Descending Marr's levels: Standard observers are no panacea

Commentary on D. Rahnev & R.N. Denison,"Suboptimality in Perceptual Decision Making", to appear in Behavioral & Brain Sciences

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Abstract: According to Marr, explanations of perceptual behavior should address multiple levels of analysis. Rahnev & Denison (R&D) are perhaps overly dismissive of optimality considerations at the computational level. Also, an exclusive reliance on standard observer models may cause neglect of many other plausible hypotheses at the algorithmic level. Therefore, as far as explanation goes, standard observer modeling is no panacea.

Rahnev & Denison (R&D) argue that "we should abandon any emphasis on optimality or suboptimality and return to building a science of perception that attempts to account for all types of behavior" (sect. 1, para. 4). We agree that the current fixation on optimality is unhealthy. At the same time, however, we question whether standard observers are really sufficient to "account for" perceptual behavior. Because they cut across different tasks, they may provide some much-needed unification (Colombo & Hartmann 2017). Nevertheless, they are by themselves unlikely to constitute full-fledged explanations. Following Marr (1982), explanations of perceptual behavior should answer questions at three distinct levels of analysis. Alas, it is not clear how standard observers help descend Marr's levels from the computational level to the algorithmic and implementational levels.

At the computational level, investigators ask “what” a perceptual system is doing and “why.” The popularity of ideal observers (Swets et al. 1961) stems in part from answering both of these questions. Because ideal observer models are tweaked to fit behavioral data, they provide mathematical descriptions of “what” a perceptual system is doing. They also answer questions about “why”: A perceptual system behaves as it does because that behavior is optimal for the task (Bechtel & Shagrir 2015).

Like ideal observers, standard observers address “what” questions at the computational level by fitting behavioral data. Whereas ideal observer models are often criticized for failing to address questions below the computational level (Jones & Love 2011), R&D’s standard observer models also address “how” questions at the algorithmic level. Many (but not all) of the hypotheses in Table 1 of the target article emphasize algorithmic-level features such as capacity limitations, imprecisions, ignorance, or the inability to employ complex decision rules. These algorithmic-level aspects are easily accommodated once optimality is given up. In other words, R&D trade in the ability to answer questions about “why” for an improved ability to answer questions about “how.”

We applaud this shift in emphasis from “why” to “how.” However, we feel that (a) “why” questions should not be dismissed quite so quickly, and that (b) properly answering “how” questions may require taking into account hypotheses that are unlikely to be considered within the standard observer approach.

Regarding (a), R&D’s dismissive attitude towards optimality is understandable insofar as the explanatory value of “why” questions remains unclear (Danks 2008; but cf. Shagrir 2010).

Nevertheless, such questions can still have pragmatic import; considering what a system is supposed to be doing may lead to an improved understanding of what it is actually doing. R&D admit as much in section 4.2 but do not go far enough. Many historical attempts to uncover mechanisms in biology and neuroscience begin by specifying these mechanisms' roles in the containing environment: The heart is viewed as a pump for the circulatory system (Bechtel 2009), and dopamine is known to contribute to the regulation of emotions (Craver 2013). In this vein, Swets et al. (1961, p. 311) argue that ideal observers should be used not only to describe optimal behavior, but also as a "convenient base from which to explore the complex operations of a real organism." In line with this view, we believe that perceptual scientists may productively tweak an ideal observer's optimal solution so as to eventually arrive at an organism's actual solution (see also Zednik & Jäkel 2016). Hence, although we agree that it is a mistake to rely too heavily on the unclear explanatory value of optimality considerations, we believe that it would be a mistake to dismiss these considerations altogether.

Regarding (b), more should be said about the transition from "what" and "why" questions at the computational level to "how" questions at the algorithmic level. We have previously argued that Marr's hierarchy can be descended by applying heuristic strategies to identify candidate hypotheses at lower levels of analysis (Zednik & Jäkel 2014; 2016). Many of the hypotheses summarized in Table 1 result from the "push-down" and "plausible-algorithms" heuristics: Whereas the former involves hypothesizing that an ideal observer's computational-level structure reflects an algorithmic-level description of the underlying mechanism, the latter involves adapting this description according to established psychological principles about, for example, capacity limitations. Additionally, R&D's plea for standard observers that can unify models across different tasks attaches great importance to what we have called the "unification" heuristic. Many other useful heuristics are not considered in the target article, however. In particular, some of the most promising recent work is driven by the “tools-to-theories” heuristic (cf. Gigerenzer 1991), in which algorithms developed in, for example, machine learning and Bayesian statistics are co-opted as algorithmic-level hypotheses for explaining how real organisms approximate (or fail to approximate) ideal observers. In particular, Sanborn et al. (2010) suggest that particle filters – a class of algorithms for approximating Bayesian inference – accurately describe the algorithms that humans deploy to learn categories. Interestingly, these algorithms approximate priors and posteriors through samples and thereby suggest very different components and processes than the original ideal observers. Hence, whereas developing standard observers may be one viable way of addressing “how” questions at the algorithmic level, other approaches may lead to different answers that also merit consideration.

In summary, although we agree that perceptual scientists should in fact shift from questions about “what” and “why” to questions about “how,” we warn against thinking of the standard observer framework as a panacea. For one, “why” questions may continue to play an important role in the process of scientific discovery at the computational level and should not be dismissed prematurely. For another, although standard observers may be one promising way to answer “how” questions at the algorithmic level, other approaches might yield diverging and even incompatible answers. Finally, very little has yet been said about “where” questions at the implementational level (Stüttgen et al. 2011; Zednik 2017). Therefore, although standard observer models may play an important role in explanations of perceptual behavior, until we have satisfactory explanations on all three of Marr’s levels, we should be patient and let different research strategies run their course.

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