

Q&S point out, a cardinal feature of representation resides in the topography of connections. A recent quantitative study of the topography of extrinsic and intrinsic cortical connections in cats showed that the divergence values of the bulk of connections in developing pathways were within the adult range, suggesting that this feature of connectivity develops largely independently of selective processes (Kennedy et al. 1994). These studies in the kitten fail to distinguish feedforward and feedback connections. This difficulty can be overcome in the exquisitely compartmentalised extrastriate visual cortex of the primate. Using this model we examined the development of functional feedforward pathways and showed that directed growth plays a major role; the adult pattern of connectivity is accordingly acquired early in development with little or no elimination of inappropriate target axons (Barone et al. 1996).

So far, the development of association feedforward pathways could well be in accord with the constructivist manifesto, although it needs to be stated that even the small amount of developmental pruning observed could reflect important selective processes. However, feedback connections do not show the early specification of the feedforward pathways. Here selection leads to a massive reorganization of the laminar distribution of corticocortical neurons participating in feedback projections (Barone et al. 1995), suggesting that the relative role of progressive and selective mechanisms differs according to the functional role of the cortical pathway (Singer 1995). These findings suggest that understanding the functional role of feedback and feedforward connections gives a better understanding of where one could expect constructivist mechanisms to operate.

The manifesto gives short shrift to the early specification of cortical areas and declares: "the cortex . . . is largely equipotential at early stages" (sect. 4.1.1, para. 2). This is curious because it suggests a selective stance: if the cortex were equipotential, it would have a uniform connectivity so that selective axon loss must be proposed for the emergence of specific regional connections. In any case, the hypothesis of the equipotential cortex is no longer viable in view of recent results with molecular markers showing early regionalization prior to thalamic innervation (Arimatsu et al. 1992; Barbe & Levitt 1991; Cohen-Tannoudji et al. 1994) and axonal tracers showing adult-like distributions of immature corticospinal projections (Meissirel et al. 1993; Oudega et al. 1994). Finally, the concept of an equipotential immature cortex has been definitively refuted by the quantitative analysis of grafting experiments (Ebrahimi-Gaillard & Roger 1996).

The difficult task which remains is to conceptualise the afferent specification by the internal environment (Killackey 1990; O'Leary 1989) with early cortical regionalization (Rakic 1982). Attempts to do this have largely referred to prenatal enucleation experiments in the monkey (Kennedy & Dehay 1993a; Rakic 1988). These experiments show that the dimensions of striate cortex are determined by the number of thalamic afferents and that in their absence, cortex which was destined to acquire striate features instead takes on the phenotypic features of extrastriate cortex, which, however, still continues to display a number of unusual features, possibly of striate origin (Dehay et al. 1996a; 1996b; Rakic et al. 1991). Clearly, the early regionalisation of cortex places important constraints on the amount of instruction that can be derived either from external events or the internal environment.

In conclusion, there are many progressive phenomena in cortical development, particularly in feedforward connections. However, for this to correspond to a constructivist model, external events need to influence the underlying growth processes. The paradigm for such a phenomenon is curiously suggested by numerous reports of cortical plasticity in the adult (reviewed in Kaas 1995), largely unmentioned by the manifesto. That field of research reminds us that the cortex is a universal learning machine and raises renewed interest in the continuity hypothesis (Pinker 1984). It links adult and developmental plasticity (Cramer & Sur 1995) and suggests a neotenuous phenomenon as a central feature

of cortical function. More specifically, the manifesto needs to pay particular attention to the timing of cortical development and to recognise the improbability of external events influencing *early* development (Kennedy & Dehay 1993b). Because much of cortical pathway formation occurs prior to activity evoked by the external world reaching the cortex, it seems likely that constructivist control concerns the late fine tuning of the feedback cortical connections required for cortical function.

## From neural constructivism to children's cognitive development: Bridging the gap

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**Abstract:** Missing from Quartz & Sejnowski's (Q&S's) unique and valuable effort to relate cognitive development to neural constructivism is an examination of the global emergent properties of adding new neural circuits. Such emergent properties can be studied with computational models. Modeling with generative connectionist networks shows that synaptogenic mechanisms can account for progressive increases in children's representational power.

Quartz & Sejnowski describe an exciting new approach to relating brain development and cognitive development. Although constructivist accounts of cognitive development have a long history (e.g., Case 1985; Fischer 1980; Piaget 1970), there have been few attempts to ground the principles of constructivist development in a neural or biological substrate. The few attempts have either failed to relate development to specific brain processes or have failed to show how neural changes increase representational power. For example, Piaget (1980) describes cognitive development in terms of biologically plausible competitive mechanisms but fails to specify how these mechanisms are implemented in the brain. In contrast, others – such as Case (1992), who attributes much of cognitive development to greater myelination in the frontal lobes, or Fischer (1994), who argues that patterns of cyclical brain activity correspond to stage like transitions in brain reorganization – fail to specify how these neural processes increase representational power. Q&S are to be commended for tackling both sides of the issue.

However, an important element is missing from Q&S's argument if they wish to support the hypothesis that the neural mechanisms they describe actually underlie the development of behaviors observed in children. They suggest a means by which constructivist development can occur at the neural level but it is possible that other, more global processes dominate children's cognitive development. Indeed, the global interactions that emerge from a complex system may overshadow the effects of constructivist development at the level of individual neurons. To substantiate the claim that a constructivist neural mechanism empowers a system to learn complex relationships in the same way children do, it is necessary to explore whether the developmental profiles of a generative neural network match the developmental profiles observed in real children when presented with identical learning tasks.

One way to test this is through computer modeling. Computer models of child development provide a way to investigate the mechanisms that may underlie observed behaviors (Halford & Simon 1995). A mechanism that does not produce the correct developmental profile can be ruled out as a candidate. Generative connectionist networks (networks that grow their own architectures as part of learning) are being explored as models of constructivist cognitive development (Mareschal & Shultz 1996). Models

of children's performance on the balance-scale task, the seriation task, the integration of time, distance, and velocity information, a pronoun reference acquisition task, and a causal judgment task concerning the potency and resistance of an effect have all been developed using the cascade-correlation learning algorithm (see Shultz et al. 1995 for a review). In many cases, the generative connectionist models capture the developmental profiles of children better than do static feed-forward connectionist networks, which often miss important stages (Buckingham & Shultz 1996; Mareschal & Shultz 1996; Shultz et al. 1994).

Generative connectionist algorithms like cascade-correlation allow for both quantitative changes (through connection weight adjustments) and qualitative restructuring (through recruitment of hidden units). The former permits knowledge acquisition within an existing representational framework, and the latter an increase in representational power. The question of whether development is driven by quantitative or qualitative change is central to cognitive development (Keil 1990). The cascade-correlation models suggest that both types of mechanisms are necessary to account for development over a variety of domains, although particular developments may be attributed to one or the other. In addition to conventional quantitative adjustments of synaptic strength, the neural mechanisms reviewed by Q&S allow for qualitative restructuring, thus putting this fundamental psychological distinction on a firm neurological basis.

The cascade-correlation algorithm forces a network to develop initially through a phase of limited representational power and then through successive phases of increasing representational power. That is, the system must develop limited representations and then build on them when added power is developed. The simulations suggest that this is a necessary feature for capturing realistic cognitive development in many domains.

The renewed research interest in the periodic need to increase the representational power of a system (as illustrated in both the target article and the modeling work) suggests that research in cognitive development should move away from the search for ever more precocious proto-representations in children and return to the study of what children can and cannot assimilate at particular stages of development. Constraints on early representations are provided by what the child cannot represent as well as by what the child can represent. Finally, these constraints should be yoked to neurophysiological constraints like those described by Quartz & Sejnowski.

## More mathematics: Bodily-kinaesthetic intelligence

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**Abstract:** Although the idea that cognitive structure changes as we learn is welcome, a variety of mathematical structures are needed to model the neural and cognitive processes involved. A specific example of bodily-kinaesthetic intelligence is given, building on a formalism given elsewhere. As the structure of cognition changes, previous learning can become tacit, adding to the complexity of cognition and its modeling.

Quartz & Sejnowski's (Q&S's) philosophy that we build on our learning is liberating, as is the less strongly stated point that our behavior is not genetically determined (sect. 4.4) and that minds are not computers (sect. 1). A further liberation is needed from narrow and fashionable views of representation and from dependence on artificial neural network modeling. "Selectionism brings increased tractability to modeling efforts" (sect. 2.2.1) only in a narrow range of modeling types.

It is not clear that activity in the cerebral cortex is "representing" anything; it is more accurate to speak of neural ensembles as

"transforming" activity. The question is then to characterize the transformation mathematically. That is, a better characterization is needed of the mathematical structure(s) of the cerebral cortex itself. While it is possible that "representational complexity" depends monotonically on synaptic numbers, axonal arborization, or dendritic development, there is no necessary relationship. One can use more words to say less. The complexity of function depends instead on the complexity of patterns among the synapses, axons, and dendrites and on their particular relationship to the neural and cognitive environment.

It follows from Q&S's views that learning is not only meeting some task criterion but also elaborating a set of behavioral (or imaging) strategies. Learning is creation, not limitation. In order to make sense of the role of the cerebral cortex in learning, it is necessary to formalize the interactions of cortical ensembles with other parts of the nervous system and with the environment. An example of a unified mathematical characterization of a simple combined neural-behavioral system is given by Roberts and McCollum (1996).

The cortex's environment in the nervous system is enough to vary the type of mathematics needed. In our studies of movement-related parts of the nervous system, different mathematical systems fit different neural ensembles (Holly & McCollum 1997; McCollum 1992; 1993). Combined mathematical characterizations of cortical and extra-cortical systems will therefore differ, depending on the parts of the nervous system involved.

A good area to model is bodily-kinaesthetic intelligence, to use Gardner's (1983) expression. The modeling of movement is grounded in physics, with its agreed-upon formalism. Brenière et al. (1989), conclude that children in the early stages of walking integrate physical principles of movement sequentially. That conclusion fits well with our own study of the physics of learning to walk (McCollum et al. 1995).

One can imagine extending that study to include the cortical role in movement. For example, the twist style of early walking involves a movement like that of a drawing compass, in which early efforts at walking alternate from foot to foot after each twist. The pattern of reafference encountered in early practice gives rise to a hypothesis (sect. 4.2) that there is a relationship between aspects of sensory reafference and progression toward some goal. For instance, it would be natural to use the vestibular system to gauge the extent of twist. If we assume that the role of the cerebral cortex is to grasp connections and envision possibilities, it would make sense that the cortex would oversee (1) the integration of the connection between reafference and twist (after the fact) and (2) the calibration of twists to reach predetermined goals.

This is an example of second-order learning (I wouldn't call it nonstationary): of finding a goal during learning or laying down the road in walking (Varela et al. 1991). The various elements are available for modeling and many are even available for observation. In constructing this specific example, I am extending Q&S's point that the cognitive structure changes with learning. I would like to emphasize another aspect of real-world learning: the surprises that come in trying something out, for example, walking. Because of such surprises, second-order learning may not be a refinement of an original goal but may take entirely new turns.

Second-order learning also involves burying earlier conclusions: previously learnt skills and procedures become tacit and unavailable for modification. This is a way to understand some of the difficulties faced by recovering stroke patients. A patient who once *learned* to guide footfall by the vestibular system may no longer be able to walk successfully following that procedure (McCollum 1994).

Elaborating and specifying second-order learning will require patience for complexity. One must not get stuck in one's metaphors and methods.