Predictive processing: is the future just a memory?

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Abstract: Predictive processing seems like a radical departure from traditional theories of information processing in the brain, but a broader view of predictions highlights many similarities with standard frameworks. Predictive processing is memory and competitive bias in a new outlook – and we should use this correspondence to advance research on both fronts.

Keywords: Predictive coding, neural code, competitive bias, top-down processing, active inference

Main text

The predictive processing (PP) framework has been hailed as paradigm shift in neuroscience. Its modern guise was initially developed in the context of visual information processing, where PP inverted the logic of established theories (Srinivasan et al., 1982; Rao and Ballard, 1999; Friston, 2018). The standard view had emphasized bottom-up information flow, with top-down gain modulation (which can convey contextual information based on situation, emotions or goals) biasing competition between neurons in the visual cortex (Beck and Kastner, 2009). PP, on the other hand, poses that the brain generates models of the world and uses them to try and predict sensory input. In this view, top-down projections from higher-order areas to the visual cortex are sending

predictions, while the bottom-up stream conveys prediction errors (Rao and Ballard, 1999; Friston, 2018).

While the clash between PP and biased competition models started in the visual cortex, it did not end there. Both views of information processing and neural representations in the brain have great potential to illuminate the workings of other brain regions. The view of neural representations being underpinned by groups of neurons competing and being biased by varied forms of modulation is all pervasive in the study of most brain regions and functions, being found in studies from perception to motor control. And while PP has been on the spotlight for a relatively short period of time, it has already been applied to contexts way beyond visual perception (e.g., Adams *et al*., 2013). PP has been increasing in popularity, it stimulated some very interesting attempts for a broad framework for the brain (e.g. Seth, 2015) and has been viewed by some as a strong candidate for the basis of a "unified theory" for the brain's workings.

But while PP has indeed great potential, it has often received a rather limited treatment, specially with regard to the concept of prediction. Defining what counts as a prediction is a conceptual issue with important implications for PP and the concept of prediction has been continuously extended. For example, models of PP tended to focus on predictions conveyed by top-down projections with inhibitory effect, suppressing predicted signals and leaving only prediction errors to go forward (Teufel and Fletcher, 2020). But this is not the only form predictions can take. For starters, some recent studies show that top-down projections may actually sharpen the representation of predicted signals (Teufel *et al.*, 2018), something that has been incorporated in the theory (Teufel and Fletcher, 2020).

However, what may have been the main limitation in many treatments of PP is its narrow focus on predictions as only top-down projections – something that has been changing. For example, a recent

paper by Teufel and Fletcher (2020) made a strong case for broadening the set of processes we consider as predictions. In the paper, the authors argue that the focus on top-down predictions has led to a neglect of predictions embedded in the structure supporting bottom-up information processing. They note that constraints placed by local circuits on the bottom-up flow of information shape the way information is represented, acting as a form of context-independent predictions. This kind of prediction has been attracting increasing attention from part of the PP community and it is subject of active investigation under the rubric of structure learning, which considers the phylogenetic, neurodevelopmental and experience dependent mechanisms that shape cortical hierarchies such that they become an apt generative model for prediction (Tervo et al., 2016; Gershman, 2017; Smith et al., 2019)

Those extensions of PP broaden its framework and can make it more powerful and capable of explaining more aspects of the brain's workings. However, they also show that PP may be more similar to older frameworks than originally seemed. The broader view of the forms of top-down predictions and of predictions as whole highlights an isomorphism between prediction and memory that, when explored, shows that PP is not so different from the biased competition view of information processing and neural representations.

It is common-place that experience shapes the brain's connectivity pattern, that it can change the number and efficiency of synapses, the sensibility of neurons to neuromodulators and so on. Such changes are one of the general definitions of memory in modern neuroscience. Memories are stored throughout the whole brain, in its structure and in physiological parameters of neurons and synapses, and may receive different names depending on where (and when) they are stored and what information/process is affected by them (Fuster, 2001; Kandel *et al.*, 2014; Kukushkin and Carew, 2017). As such, memories essentially define what is made with incoming information and what neurons are recruited to the assembly representing any given input in any brain region.

From this perspective, PP does not seem such a radical paradigm shit (though this is easy to say having the advantage of hindsight). What is seen as prediction in PP is nothing more than different forms of biases in the processing of information shaped by development and the effects of past experience on brain circuits – in other words, predictions (like competitive biases) are generally the consequence of memories. Memory is all pervasive – it is present, in some form or another, in every brain region. Thus, prediction, in its broader view, must also be all pervasive. Memories/predictions, in the form of connectivity patterns, gene expression patterns and myriad forms of functional changes in individual neurons and synapses, shape and constrain the representations obtained from the converging information everywhere in the brain.

Crucially, if PP and competitive bias frameworks can be seen as isomorphic, then this gives us a golden opportunity. By clarifying the links and correspondences between the two, and between models based on them, we could be able to switch between these different perspectives as we please. This could be helpful as the solution for some problems may be clearer when looked through lenses one or the other framework. Moreover, it is possible that conceptual problems in each framework have a mirror on the other, but are just harder to pin down and/or to solve. Thus, communication between researchers in the two fronts may create synergy for advancing both research programs.

Some efforts in bridging PP models and biased competition models have already been carried out. For example, Spratling (2008) showed the mathematical equivalence between a particular biased competition model and a linear predictive coding model; however, that paper dealt with models that, despite their mathematical equivalence, differed in their implementation. Another point of contact between PP and the competitive bias happened when Feldman and Friston (2010) framed attention as a special kind of prediction – a prediction about the precision of sensory data. Here,

competitive bias sprung naturally from Feldman and Friston's formulation. Importantly, the whole thing hinged on a generalization of predictions to both states and precision – perfectly illustrating how, when the concept of prediction is broadened, PP and competitive bias frameworks can converge on the same mechanisms, only seen from different perspectives.

Going forward, it will be important to stimulate and broaden such bridging efforts beyond specific models and implementations. It will be important to clarify the equivalences between the views regarding neural representations and information processing of PP and biased competition before these lines of research diverge so much under the crushing trend of specialization that a synthesis becomes almost impossible. If this happens, we may end up with a fractured field, full of unrealized links between works, increasing the already vast amount of what Don Swanson (1986) called "undiscovered public knowledge", which drips through the cracks between sub-disciplines in every field of science.

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Competing interests

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