Dynamical and Connectionist Approaches to Development:

Toward a Future of Mutually Beneficial Co-evolution

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Introduction

When modellers who exploit different approaches get together, there is a tendency to extol the virtues of one's own approach and try to promote it over the approaches of others. This can lead to a funny kind of either-or mentality – is it better to be a connectionist or a dynamical systems modeller? To us this is truly the wrong question. We agree with Smith when she says (this volume, p.xxx), '[which approach is better is] not an argument much worth having.' Much more important are the insights that each approach offers toward an understanding of the nature of cognition and behaviour, and the processes that underlie the development of cognitive and behavioural capacities. And of course, there are a number of reasons why any sort of either-or decision would be misguided. Neither school of thought is stationary; neither school of thought is unitary. Schlesinger (this volume) goes so far as to liken connectionism and dynamical systems theory (DST) to organisms evolving over time and increasing their adaptive fit to the environment (of explanation); and a cursory inspection *within* each field reveals separate groupings of researchers exploring different psychological phenomena with diverse (albeit related) modelling techniques and assumptions.

For example, within DST, one can distinguish (1) *Dynamical Field Theory* (e.g., Thelen, Smith, Schöner, Spencer) focusing on behaviours unfolding in the millisecond and second range, such as sensori-motor control in relation to objects; (2) *Growth Models* (e.g., van Geert, Fisher) that focus on phenomena such as vocabulary development occurring over days, weeks, months and years, and exploiting linked growth functions; and (3) *Catastrophe Theory* (e.g., van der Maas, Raijmakers) focusing on development in reasoning occurring over hours, days, and weeks.

Within the connectionist modelling framework, one may also find a great deal of diversity. Some researchers use *Feedforward backpropagation network models* and target cognitive development over days, weeks, months, and years in domains such as language, semantics, and reasoning (McClelland, Plunkett, Plaut, Thomas) while others employ constructivist networks (most notably Schultz and colleagues). Some researchers use *Recurrent attractor models* and target both behaviour unfolding in the moment, and development over weeks, months, and years, in domains such grammar development and objected directed behaviour (Elman, McClelland, Plaut, Mareschal, Munakata, Thomas). There are also those who use what might be called *Neurocomputational models*, targeting specific neural structures such as the pre-frontal cortex, basal ganglia, or the hippocampus (Cohen, O'Reilly, McClelland). These choices are not based on doctrine, and do not reflect doctrinal differences; rather they are generally pragmatic choices. The goal is to capture certain key features of human performance and human development – its experience-dependence, its partial but not complete tendency toward regularity, its graded sensitivity to various variables, and many other key features.

For us, the aim of juxtaposing connectionist and DST approaches within the same volume is to identify the common themes of (successful) models of developmental phenomena, so that future work can benefit from the combined insights of both approaches. These themes will lie at the heart of any new theory of development, and their future evolution will, we suggest, be enhanced by maintained interaction among connectionist modellers and dynamical systems researchers.

It is true that at times a tension has existed between connectionism and DST, and it is instructive to consider why this should be the case. But in what follows, one should remember that the similarities between the two approaches far outweigh their differences. In this chapter, we argue that much of the tension in fact arises from a tenet that the two approaches share: both rely on the explicit quantitative instantiation of ideas in mathematical or computational models. We argue that the use of such models is responsible for much of the theoretical progress generated by connectionism and DST beyond the theories of Good Old-Fashioned Cognitive Development (GOFCD) (see Oaks, Newcombe & Plumert, this volume, for an exposition of those theories); but we also argue that the use of explicit quantitative models brings with it a new set of problems. In the next section, we discuss several consequences of the use of such models that are pertinent to any potential integration of dynamical and connectionist approaches. To illustrate these ideas, we then consider three points of apparent disagreement between connectionism and DST. These include the nature of children's reasoning on the Piagetian balance scale task, the importance of embodiment, and the role of stability. We finish with a brief summary of the themes that we imagine will feature in any future integration of connectionist and dynamical systems approaches. We believe that they are all consistent with the current direction of connectionist theorising.

Explicit quantitative models and cognitive development

Several concepts have gained greater prominence in developmental theory through the work of connectionist and DST researchers. These include the idea of emergence; the demonstration that relatively sudden (apparently stage-like) transitions in behaviour can arise from continuously changing underlying mechanisms; the idea that instability or variability is often associated with change; and that behavioural patterns may arise from the competition between latent and active representations of knowledge.

Some have doubted that these ideas are genuinely new, arguing instead that connectionism and DST have simply served to shift the relative emphasis among pre-existing ideas in our understanding of cognitive development (Oaks, Newcombe, & Plumert, this volume). In some sense, it is not important to establish who-thought-of-the-idea-first (in most cases, it happened a very long time ago). Instead, we argue that the core contribution of connectionism and DST has been their reliance on explicit quantitative formulation. These methods have provided a new and sharper set of tools to drive forward theoretical progress in our field. In many scientific fields, explicit quantitative methods have historically followed an earlier phase of exploratory data collection that was guided by informally specified theories. Progress via this route often asymptotes because the theories aren't sufficiently explicit to know what exactly they predict. Moreover, their terminology frequently glosses over deeper conceptual problems. For example, a verbal theory may claim that different rules appear at different ages in children's reasoning on the balance scale task, but this theory hides the serious problem of specifying the nature of the experience-driven (or even maturational) mechanisms that can generate new rules. Ultimately, an explanatory theory must strive for mechanism, that is, a way in which behaviour can be explained by the operation of the causes that shape it.

It is here that explicit quantitative models of development, be they connectionist models, dynamical systems models, or some other kind, offer so many advantages. The advantages have been much discussed elsewhere (see, e.g., Elman et al., 1996; Mareschal & Thomas, 2007; McClelland & Rumelhart, 1986; Munakata & McClelland, 2003; Thomas & McClelland, in press). Here we simply allude to a few of them. Explicit quantitative models necessitate that the theorist be much more specific about the causal entities in the theory – the same verbal term cannot be used (unwittingly) in subtly different ways. Unexpected behaviours may emerge from the complex interactions of many simple components, along with the structure of the problem domain. A formal model can test whether the theory as specified indeed generates the behaviour it is supposed to explain at a quantitative level. Models can unify experimental data, for instance bringing together data from development, adult function, and breakdown with reference to a single well-specified system. Models can generate new predictions to be tested against quantitative data. They can produce general explanations by demonstrating how a small set of processing principles, when combined with the features of particular cognitive domains, can account for experimental data across a range of behaviours. Where new models are controversial, they stimulate further theoretically focused data collection, which advances the field. And so on.

A key point about explicit quantitative models is that they are not generally intended to provide a detailed account of all aspects of a situation or phenomenon. Rather, their role is to help us understand the consequences of certain constellations of assumptions. Central to the effort to achieve understanding is the role of simplification. All models make certain simplifications in order to focus on explaining the phenomenon of interest. This may mean focusing on a very restricted range of task situations and experiences relevant to them (for example, in the case of the balance scale task, there is a focus on experience with balance) and considering change only over a certain timescale. Finer time scales believed to involve a graded and continuous real-time process may be replaced with single computations that are essentially treated as occurring instantaneously. Simplifications will often also be made in the way the environment is represented. For example, in the A-not-B task, the exact perceptual features of the objects that are manipulated in front of the child are not all held to be important to the phenomenon, so a model may provide only a single dimension for the presence or absence of each object. The art of using explicit quantitative models is to make simplifications only in those aspects of the cognitive domain (regarding representation, process, or environment) that are not considered to be crucial in addressing the focal issues under consideration. Decisions about what these issues are and which simplifications are best to address them are themselves reflections of scientific judgment, and they are subject to disagreement – not all researchers find the same aspect of a particular phenomenon to be its most central feature. Furthermore, there are natural differences among investigators in the factors that contribute most importantly to the explanation of a phenomenon. Thus, there is no single ‘correct’ set of simplifications; and even if there were, there is no known algorithm for discovering what they are. This is why explicit quantitative modelling is for us best understood as an ongoing process of exploration.

The central role of simplification adds some complexity to theory development, in particular in evaluating the success and failure of particular models. When a model works, what does this mean for the underlying theoretical commitments from which it was derived? If a model appears to succeed in capturing the development of some target phenomenon, is this only because it has included unrealistic simplifications in its design? If a model fails, is this fatal for the underlying theoretical perspective that it attempts to embody? Often, it may not be fully clear what those commitments actually are – thus assumptions that may be introduced either as simplifications or because the modeller did not choose to focus on a particular aspect of the phenomenon under consideration may appear to other readers to be matters of theory or principle. The ensuing dialog is in our view a healthy process that, carried on over the course of several years, often leads to considerable progress.

It is here, however, that we come to the source of the tension that exists between connectionism and DST. Frequently, connectionist and DST models include different simplifications because they are targeting different issues. The simplifications include differences in the timescales over which developmental change is examined; the relative emphasis on the role of learning (structural adaptations) versus priming (temporally continuous activation states) in modulating behaviour; simplifications regarding the importance of the structure of the problem domain in driving behaviour (e.g., representations in connectionist models are typically of higher dimensionality than in DST and place greater emphasis on the role of experience in the problem domain in shaping behaviour); the relative emphasis placed on the role of embodiment; the level of abstraction encoded in representations; and the roles of variability and stability in representational states. Indeed, in looking back across two decades of connectionist and DST models, it is striking how often these models have employed complementary simplifications. However, this may not reflect any fundamental theoretical incompatibilities; it may instead reflect differences in the specific issues and phenomena that are the focus of the modeller’s attention.

The problem is not restricted to comparisons between connectionist models and DST. Model simplifications can vary as much within the approaches as between them. One solution is to encourage researchers to be as clear as possible about what they take to be the core assumptions and what they consider to be simplifications introduced only for the sake of tractability and transparency. Then it will become more apparent where actual theoretically important points of contention lie, and which differences between models merely reflect differences in where the modellers have chosen to make simplifications. What might such a list look like? As an exercise, in Box 1 we list the simplifications made in one connectionist model of the development of syntax comprehension (Thomas & Redington, 2004), along with the rationale for making them. If there were more efforts of this type, it would make it easier for researchers to be clearer about points of principle and points of strategic simplification. This in turn should lead eventually to a clarification of exactly what aspects of a particular model are responsible for its successes and/or failures. Of course, even listing everything relevant in such a table is no easy task, since modellers may not always have in the focus of their attention all the factors that could potentially be relevant to their simulations. And knowing which factors are crucial for success and failure is even harder. In general, we adopt simplification for the sake of tractability – were the simplifications to be replaced, the model could become intractable, making it in fact very difficult to know just how important the role of the simplification is.

The complementarity between models frequently hinders a comparison between connectionism and DST. However, in support of our claim that these approaches have much in common, when the respective researchers have turned their minds to explaining *the same* developmental phenomenon, their models have tended to converge. The A-not-B error in infants provides one such case (Smith, this volume; Morton & Munakata, this volume). As we shall shortly see, both connectionist and DST models of this phenomenon employ uni-dimensional representations of objects and motor actions; both employ settling attractor states driven by recurrent connections; and both explain behaviours in terms of a competition between states induced by a sequence of previously encountered situations and the most recent event witnessed. First, we turn to consider another developmental phenomenon where connectionist and dynamical approaches have collided.

Insert Box 1 around here

Connectionist and dynamical modelling of children's development on the balance scale task

As discussed in McClelland and Vallabha (this volume), connectionist models often focus on the overall time course of development, neglecting some of the details of shorter term processing. In the context of modelling the balance scale task, this focus on overall developmental trends has in part led to a neglect of the question: exactly how well do these models capture the details of transitions between stages? Van der Maas and Raijmakers (this volume), researchers who use catastrophe theory as a framework for understanding stage transitions, have criticized connectionist models for not exhibiting the abrupt transitions between stages of the balance scale task that they claim are present in experimental data. In their view, these transitions exhibit several catastrophe flags that they see as indicative of underlying phase transitions in behaviour. Looking for evidence of such catastrophe flags in the McClelland (1989, 1995) balance scale model, they argue that these flags are not exhibited in the model's behaviour (Raijmakers, van Koten, & Molenaar, 1996).

There have been many interesting contributions made in the application of catastrophe theory to the balance scale task and in the related effort at analysis of the connectionist model's ability to account for these effects (see also Jansen & van der Maas, 1997; 2001; 2002; Quinlan et al., 2007). Indeed, the McClelland (1989, 1995) model does have some shortcomings in accounting for several aspects of the relevant experimental data. However, these shortcomings arise from simplifications in the model in relation to its initial focus on the longer time scale over which developmental change occurs in tasks such as the balance scale. Are these shortcomings deficiencies in the underlying theory embodied in the model? There can be several different perspectives on this issue. We will come back to this question after observing that recent extensions to the McClelland model (1989, 1995), which incorporate shorter-term dynamics into the architecture, show that it is able to exhibit the indicators of the transitions in development that van der Maas and Raijmakers (this volume) have suggested it cannot capture (Schapiro & McClelland, in preparation).

The data recently modelled are from Experiment 1 of Jansen and van der Maas (2001). A paper-and-pencil version of the balance scale task was administered to over 300 children between the ages of 6 and 10. The study contained a pre- and post-test to assess children's performance on several items of various problem types. Between the pre- and post-tests the investigators inserted a 'hysteresis test', a special series of items progressing stepwise from a minimum to a maximum difference in the distance of the weights from the fulcrum on the two sides of the scale, then stepping back down from the maximum to the minimum again. Key findings from the study were a tendency toward bimodality in test scores (most children got all or none of the distance problems correct on the pre-test and most got all or none of the distance problems correct on the post-test); an upward shift in the distributions of scores from pre- to post-test; and the presence of transitions in performance during the hysteresis test.

The original McClelland model had some degree of bimodality in test scores, but no shift in the distributions of scores from pre- to post-test and no transitions during the hysteresis test. There are three extensions to the model, however, which allow a good fit to nearly all aspects of the Jansen and van der Maas (2001) data. The first is to allow the model's own output to serve as a teaching signal that can lead to a change in behaviour. The lack of a mechanism addressing how change can occur without a teaching signal was not explicitly recognized as a simplification in the initial formulation of the model; the focus was on how experience with situations involving weight and distance might lead to progress in understanding balance scales and an apparent succession of developmental stages. However, it is clear that when we behave, the responses we make can lead to changes in our behaviour, and any satisfactory model should provide a mechanism that makes this possible. To address this, Schapiro and McClelland used the network's output for a given problem as the basis for assigning it a corresponding teaching signal. This assignment was based on the same discrete categorization of the network's continuous output that was used to assign one of the three possible responses to the network's output. For example, if the activation of the left output unit was .333 or more greater than the activation of the right output unit, the output was scored 'left side down' and a teaching signal of 1 for the left output unit and 0 for the right output unit was assigned. The other two extensions were (a) the incorporation of noise, or intrinsic variability, into the model, and (b) the use of the teaching signal to modulate the 'gain' on the inputs to the hidden layers in the model during network testing. Concerning the first of these extensions, we drew on earlier work (McClelland, 1991; 1993; Movellan & McClelland, 2001; Usher & McClelland, 2001) indicating the importance of including intrinsic variability in the activations of units throughout the network. Based on this work, a sample of normally distributed zero-mean Gaussian noise was added to a given unit's net input before its activation was calculated. The addition of noise is an example of a more detailed level of modelling that can be quite important but is missed in a model that focuses only on overall developmental patterns.

Regarding the second extension, the adjustment of gain has been proposed as one way of implementing an attention-like mechanism in connectionist networks (Kruschke & Movellan, 1991; Kruschke, 1992). The 'gain' is simply a scalar multiplier that scales the net input to the hidden units in the model. An increase in gain thus corresponds to an increased sensitivity to the inputs coming to the affected units. Following Kruschke (1992), we adopted the idea that dimensional attention, operationalized as an adjustment to a dimension-specific gain parameter, might be adjusted using the back-propagated error signal, which in this case is derived from the teaching signal generated by the network's own output. Adjustment to the gain variable provides one possible mechanism that may explain changes in children's sensitivity to the distance dimension during testing.

The model still contains simplifications. In other work, we and many other connectionists have assumed that processing within connectionist networks is itself a real-time continuous process; indeed, it was with this specific assumption that McClelland (1979) first began to explore connectionist models, and this assumption is part of the set of basic processing principles that McClelland (1993) later proposed. But we have maintained the simplification of relying on a single-pass feedforward computation in the present extension of the McClelland (1989) balance scale model. The addition of a self-generated teacher, and the use of gain and noise, seem to be sufficient to produce all the evidence of catastrophe-like transitions in behaviour found in the data from Jansen and van der Maas (2001), as discussed in Schapiro and

McClelland (in preparation), including those enumerated above. In particular, the model showed a pattern of bimodality quite similar to that seen in the Jansen and van der Maas data. It also showed a progression to higher scores from pre- to post-test, and a pattern of transitions in the hysteresis test quite similar to that observed by Jansen and van der Maas, including the tendency they viewed as most clearly demonstrative of a catastrophe: the so-called ‘delay’ pattern, in which the participant switches from making an incorrect ‘balance’ response to a correct distance-based response at some point during the sequence of increasing distance problems, and then persists in making the correct response on the way back down through the series of distances past the point of the switch-over during the earlier increasing sequence.

It is interesting to consider the consequences of the model’s ability to account for the presence of these catastrophe flags. Is there really a phase transition happening in the model? Our inclination is to say no; the delay patterns displayed by the model (and many of the so-called ‘sudden-jump’ patterns, see Schapiro and McClelland for discussion) appear to be the result of relatively small changes in unit activations.

In fact, there seem to be several indications in the Jansen and van der Maas (2001) data that the transitions exhibited by many of the children tested are actually more continuous than the presence of catastrophe flags might at first suggest. First, both on the pre-test and the post-test, there are many children who get some but not all distance problems correct. The distance problems these children are most likely to get correct involve larger variations of distance. In other work, Jansen and van der Maas (2002) actually identified such a pattern as characterising a group of children, and treated it, as we do, as a developmental phase that lies between the more categorical patterns associated with what Siegler (1976) called “rule 1” (relying only on weight) and “rule 2” (relying on distance only when weights are equal). Furthermore, about half of the transitions to the categorical rule 2 pattern on the post-test are from intermediate patterns on the pre-test, and most of the transitions from the rule 1 pattern on the pre-test are to an intermediate pattern on the post-test. These results suggest that many children have a graded sensitivity to the distance cue which increases over the course of the experiment, instead of a sudden realization that distance is important prior to showing no previous awareness of the distance dimension. Such a change in an underlying graded pattern is, of course, the core claim of the connectionist model, distinguishing it from approaches based on the actual representation and use of categorical rules, as in models such as those of van Rijn, van Someren, and van der Maas (2003) or Klahr and Siegler (1978).

Having said all this, there do seem to be a small number of cases of children who really do make a bigger jump, moving from taking only weight into account on all the problems on the pre-test to consistently relying on distance in the post-test when the weight on both sides is equal. This pattern, as well as some large jump patterns seen in the hysteresis test, is sometimes seen even in our model, but is also consistent with the possibility that more categorical or stage-like change may be occurring in a small number of children. Even so, there appears to be a persistent tendency to see performance in this task as essentially more rule-like, and transitions as more discrete or categorical, than the data actually warrant. Several phenomena we have considered, and others that are not reviewed here (see McClelland, 1995, for more discussion) point to an underlying continuity, especially around points of transition, at least for a substantial proportion of participants.

What is of fundamental importance for the present analysis is the observation that, by replacing simplifying assumptions (such as noise-free processing) with assumptions that are considered crucial in dynamical systems research (such as intrinsic variability) we have increased the extent to which the connectionist models can be successful. The absence of intrinsic variability from the McClelland (1989) model was not a point of principle, but only one of simplification. The successful outcome of its reintroduction, prompted by findings offered by proponents of the dynamical systems approach, points toward a future convergence in which the principles on which both approaches have focused are seen as part of an integrated and improved approach that exploits the key insights of both.

Embodiment

Corbetta (this volume, p.xxx) illustrates the emphasis that DST frequently places on embodiment: 'the body with its physical properties is the vital liaison between the mind and the outer world and this liaison is constant throughout the lifespan as we grow and interact with the environment'. In this view, we cannot escape the fact that the mind is encapsulated within a body. Moreover, this body undergoes a series of changes throughout life – particularly during early development as we learn to carry out basic actions, such as reaching, grasping, and walking. The extent to which our physical status constrains the formulation of our intentions to act upon the outer world is a topic of debate, and is intimately linked to the nature or indeed actual existence of internal representations.

There is a range of different perspectives on the nature of embodiment. One perspective, perhaps the middle of the road between extreme representationalist and anti-representationalist approaches, is that embodiment acts as an additional constraint on cognitive processing (Mareschal, Johnson, Sirois, Spratling, Thomas, & Westerman, 2007). This stance recognises the contribution of our physical status, whilst at the same time not rejecting out of hand or devaluing the significance of internal representations – a point of contention between connectionist and DST approaches to cognition. This perspective is consistent with the ideas of Glenberg (1997), who argues that representations held in memory reflect the structure of the environment – making them analogical or *embodied* – because they are mapped to the outside world. This allows the representation of perceptual states to become meaningful in themselves through their use in interpreting the environment, making our own actions central to our understanding. Evidence for physical constraints in our internal representations can be found in studies investigating the correlation between real rotary movements and mental rotation. These studies concluded that the same laws of motion govern mental rotation as actual movement (Decety, 1996; Jeannerod, 1995; Georgopoulos & Pellizzer, 1995; Wexler, Kosslyn & Berthoz, 1998). The role of embodiment can be found even under conditions that do not directly invoke any physical aspects of task performance. For example, when van den Bergh, Vrana and Eelan (1990) presented letter pairs to typists and non-typists and asked them to express preferences between competing pairs, they found that typists preferred letter pairs that were typed with two different fingers to letter pairs that could be typed with the same finger. The non-typists showed no such preference. Judgements were implicit, in the sense that the typists were unable to verbalise an explanation for their preference. Van den Bergh et al. concluded that motor programme information is encoded within the representations for letter pairs, which then influences the selection of the preferred pair for typists.

Consideration of embodiment can certainly lead to elegant explanations of phenomena that must be explained very differently (and perhaps incorrectly) from a cognitive or neurocomputational viewpoint. For example, Thelen and Fisher's (1982) embodied account of the disappearance of infants' stepping reflex is that as the legs grow heavy with subcutaneous fat during development, for a time the infant does not have the strength to lift them when supported upright. This contrasts with an alternative explanation that the disappearance reflects a process of cortical inhibition of the reflex. Thelen (1986) later found evidence against the inhibition theory by demonstrating that the infants could still make stepping movements under certain conditions, such as when are placed on a treadmill.

Given the potential insights that embodied accounts offer, why have connectionists so often chosen to simplify their models by excluding the constraints of embodiment? Why have they instead construed developmental problems in terms of learning transformations between abstract (disembodied) representational states? In many cases, connectionists would argue that this is because the phenomena they are targeting are those where embodiment is less relevant – for example, in the study of language acquisition. Indeed, when DST researchers turned their attention to the sensori-motor basis of learning object labels in infancy, they too found that the infants' application of these labels generalised beyond the sensori-motor circumstances of acquisition. Object labels therefore seem to require a more abstract level of encoding than sensory-motor links (see Smith, this volume). The role of embodiment in constraining the design of explicit quantitative models becomes more apparent when we compare connectionist and DST models of precisely the same phenomenon. For this, we turn to the A-not-B task.

The A-not-B task is a classic Piagetian task, in which infants demonstrate perseverative reaching behaviour. The typical task set-up consists of two covered hiding locations (A and B, respectively). During 'A' trials, the experimenter waves a toy near location A and hides the toy under the cover in that location. The infant then reaches for the toy. This procedure is repeated for several trials in location A.

Following these trials, the toy is then waved near and hidden in location B. Typically, 8- to 11-month-old infants will (erroneously) continue to reach to location A to retrieve the toy on these ‘B’ trials (Piaget 1954; Diamond, 1985). Interestingly, infants have been found to *gaze* at the correct B location on ‘B’ trials but still *reach* perseveratively to location A (Diamond, 1985).

The connectionist account of perseverative reaching (Morton & Munakata, this volume) focuses on a competition between active and latent internal representations that link object locations to actions such as reaching and gazing. Active representations correspond to sustained neuronal firing for current events, implemented through recurrent connectivity. By contrast, latent representations correspond to a longer-term memory of previous events, implemented through experience-dependent change to connection weights. During ‘A’ trials, the model learns that objects will be at the A location, thereby building up a latent representation that biases interest to that location and explains correct reaching performance on the A trials. On the B trial, the system must overcome its bias to reach to the A location based on the observation that the object is now at B. During early development, the strength of recurrent connections for maintaining active representations of current events is low. If there is a delay between the observation and the opportunity to reach for the object, infants may be unable to overcome the latent bias of location ‘A’ on B trials – resulting in perseverative reaching. Across development, the strength of recurrent connectivity is increased, allowing active representations to be maintained in memory with a sufficient strength to override the bias of latent representations – resulting in a decrease in perseverative reaching and correct reaching to B.

The DST account, by contrast, explains perseverative reaching in the A-not-B task in terms of the infants’ inability to break the “motor habit” of reaching towards location A on ‘B’ trials. The crucial difference is a claim that the key internal state is an embodied motor programme for reaching to a certain location in space. Infants learn a motor programme during ‘A’ trials and keep on using it even when no longer appropriate. There is considerable debate about the nature of motor programmes and the extent to which they are effector specific (for example, one’s signature looks broadly similar if one writes it very small on a piece of paper or large on a whiteboard, even though different muscle groups are involved in the producing the movements in each case). Nevertheless, the claim of motor specificity is motivated by empirical data that indicate that the A-not-B error can occur even when infants are simply reaching to visible covers over empty containers (Smith, McLin, Titzer, & Thelen, 1995) and can be eliminated by altering the infant’s body position between the A trials and the B trial (Smith et al., 1999; Smith, this volume). The DST model focuses on the evolution of activity in a dynamic field representation of the motor programme over time. The dynamic field is influenced by the current sensory input, the most recent event, and long-term memories of previous reaches. When the field’s activity exceeds threshold, the location of the peak activity drives a reach to a certain location in space (either the A or B location, in this case). Perseverative reaching occurs when the long-term memory comes to dominate the persisting activation from the last event (the B trial). Errors are overcome across development through a change to an external control parameter *h,* which modifies the influence of the reaching bias built up during previous trials (Thelen, Schöner, Scheier & Smith, 2001).

Now these accounts do place a different emphasis on the role of embodiment in how the activation states of the models are characterized – but *underneath the hood*, how different are they? Both formalizations consist of two forms of memory that may be placed in competition; both involve an in-the-moment memory system that involves cycling activation in a recurrent computational circuit; both utilize (externally applied) parameter changes that affect the strength of active representations of the cue on the B-trial in order to capture developmental change in levels of perseveration; both simplify the encoding of objects, spatial locations, and motor actions to uni-dimensional variables (representing, for example, a reach to location A). They differ as follows. The connectionist model includes a learning mechanism for building up the latent representations of A-trials, whilst the DST model assumes the build-up occurs without providing a mechanism for it. The dynamics of the DST model enable it to account for the trial-by-trial stochasticity shown by infants (Thelen et al., 2001) while the connectionist model does not.

It appears the primary role of embodiment in the DST model is in its characterisation of the dynamic field as encoding a motor programme, while the connectionist account includes more abstract internal representational states that intervene between sensory systems and motor behaviour. Neither model actually incorporates any biomechanical aspects of reaching. Is the difference between the models just skin deep, then? Are these similar computational systems merely labelled in different ways, with no body in sight? Perhaps. But the difference in labelling nevertheless reflects the theoretical concerns of each set of researchers and it results in real consequences for the interface between model, theory, and empirical data. It leads the DST researchers to focus on bodily manipulations to the infant, on manipulations to the sensory properties of the objects, and on situations in which the role of motor habits may be adaptive in learning, as avenues of further research of the A-not-B phenomenon (Smith, this volume). By contract, connectionist researchers have focused on the graded nature of the internal memory representations without particular regard for their content, and therefore their potential to drive different behaviours (e.g., comparing reaching behaviour versus gaze behaviour) and to account for perseveration in other tasks (such as children's rule-guided behaviour in card-sorting and speech interpretation tasks; Morton & Munakata, this volume). In the example of A-not-B errors, then, the common developmental phenomenon has led connectionist and DST researchers to include many of the same assumptions and simplifications into their explicit quantitative models, whilst retaining subtly different emphases in the theories that these models are claimed to instantiate. It seems likely that a synthesis of the two would lead to a more complete model than either of the current models taken on their own.

Stability

Many connectionist models of development to date have explored the ability of associative neural networks to learn transformations between representations that encode cognitive domains. For example, infamously, Rumelhart and McClelland (1986a) trained a network to learn the relationship between phonological representations of the present and past tense of English verbs, and explored whether it would go through the same stages of development that children exhibit when learning this feature of language. Other examples can be found in models of reasoning, memory and category/concept formation (see Elman et al., 1996).

If one puts the issue of embodiment to one side, DST researchers have expressed further reservations about models of this type. First, as Schlesinger points out, connectionist models have rarely investigated timescales at the fast end of 'real-time' (i.e., milliseconds), despite being inspired by the concept of neural processing that operates over such timescales (Schlesinger, this volume). Moreover, it is far from obvious that the abstract, stable representations employed in some connectionist models of development are a realistic starting assumption. The real cognitive system is in a continuous state of flux – the world usually offers a continually shifting stream of sensory data, much of it a consequence of the individual’s own actions in the world. Perhaps in downplaying sensori-motor contributions to cognition, connectionists have created artificial, neat-and-tidy, abstract problems for their networks to solve, problems that are nothing like those faced by the child embedded in his or her own, continuously unfolding subjective world. Indeed, perhaps the leisurely timescales over which these connectionist models operate are simply too blunt to reveal the key phenomena that characterise developmental change.

Stability is a concept that is central to dynamic systems theory. Schöner (this volume) describes how cycling activation in recurrent circuits can produce representational states that are stable over time, both in being self-sustaining and (potentially, where appropriate) robust to perturbations. Given a gradual change in external input, the system can appear stable up until a certain point, when it may flip into another stable pattern of behaviour. Changes in control parameters in the system may have similar effects, leading the system to change qualitatively in nature despite the quantitative (and perhaps linear) change in the control parameter. Moreover, before a flip takes place, it may be anticipated by a period of increased instability. Stability and instability in behaviour therefore themselves become a focus of investigation in the study of developmental change. These arguments are often illustrated with the example of motor control but are also viewed as pertinent to the development of higher cognition (see, e.g., van der Maas & Raijmaker’s analysis of children’s reasoning, this volume).

As before, our interest in this chapter is to consider whether there is a fundamental difference between connectionism and DST on the issue of stability, or whether the difference arises from model simplifications made in the service of explaining divergent developmental phenomena. Our sense here is very much the latter, and perhaps even that connectionist models are *better situated* to address issues of stability in development.

Mareschal, Leech and Cooper (this volume) convincingly argue that much of the disagreement on the centrality of stability lies in the different historical origins of connectionism and DST. Connectionism arose from the study of neural memory systems, where the objective is the retrieval of a stable representation of a memory given an appropriate cue. By contrast, DST arose from the study of motor control, where the task involves a continuous computational loop of motor commands given the goal and the unfolding sensory information that is (in part) the consequence of previous motor commands. In this domain, the adjustments are continuous.

It is true that connectionist models have tended to examine developmental change over longer time periods, simplifying away questions of change over shorter time ranges. Thus, the model of sentence comprehension described in Box 1 assumes the existence of distinct representations of individual words and has a temporal dimension specified by the rate at which words arrive. It is not clear what is to be gained in such a model by including the millisecond range, other than to force attention onto the issues of phoneme recognition and word recognition and away from those touching on sentence comprehension.

However, importantly, connectionist models can and do operate at finer timescales. Simple recurrent models of the type proposed by Elman (1991) allow the researcher to study developmental change over months as the model adapts to the training set. They also allow the researcher to study the on-line recurrent processing dynamics as each subsequent word is processed in the sentence. Even simple feedforward networks can be treated in this way, by allowing activation to build up in a cascading fashion rather than to be computed in a single pass (Cohen, Dunbar, & McClelland, 1990; McClelland, 1979). In these models, the chosen timescale can be arbitrarily small as mathematically, the difference equations used in connectionist models approach the differential equations of DST. The temporally extended versions of connectionist models have allowed researchers to examine the consequences of persisting activation states in networks, for example to explain short-term priming effects in word recognition (Thomas, 1997). Mareschal et al. (this volume) use precisely this approach in an attractor network to model the development of analogical reasoning in children. If the model is given an initial pair ("**Cat** is to **kitten** as . . ."), cycling activation causes the network to settle into a state that encodes the implicit relation ("**parent_of**"). When a new first term is applied to the network's input units (" . . . **Dog** is to . . ."), this input combines with the persisting activation state to settle into the solution to the analogy at the output ("**Puppy**").

Crucially, the Mareschal et al. model demonstrates how connectionist models offer a wider perspective than the short-range dynamics of behaviour considered in DST. This is because the settling activation states (attractors) exhibited by a recurrent connectionist network are created by a longer-term, experience-dependent development process. The Mareschal et al. model is trained on the relationship between pairs of terms ("Cat is parent of kitten"). As it develops this conceptual knowledge, the nature of the analogies it can draw 'in the moment' alters. The model exhibits a developmental phenomenon known as the *relational shift*, in which its analogies move from being driven by perceptual similarities to relational similarities as a function of the knowledge that has been acquired. In the same vein, Thomas (1997) demonstrated how short-term and long-term word priming effects could be reconciled via considering the first to be a consequence of persisting activation states in the word recognition system and the second a consequence of experience-dependent structural (weight) change produced by recognising words. DST examines how the attractor states that it builds into its equations impact on behaviour, but connectionism is able to show how these dynamic properties arise as a consequence of change over a longer time period – or as McClelland and Vallabha put it, how new macroscopic behavioural properties emerge from microscopic mechanistic changes within adaptive systems (McClelland & Vallabha, this volume). Connectionist models, therefore, offer a potential bridge between timescales – even if connectionist researchers have often focused their attention on developmental changes occurring at longer timescales. As previously discussed, a similar bridging of timescales has also been achieved by Schapiro and McClelland's augmented version of the earlier McClelland (1989) balance scale model.

Does the issue of stability solely revolve around the question of incompatible model simplifications? We would argue that there are a number of areas where it does not. First, as in the case of embodiment, empirical data about stability – of input, of representations – are additional constraints that must influence the construction of models. For the computation of syntactic relations in sentences, it may be reasonable to assume some prior availability of stable word level information. But in other domains, particularly those closer to the senses or to motor interfaces, an assumption of stability may be more questionable.

Second, connectionism usually commits to a richer representation of knowledge than the uni-dimensional variables present in DST models. This has led connectionism to face what is called the *stability-plasticity dilemma*, that is, how new knowledge may be incorporated into an information processing system while preserving existing knowledge (see Richardson & Thomas, in press, for discussion). The stability-plasticity dilemma has particular importance where the individual's environment is non-stationary – that is, where the information content of experience tends to change over time. In models employing distributed representations, the stability of knowledge may be especially problematic and necessitate intermediate memory systems to 'damp' the changes on long-term knowledge wrought by fleeting, in-the-moment experiences (see, e.g., McClelland, McNaughton & O'Reilly, 1995).

Lastly, some connectionist theorists have taken the issue of stability very seriously and argued that the presence or absence of stability in a dynamic representational state may have real consequences for the experiential states of the organism. For example, O'Brien and Opie (1999) proposed that stable, explicit, neural representations are the only states that contribute to the contents of consciousness. These authors further proposed that the connectivity within parallel distributed processing systems provides a set of 'potentially-explicit' representations that may influence future behaviour, an idea similar to that of latent representations discussed previously in the context of the A-not-B models (see Morton & Munakata, this volume). If stability is indeed key in generating phenomenal states, this leads to the intriguing idea that the continuously unfolding processes characterised by DST in domains such as motor control may be causally efficacious but not contribute to the contents of consciousness.

Conclusion

We believe a constructive integration of connectionist and DST approaches is not only possible but desirable. It will be driven beyond the borders of GOFCD by the use of explicit quantitative models championed by connectionism and DST. We have argued that such models may appear to exaggerate the differences between DST and connectionist theories of development by virtue of their different simplifications in service of explaining different empirical phenomenon. We have illustrated this point via the examples of the balance scale task, the role of embodiment, and the role of stability. Equally, we could have considered other points of debate, such as the level of abstraction or the appropriate dimensionality of representational states employed in explicit quantitative models, and we would have drawn similar conclusions. Connectionism and DST share the greater part of their vision of cognitive development, a vision that is conditioned by the neurocomputational substrate that delivers cognition. The nature of (what we believe will be) an eventual convergence is as yet hazy on the horizon but already some of its features can be discerned. These include concepts such as distributed and graded knowledge, experience-dependent change, attractor dynamics, partial representations, soft assembly and the constraints of embodiment. The concept of cognitive development itself may have to expand to embrace constraints from as low as the genome, from as high as society, and from as wide as evolution. But, crucially, we also see the future in pluralistic terms. No one single set of assumptions makes sense for all models, and workers within and between the two converging approaches will continue to exploit a range of different simplifications appropriate to the specific focus of their interests and the demands of the tasks and issues under consideration. This convergent but still pluralistic activity will continue to depend on explicit quantitative models of cognition and behaviour and of the mechanisms of change. The great opportunity that remains is to apply such models across the full range of developmental phenomena that constitute human cognition.

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Box 1.

Example Explicit Quantitative model of development:

"A Simple Recurrent Network model of the development of syntax comprehension"

The Task:

- Participants listen to sentences and make a binary response to identify the agent of the sentence. Data for accuracy and speed of sentence classification have been collected for children and adults in various typical and atypical populations

Phenomena to be captured:

- Order of difficulty of accuracy for comprehending different sentence types (e.g., actives, passives); order of acquisition for the sentence types in children
- Changes in this pattern in adult breakdown and in different developmental disorders
- The type of information that is exploited in learning this task with an impoverished system (word specific, sequence specific)

Assumed essential characteristics:

- Stable, abstract representations of words (though not necessary grammatical word classes)
- Other components of a language system
- World that delivers examples of sentences where agent-patient knowledge is available to the system (the training set can be assumed to occur via episodes of experience rather than as an internally stored set)

Representation of information in the model:

- Localist input representations depict individual words in the sentence to be understood
- Localist output units (a) predict the next word in the sentence and (b) classify the sentence as *agent-precedes-patient* or *patient-precedes-agent*

Simplifications:

- **System is not embodied: s**table input representations and training signals (some auto-predictive) are delivered by an assumed external cognitive system, body, and world
- **Learning algorithm:** Backpropagation of error signals as a proxy for some more plausible error-driven neural learning algorithm

Timescale:

- Real-time is simulated in discrete steps, each time step aligns with the presentation of the next word in the sentence. Network contains internal units. Activation is feedforward from the input but recurrent from the internal units (a copy of activation on the previous time step). No noise under normal conditions
- Target timescale is performance over seconds
- Shorter time scales simplified in activation dynamics of the model (steps of vector matrix calculation)
- Change over longer time scales (hours, months) assumed to be an accumulation of changes in the second range