Target Article: "Suboptimality in Perceptual Decision Making" by Dobromir Rahnev and Rachel N. Denison
Word Counts: abstract (52), main text (449), references (78), entire text (579)

Commentary Title: "Model Comparison, not Model Falsification"

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Abstract

Systematically comparing models that vary across components can be more informative and explanatory than determining whether behaviour is optimal, however defined. The process of model comparison has a number of benefits, including the possibility of integrating seemingly disparate empirical findings, understanding individual and group differences, and drawing theoretical connections between model proposals.

Main Text

Determining whether behaviour is optimal can be difficult because what is optimal is often a matter of debate. For instance, optimality can be defined in terms of task, related real-world environments, hypothesised evolutionary environments, short- vs. long-term rewards, etc. Furthermore, notions of optimality can be expanded to respect resource limitations, such as constraints specified in terms of energy, time, effort, or cognitive resources. More thought may go into choosing a measure of optimality than in evaluating how people compare to the chosen yardstick. Many of these issues recapitulate criticisms of rational approaches to understanding perception and cognition (Jones & Love, 2011).

Sensibly, Rahnev and Denison (2018) argue for moving away from notions of optimality. Instead, they specify various ways in which people can be suboptimal. Although one can argue about the particular set of components identified as sources of suboptimal decision making, the basic approach is promising. Careful comparison of models has the potential to identify the root causes of behaviour as opposed to making a blanket statement about a debatable notion of optimality.

Indeed, one could go further and simply advocate for model comparison without considering optimality. Although thinking about optimality can be a useful starting point for developing models and evaluating human performance, a strong focus can be restrictive. The question of whether people are optimal invites a Popperian odyssey to falsify the claim. Unfortunately, accepting or rejecting a hypothesis in isolation is usually not very informative or explanatory. Alternatively and perhaps more productively, one could specify a rich set of hypotheses, formalise these hypotheses as models, and perform a proper model comparison. The outcome of such a process is the best available explanation (i.e., model) of the data.

Model comparison offers a route for model and theory development. New model proposals can draw on past models that have enjoyed success. For example, in the category learning literature, the lineage of models stretches across decades. Past work has influenced my own proposals (e.g., Love, Medin, & Gureckis, 2004). As new sources of data become available, such as brain imaging data, model comparison approaches can embrace these new data sources (Mack, Preston, & Love, 2013).

Finally, model comparison offers a number of advantages for our science. Model comparison requires specifying what the relevant data are. In doing so, the scope of models becomes clearer. Formalising theories as models of course has its own advantages in terms of making assumptions clearer, enabling quantitative prediction in novel circumstances, characterising individual and group differences in terms of fitted parameter values, directing future experimentation, and identifying broad principles that span datasets and models. Overall, model comparison offers a path to explain behavioural phenomena that can be more integrative and explanatory than blanket statements about optimality.

References

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Mack, M.L., Preston, A.R. & Love, B.C. (2013). Decoding the Brain's Algorithm for Categorization from its Neural Implementation. *Current Biology*, 23, 2023-2027.

Rahnev and Denison (2018), Target Article.