tfrac{q-m_{ij}}{s_{ij}})$$
$$\alpha_{ij} = s_{ij} y_{ij}$$
$$\beta_{ij} = s_{ij}(1-y_{ij})$$

$$\rho \sim U(0,1)$$
$$\phi \sim U(0,1)$$
$$p_{ij} \sim \begin{cases} \phi\rho & \text{if } y = 1 \\ \phi(1-\rho) & \text{if } y = 0 \\ (1-\phi)\text{Beta}(\alpha_{ij},\beta_{ij}) & \text{if } 0 < y < 1 \end{cases}$$

## Results




Cumulative distributions for participants (gray) and aggregated for each condition (red & blue) for each of four studies (horizontal facets) and aggregation methods (vertical facets).

## Conclusions

- Prior effect sizes were uniformly smaller in magnitude than those estimated by published studies.
- Different aggregation methods produced similar prior effect size estimates.
- Partially pooled Bayesian estimates are less extreme relative to unpooled ML estimates, making them potentially more useful when individual estimates are of interest (though at a substantial computational cost).
- This relatively inexpensive method of estimating priors allows us to make more efficient use of the consistently underwhelming sample sizes in Psychology.

## References


- Tidwell, J.W., Wallsten, T.S., Yang, H., & Moore, D.A. Galton meets Goldberg: Eliciting and Modeling Probability Forecasts of Event Dates and Other Continuous Quantities.
- Gelman, A., Carlin, J.B., Stern, H.S., & Rubin, D.B. (2015). Bayesian data analysis (2nd Ed.). London: Chapman & Hall/CRC.
- Turner, B.M., Steyvers, M., Merkle, E.C., Budescu, D.V., & Wallsten, T.S. (2014). Forecast aggregation via recalibration. *Machine learning*, *95*(3), 261-289.


jchrabaszcz at gmail dot com