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The nature and role of cortical feedback in perception, imagery, and synaesthesia

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Abstract

In his Discussion Paper, Seth makes the case for counterfactual richness of predictive processing models in explaining perceptual presence and its absence in synaesthetic concurrent percepts. Here, we question the relevance of counterfactual richness for these and related phenomena, and we argue that alternative theories of perception that incorporate top-down/bottom-up facilitatory interactions are at no relative disadvantage in addressing them.

In his creative and thought-provoking paper, Seth lays out the case for modifying the Predictive Processing theoretical framework to incorporate more explicitly "counterfactual richness" - conditional elements of the representation that describe how sensory inputs would change under a family of possible actions - within hierarchical generative models of sensorimotor contingencies. This new account, termed Predictive Perception of SensoriMotor Contingencies (PPSMC), is argued to explain the phenomenon of "perceptual presence", that perceived objects are experienced as real and belonging to the world, as well as the lack of perceptual presence in synaesthesia for concurrent percepts (e.g. when a particular grapheme evokes a particular color percept, the color percept is not interpreted as real). In synaesthesia, Seth argues, the concurrent percept is counterfactually poor, and is therefore distinguishable from percepts induced by real objects in the world, with this same property available for discriminating between imagery and reality.

We agree that as sensorimotor contingencies are mastered by experience with objects in the world, counterfactual information is undoubtedly encoded along the way. However, we think it unlikely that this is the critical addition that allows an object to be perceived as real and part of the world. Setting aside the challenge for Seth's view of defining counterfactual richness for the domain of color, perception of novel objects poses a central challenge. Throughout adulthood, new man-made artifacts are constantly introduced. Even according to Predictive Processing models, new objects must be counterfactually poor relative to well-known objects as evidenced by the ubiquitous phenomenon of "repetition suppression" (see Gotts et al., 2012, for recent review), yet they certainly aren't perceived as non-veridical. Similarly, following stroke and other forms of brain damage to cortical circuits that process and represent crucial information about sensorimotor contingencies, certain patients can selectively lose higher-level perceptual, conceptual, and motor knowledge about objects, preventing their appropriate identification and object use (e.g. associative agnosia for objects or faces; see De Renzi, 2000, for review). Nevertheless, such patients still perceive these objects as being present in the world, and they continue to engage with them and act on them as veridical. These facts would appear to strongly undermine the importance of counterfactual richness to the experience of perceptual presence.

What then might explain our ability to distinguish imagery from perception or the lack of perceptual presence in synaesthesia? We concur with Seth about the crucial role of top-down and bottom-up cortical interactions in mastering sensorimotor contingencies in perception, as well as the likely role of aberrant top-down, cross-modal interactions in generating synaesthetic concurrent percepts. However, we differ from Seth and from Bayesian Predictive Processing models on the exact nature and role of cortical feedback in perception. One virtue of neural models that posit bi-directional top-down and bottom-up facilitatory interactions is the flexibility of knowledge application across a wide range of task contexts. Examples include Adaptive Resonance Theory (e.g. Grossberg, 1987), Biased Competition (Desimone & Duncan, 1995), and a variety of recurrent connectionist models. Prediction is intrinsically involved in all of these models, yet perhaps not in quite such an overt and qualitatively distinct manner as in Predictive Processing. Indeed, a recurrent connectionist model such as the Boltzmann machine (e.g. Ackley, Hinton, & Sejnowski, 1985) has much the same starting point as Bayesian Predictive Processing, with the goal of the model being to minimize differences between the joint distributions of pre- and post-synaptic activity states in the absence of sensorimotor input and those present during active stimulus processing. Predictive Processing models minimize much the same quantity by distributing the basic terms of the related equation in space, utilizing distinct populations of cells (e.g. "prediction error" versus "conditional expectation of perceptual causes"). The Boltzmann machine uses time instead of space, with statistics assessed for the same cells over distinct time windows. In other words, despite having similar goals and capabilities, the Boltzmann machine and other recurrent connectionist models make no distinction between prediction error and other cells, and they use top-down feedback in a simpler, excitatory manner. Imagery is possible in these models through the selective top-down excitation of cells in lower-levels that have corresponding synaptic connections. A range of experimental data suggest that, relative to sensory-driven perception, such top-down feedback results in weaker overall activity levels and a distinct laminar profile of activity (e.g. Lakatos et al., 2007; O'Craven & Kanwisher, 2000), either of which could serve to distinguish imagery or synaesthetic concurrent percepts from veridical perception. Unfortunately, given the similarity of the quantities that these different classes of model are optimizing, we view it as unlikely that additional behavioral experiments will distinguish amongst them. Rather, it will likely require the evaluation of predictions at a neural level.

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