Observer Models of Perceptual Development

Commentary on Rahnev & Denison, Suboptimality in Perceptual Decision Making

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We agree with Rahnev & Denison that to understand perception at a process level, we must investigate why performance sometimes deviates from idealised decision-models. Recent research reveals that such deviations from optimality are pervasive during perceptual development. We argue that a full understanding of perception requires a model of how perceptual systems become increasingly optimised during development.

Perceptual abilities undergo major development during infancy and childhood – for example, for detecting low-contrast stimuli (Adams & Courage, 2002), noisy patterns of motion (Hadad, Maurer, & Lewis, 2011), or recognising complex stimuli such as faces (Mondloch, Le Grand, & Maurer, 2002). Classically, the focus of perceptual development research has been on improvements in sensitivity (likelihoods). As reviewed in the target article, decades of adult research show how sensitivity changes can result from changes within a decision-model framework that incorporates likelihoods, priors, cost functions, and decision rules. Applying this framework to development, we argue that *perceptual improvements must be explained in terms of changes to these components.* This will lead to a new understanding of how perceptual systems attain their more highly-optimised mature state.

Specifically, we need to know:
(1) Which elements of the observer model are changing (developing), leading to improvements in perceptual function? Recent evidence suggests that multiple components of the decision model are developing significantly during childhood. Until late into childhood, observers are still using *decision-rules* less efficiently: mis-weighting informative cues (Gori, Viva, Sandini, & Burr, 2008; Manning, Dakin, Tibber, & Pellicano, 2014; Sweeny, Wurnitsch, Gopnik, & Whitney, 2015), or using qualitatively different decision-rules altogether (Jones & Dekker, 2017; Nardini, Bedford, & Mareschal, 2010; Nardini, Jones, & Bedford, 2008). Other studies show abilities to learn and use *priors* and *costs* also to be developing late into childhood (e.g. Dekker & Nardini, 2016; Stone, 2011; Thomas, Nardini, & Mareschal, 2010). The new, model-based approach to development pioneered in these studies paves the way for understanding how likelihoods, priors, cost functions, and decision-rules are shaped as children learn, and for testing which common processes can explain perceptual development across a range of

different tasks. Studies to date have successfully captured developmental changes in performance by fitting how parameters of specific components of the decision model change with age on single tasks. This usefully sets quantitative bounds on potential changes in these processes, but the data are often compatible with more than one account. For example, in a rewarded reaching task (Dekker & Nardini, 2016), children up to the age of 11 years aim too close to a penalty region to maximise their score, reflecting overconfidence in likelihood of hitting the target, underestimation of cost, or a central pointing prior. An important way forward is therefore to evaluate the fit of developmental models to multiple tasks, and to test their predictions on new tasks.

(2) How are more efficient and adult-like decision-rules, priors, and cost functions acquired during development? Beyond characterising the changes in decision-model components underlying perceptual development, the ultimate aim is to understand the mechanisms driving these changes. A major contributing factor is likely to be experience, which shapes the sensitivity of neuronal detectors, determining likelihoods (Blakemore & Van Sluyters, 1975), changes priors (Adams, Graf, & Ernst, 2004), and is needed to learn the potential consequences of actions (cost factors). It is not clear in which circumstances such experience is generalizable (e.g. priors or costs learned during one task applied to another), how experience drives learning of decision-rules, or whether there are sensitive periods like those for sensitivities (likelihoods) in other parts of the decision model (e.g. for learning priors). A useful approach is investigating the neural changes supporting improvements in decision-model components as perception becomes more optimised, such as more precise representation of likelihoods (Van Bergen, Ji Ma, Pratte, & Jehee, 2015) and values (Wu, Delgado, & Maloney, 2011), or more precise computing of weighted averages, perhaps implemented via divisive normalisation (Ohshiro, Angelaki, & DeAngelis, 2011). The power of this approach is demonstrated by recent studies of developmental disorders, in which there are exciting developments in linking components of observer models to specific neural mechanisms (Rosenberg, Patterson, & Angelaki, 2015). For example, in autism, tasks that involve combining new evidence with prior knowledge are disproportionally affected, and this has recently been linked to the overweighting of sensory likelihoods vs priors, possibly due to altered neural operations mediated by noradrenaline and acetylcholine (Lawson, Mathys, & Rees, 2017). In addition, a new, model-based approach to developmental neuroimaging lets us disentangle components of the developing decision model across different neural processing stages. We recently showed that development of cue integration during depth perception was linked to a shift from using depth cues independently to combining them, by neural detectors in sensory cortex (adopting a 'fusion' rule; Dekker et al., 2015). This suggests that the late development of cue integration is driven by a change in how sensory information is combined (sensory decision-rule), rather than improved read-out of the fused estimate during task performance (higher-order decision-rule or cost function). These studies demonstrate how a developmental approach can provide computational-level understanding of the crucial ingredients for building a mature optimised observer.

The end goal of this approach is an observer model incorporating processes of learning and development: a Developing Standard Observer Model. This will provide a more complete understanding of perceptual systems, and a basis for developing intelligent machines that can learn to perceive in novel environments. For example, understanding the structure of experience that scaffolds our ability to transfer previous likelihoods, cost-functions, and decision-rules from one task to another can inform the development of more flexible AI agents (Wang et al., 2017). Similarly, significant improvements in robotic grasp performance have been gained from incorporating developmental stages such as motor babbling and gradual improvements in visual acuity into the training regime (Cangelosi, Schlesinger, & Smith, 2015). In addition, understanding which developmental changes in the decision-model (e.g. sensitivity vs decision-rule) drive perceptual improvements at different ages will provide a crucial basis for better training of perception and action in patients with sensory loss.

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