

Incorporating Strength of Preference Data into Bayesian Models of Choice

Jess Mixon and John McCoy, Wharton Marketing Department

Introduction:

- Gamble choice datasets allow behavioral economists to study individual decision processes involving risk
- In making a choice between 2 dollar/probability combinations people know both which option they prefer and how strongly they prefer it
- Eliciting strength of preference (SoP) data in conjunction with choices can likely improve baseline choice models

Study Data:

- 60 participants deciding between 225 pairs of gambles
- Payoffs ranging from \$3 to \$56.70 with probabilities ranging from 9% to 94%
- Each choice elicits strength of preference rating
- Final dataset also includes attractiveness and buy ratings of each of the 36 individual gambles for each participant

Which of these two gambles do you prefer?

% chance of receiving \$

% chance of receiving \$

How strong is your preference for the gamble that you chose?

Basically indifferent between the two gambles Strong preference for my chosen gamble Extremely strong preference for my chosen gamble

Baseline Model: Cumulative Prospect Theory (CPT) Kahneman and Tversky (1992)

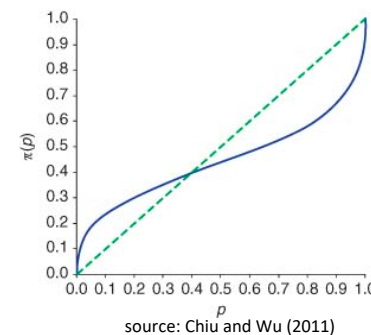
- individual level parameters α , γ , and φ
- Two-part process to arrive at an individual's probability of choosing one option over the other
- α and γ drive subjective valuation of both gambles separately
- φ translates difference between the subjective valuations into a probability of choosing the higher valued option

$$\pi(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}}, \quad 0 < \gamma \leq 1$$

$$u(z) = z^\alpha \quad (\text{for } z > 0)$$

Parameters: For a pair of gambles with dollar amounts (z) and probability (p)

- α controls the degree to which people value monetary gains
- γ controls the degree to which the probability weighting function is S-shaped (ie. The degree to which extreme probability outcomes are overweighted and low probability outcomes are underweighted)
- φ controls how strongly differences in subjective values translate to a probability of choosing one option over the other



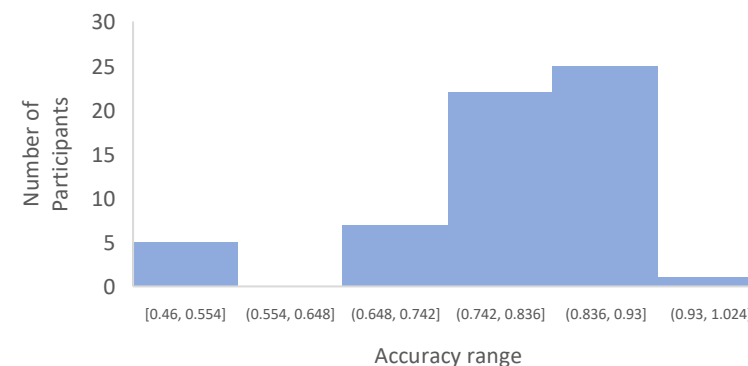
Subjective value of gamble = $\pi(p) * z^\alpha$

Probability of choosing gamble 2 = $1/[1 + e^{\varphi * (V_{gamble2} - V_{gamble1})}]$

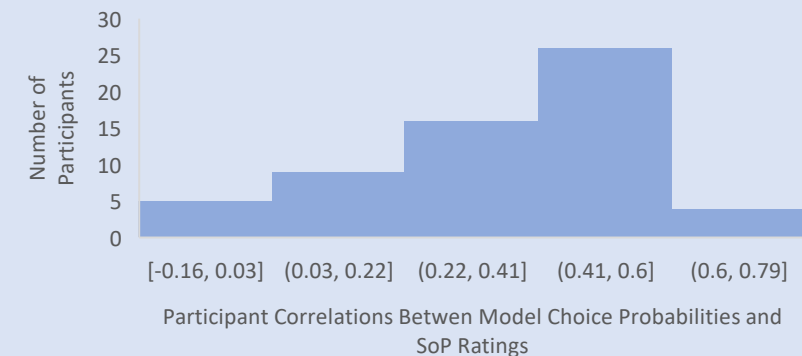
Initial Fit:

- Implemented Bayesian CPT model in PyStan to fit α , γ , and φ individual parameters for each participant
- Model fit parameters predict gamble choices for each gamble pairing in the dataset with approximately 80% accuracy overall

Model Choice Accuracy by Participant



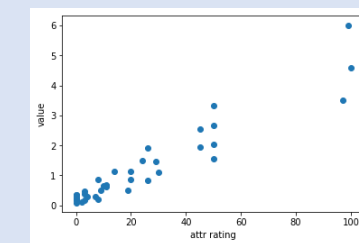
Correlation Between Model Probabilities and Participants SoP Ratings



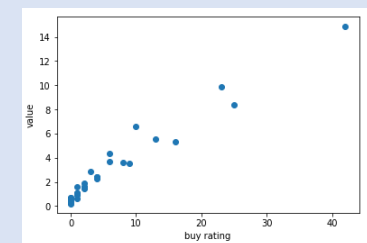
Evidence for Incorporating Strengths of Preferences into the Model

- Very significant correlations across participant strength of preference ratings and model value metrics

Illustrative Examples: Select Participant Correlations



Participant 49:
correlation between model subjective value and attractiveness rating = 0.95
study average: 0.70



Participant 19:
Correlation between model subjective value and buy rating = 0.97
study average = 0.80

Conclusions and Next Steps

- Significant information contained in SoP ratings, should be able to improve model performance
- Looking to understand best way to incorporate information
- Ex: should SoP ratings be incorporated on individual parameters in the model? or alongside choice probabilities and values?