Precisions, slopes, and representational re-description

Precisions, Slopes, and Representational Re-description*

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Jun Tani's robotic explorations reveal the power and promise of hierarchical predictive coding as a bridge linking basic forms of sensorimotor engagement with the emergence of higher and higher forms of abstraction and control. Prediction-based learning yields representational forms, at higher processing levels, that act to summarize, compress, and control, activity at lower levels. Staged development with increasing flexibility results, since the process of level-by-level re-coding make lower-level knowledge available as 'chunks' for higher-levels to 'program' (re-purpose and re-organize).

These architectures give concrete computational form to 'representational re-description' - an endogenously-driven process in which sensory information is repeatedly re-coded ('re-described') in ways that support wider and more flexible kinds of use (Karmiloff-Smith (1992) - see also Clark and Karmiloff-Smith (1993), Cleeremans (2014), and Doncieux (2015)). Prediction-driven hierarchical learning results in just such a process of staged development - one in which each higher level seeks to separate out causes and regularities that govern or explain patterns extracted at the level below. This whole process – just as Karmiloff-Smith suggested – is constrained by powerful endogenous forces favoring elegance and simplicity. This is because the learning routine (see Pezzulo et al (2015)) favors the fewest-parameter model able to deliver (across a wide variety of contexts) apt action and choice. Complexity-reducing re-descriptions will thus continue to be sought even after behavioral success has been achieved. Such systems continually work on themselves to generate better and better (more powerful, less complex) models.

It is interesting to consider the potential (and potentially synergistic) influence of some potent additional elements prominent elsewhere in the literature on the 'predictive brain' (for a review, see Clark (2016)). One such is the variable ' precision-weighting' of the prediction error signal. Precision-weighting reflects the self-estimated reliability, for a given task in a given context, of specific prediction error signals. Increasing precision means increasing the post-synaptic gain or 'volume' on select prediction error signals, thus temporarily accentuating their influence. On a foggy day (to take a common example) this would enable the system to increase the influence of auditory information and to reduce the impact of incoming visual evidence, allowing a greater-than-usual role for top-down visual prediction.

Estimated precision also helps determine the nature and locus of control (Pezzulo et al (2015)). 'Habitual' control occurs when reliable (precise) sensory prediction error is rapidly resolved at lower levels of the processing hierarchy. More reflective means of control occur when precise (salient, reliable) prediction error arises and is resolved at higher levels of processing. Variable precision-weighting would thus enable the selection of which 'representational re-description' should control behavior at a given moment. An important research horizon is better to understand forms of control (realized as top-down predictions) that entrain temporally extended sequences of inputs, so as to sustain long-term plans and projects of the kind we associate with distinct human agents. Distinctively human forms of conscious experience may emerge only when we ourselves turn up as 'control elements' in long-term predictive models governing our own future actions (see our ongoing project at www.x-spect.org).

Another potent additional element may be the slope of prediction-error minimization itself. An emerging proposal is that an adaptively valuable strategy is to seek out situations in which the *slope* of minimization of prediction error is itself maximized (Oudeyer and Smith (2016), Joffily & Coricelli (2013), Miller and Clark (forthcoming)). This may help bring valence and emotion into the picture. The idea is that these track the rate at which prediction errors are being minimized relative to expectations. When error is minimized at a greater rate than expected, positive valence results. Such agents will actively seek out good learning situations - 'sweet spot' learning environments, where they can significantly improve their predictive model of some salient aspect of the world.

Finally, perhaps it is not just the slope but the location (within the predictive hierarchy) of 'better-than-expected' prediction error minimization that matters. In a re-descriptive hierarchy, unexpectedly resolving prediction errors occurring at the higher levels will often signal a kind of 'falling into place' in which multiple tensions and inconsistencies are resolved at a single stroke - as when we suddenly succeed in seeing the hidden image in a 'magic eye' (autostereogram) display, or spot a mathematical derivation linking one body of results to another. Positive valance would then track not merely the rate, or the quantity, of prediction error minimization (relative to expectations) but also the quality.

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