Accelerating Scientific Throughput: Behavioral Decision Research Meets Supercomputer

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Introduction

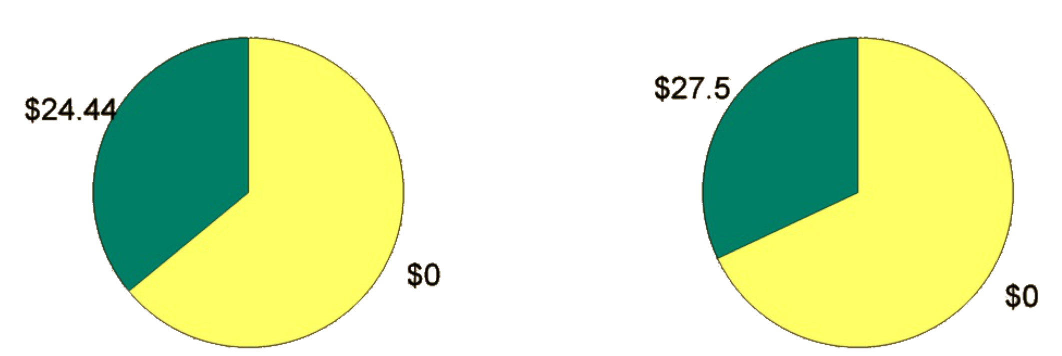
Cumulative Prospect Theory (CPT; Tversky and Kahneman, 1992) remains a leading decision theory for modeling risky choice among lotteries.

$$CPT(G) = \sum_{i=1}^{k} w_i^- u^-(x_i) + \sum_{i=k+1}^{n} w_i^+ u^+(x_i)$$

Stott's (2006) "Cumulative Prospect Theory's Functional Menagerie" considered 7 functional forms for utility for money (u), 7 functional forms for probability weighting (w), and 4 probabilistic response mechanisms modeling preference as deterministic and responses as error prone. We consider the same 49 functional forms with a broader class of probabilistic specifications and on new stimuli.

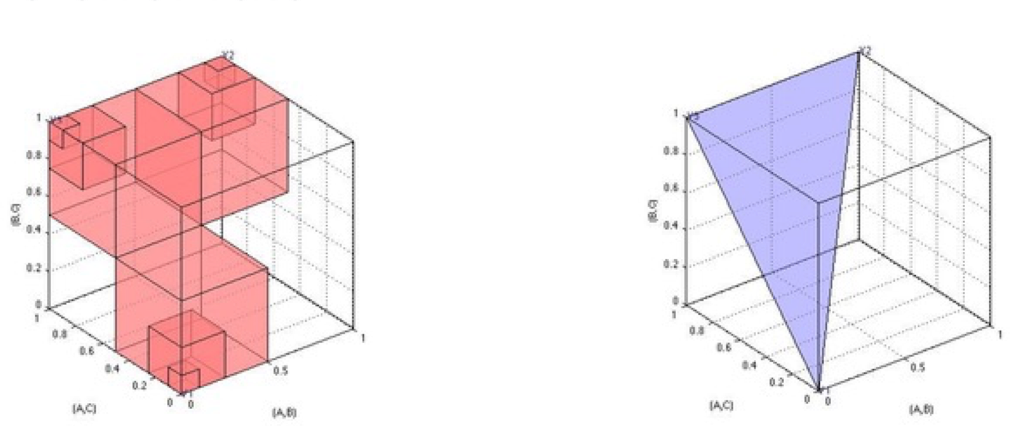
Two (2AFC) Experiments

A sample gamble pair was as follows:

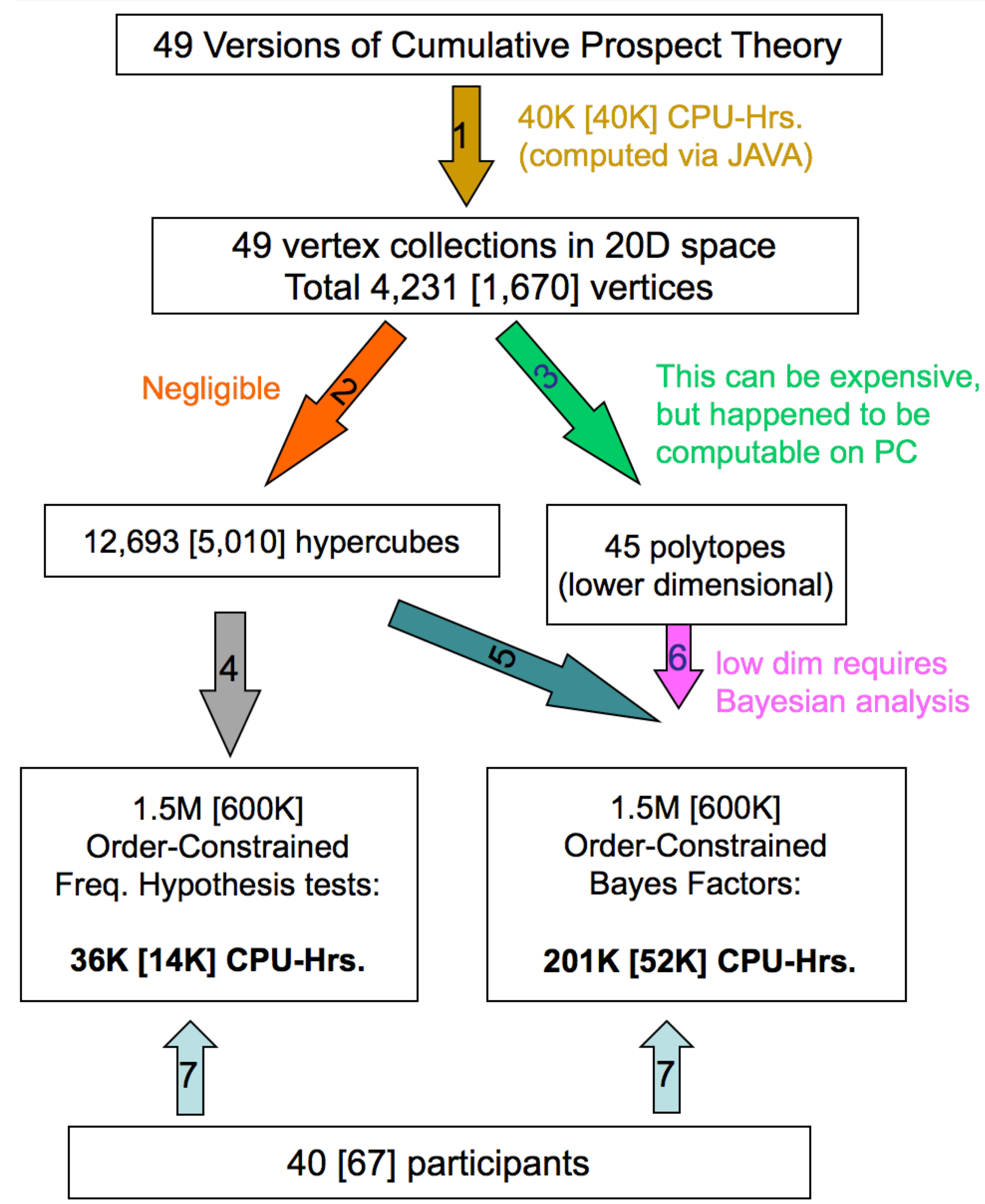


Probabilistic Specifications

In **distance-based models (red),** a DM has a fixed preference throughout the study. The DM can make response errors in any pair up to some maximum allowable error rate.



In **mixture models (purple),** a DM's preferences are probabilistic and responses are error free.



Order-Constrained Inference

Frequentist (Regenwetter et al. 2014) and Bayesian (Zwilling et al., 2018) QTEST on the supercomputer. **Workflow**: 1 find all preference patterns; 2 characterize distance-based models; 3 characterize mixture models; 4 run frequentist hypothesis tests; 5 calculate analytical Bayes factors; 6 compute simulation-based Bayes factors; 7 analyze each dataset separately as well as jointly (group Bayes factor).

Main Findings

None of the mixture models of CPT explained many participants' data. Distance-based models with error rates ≤ 25% performed very poorly throughout. Distance-based models with error rates ≤ 50% could account for up to ½ the participants but performed poorly in cross validation, suggesting overfitting. Almost ¼ of all datasets provided strong evidence against all 49 functional form combinations and against all 4 probabilistic specifications.

Conclusions

We did not find a single combination of functional forms and probabilistic specification that best explains all participants' data in all stimulus sets, e.g., according to group Bayes factor. Model comparison at the individual level showed heterogeneity across participants and stimulus sets. These results suggest it is important to perform analyses at both the group and the individual level and to use replications.

References

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