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Bridging Visual Working Memory Research from Infancy through Adulthood with Dynamic Neural Field Modeling

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Abstract

Theories that span tasks and developmental periods require explaining how a single cognitive system can flexibly adapt across contexts yet show stable age-related improvement. Here we present a computational model that embodies a unified theory of visuospatial cognitive development. We use this model to bridge between previously disconnected domains, as diverse as infant habituation and visual working memory capacity in adults. We illustrate how the same real-time and developmental processes can account for behavior across tasks and age groups. We conclude with a discussion of the implications of a unified theory for understanding cognition and development more broadly, with an eye toward early intervention.

Keywords: visual cognition; working memory; development; infancy; neural field model

A Unified Theory of Visuospatial Cognition

A central challenge in cognitive science is to create theories that generalize across tasks and developmental periods. Computational models provide a concrete tool to confront this challenge. We illustrate this using a dynamic neural field (DNF) model of visuospatial cognition. Our goal is to explicitly connect the processes that operate across the range of behavioral tasks used from infancy through adulthood to measure different aspects of visuospatial cognition. By demonstrating that such disparate tasks and phenomena arise through common underlying processes, we can construct a broader theory to contrast with prior theories that have been proposed to account for only a single task and age group.

The unified theory of visuospatial working memory development we espouse is implemented in a single model architecture with a single developmental mechanism to explain change from infancy to adulthood. Here we show how this model can bridge between previously disconnected domains and developmental periods. We begin by describing the basic dynamics of DNFs. Next, we present the specific architecture we have applied across tasks and age groups. We then illustrate how this model can be used to account for visual and spatial working memory processes across tasks and development. Finally, we close by discussing the implications of our unified theory for understanding cognitive development and interventions that strengthen cognition in at-risk or developmentally delayed populations.

Dynamic Neural Fields

DNFs belong to a larger class of bi-stable attractor networks (Amari, 1977; Wilson & Cowan, 1972) and simulate neural population dynamics to represent a continuous dimension, such as space or color (Schöner, Spencer, & the DFT Research Group, 2015). DNFs have a functional topographic organization such that neighboring nodes within a field representing similar features (e.g., shades of blue in color, neighboring locations in space). In DNFs, a stimulus input excites selectively-tuned neurons which then interact through local excitatory and lateral inhibitory connections to create a localized "peak" of activation (illustrated in Fig.1 below).

A peak in a DNF represents a real-time neuronal estimate of the stimulus. With relatively weak local excitation and lateral inhibition, peaks are only present when supported by input, that is, when the stimulus is present in the environment – we refer to this as an *encoding state*. With stronger connectivity, peaks can persist after a stimulus disappears (i.e., input is removed), which we refer to as a *working memory state*. Peaks leave excitatory memory traces, a simple Hebbian-type history of activation, that facilitate the re-formation of peaks at similar values (e.g., color, location) at future points in time. For example, when presented with a blue stimulus, the model will produce a peak that estimates the specific hue. The peak will leave a memory trace that facilitates the formation of a peak for the color blue at a future point in time. We will show that this feature of DNFs has implications for behavior in working memory tasks.

Multiple DNFs can be coupled together to create more complex neural architectures that simulate neurocognitive processes of encoding, maintenance, comparison, and recognition (described further below). To use such models to understand behavior, these neural architectures can be coupled to behavioral systems to generate the particular behavioral dynamics of interest – below we describe systems to simulate looking behavior, same/different judgments, or pointing/recall responses. In the next section, we describe a three-layer architecture that we have used to simulate performance in visuospatial working memory tasks from infancy to adulthood.

A Three-Layer Dynamic Neural Field Model

Figure 1 shows the three-layer model (reviewed by Johnson & Simmering, 2015; referred to here as the "dynamic model" for simplicity) used for the simulations we describe. This instantiation of the model consists of a fixation and visual-cognitive system. The fixation system consists of a collection of nodes that represent looking to left, right, center, and away

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locations in a virtual world. The nodes compete in a winner-take-all fashion. The winner (left node in Fig.1) opens a perceptual gate and the stimulus at that location (green and red) is input to the visual-cognitive system (see green arrow from virtual world to visual-cognitive system). The visual-cognitive system consists of a perceptual field (PF), which receives input from the fixation system representing the color of the stimulus. This input creates peaks representing the stimulus; connectivity in this field is set to the encoding state described above. Activation in PF supports continued fixation through reciprocal connectivity (see green arrow from PF to virtual world) and also feeds into a working memory (WM) field (see green arrow from PF to WM). These fields interact through a shared field of inhibitory nodes (Inhib). When WM activity for an item is strong, WM sends strong activity to Inhib (see red arrow from WM to Inhib). This, in turn, suppresses activity for that item in PF (see red arrow from Inhib to WM). In addition to this three-layer (PF-Inhib-WM) architecture, the dynamic model includes memory trace (MT) layers associated with PF and

WM that accumulate activation over a longer time scale (for simplicity, only MT_{WM} is shown in Fig.1), serving the Hebbian function described above.

Figure 1 illustrates how the dynamic model simulates encoding, maintenance, and comparison of items in WM. A critical insight gained from applying this model across tasks and development is how the same real-time processes underlying these cognitive functions can produce a range of seemingly unrelated behavioral signatures (e.g., habituation, perseveration, novelty preferences, capacity limits, dimensional attention), as described below. At the moment represented in Figure 1, WM is maintaining the colors light green and orange, which has inhibited encoding in PF (see inhibitory troughs at sites tuned to light green and orange), which released fixation from the right location (see position in virtual world). This inhibition of encoding by WM is the mechanism of recognition in the model. After fixation was released from the right location in the simulation shown in Figure 1, the model fixated the left location and is encoding a dark green and red stimulus there. This is the mechanism of novelty detection in the model – fixating and encoding items not held in WM. Notice that the model has MTs associated with the light green and orange items. This will enable the model to form robust WM peaks for those colors in the future, which can support recognition of those items as familiar.

This simulation shows the dynamic model equipped with a fixation system that looks at multiple locations, which simulates looking behavior (Perone, Simmering, & Spencer, 2011). To simulate the behaviors required by different visuospatial working memory tasks, the model can be used to generate continuous recall responses (e.g., pointing to a remembered location or color) based on peak positions (e.g., Spencer, Smith, & Thelen, 2001) or equipped with a same/different response system (Johnson, Spencer, Luck, & Schöner, 2009). Critically, however, each of these different behavioral responses is driven by the same underlying cognitive processes embodied in the three-layer architecture.

In the following sections, we synthesize recent applications of the dynamic model to provide a unified explanation of visuospatial cognitive processes across previously disconnected domains and development: habituation and visual recognition during infancy, and VWM capacity limits from infancy to early childhood and adulthood.

Common Processes Underlying Visual Working Memory from Infancy to Adulthood

In this section, we describe how this model can account for behavior and development in three domains, highlighting that a single developmental mechanism produces change in all three domains. We begin by describing how the model links infant looking at a single location to WM formation in the habituation paradigm. Next, we show how the same model looks to multiple location in a visual recognition context, the visual paired comparison task. After that, we show how the same model can once again be adapted to explain visual working memory capacity limits in children and adults.
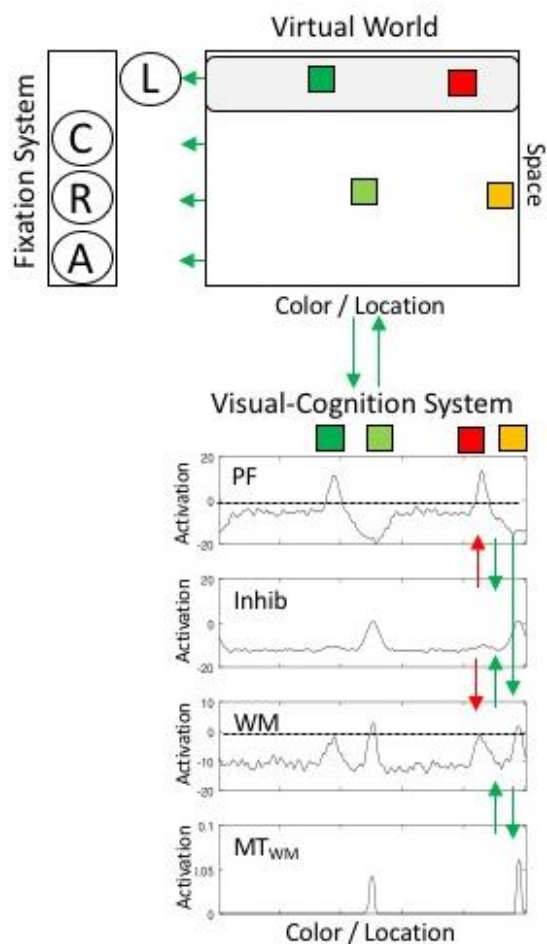

Figure 1. Three-layer dynamic neural field architecture, coupled to a fixation system viewing colors in a virtual world. Green versus red arrows indicate excitatory versus inhibitory connections; horizontal dashed lines indicate the zero threshold in each field. See text for further description.

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Habituation

Infant looking paradigms form the foundation of our understanding of the origins of human cognition. Habituation of looking behavior has been used for half a century to probe perceptual, memory, and cognitive processes during infancy. In a typical habituation task, infants are presented with a single stimulus (e.g., blue circle). Initially, they exhibit high levels of looking which decreases with repeated presentation. They typically renew looking when presented with a novel stimulus (e.g., red star). Prior theories have not considered looking behavior a central part of the learning process (Cohen, 1972) but rather as an output. However, there is evidence that how infants distribute their looking through time structures what they learn (Jankowski, Rose, & Feldman, 2001). To explore the interplay between looking and learning, Perone and Spencer (2013) used the dynamic model with a simple fixation system that stochastically oscillated between looking at a single stimulus and looking away. As described above, when the fixation node was looking to the stimulus, it opened a perceptual gate that sent input PF. Strong activation in PF supported continued looking and led to the formation of memory representations in WM and MT. When the WM representation grew robust across presentations, encoding in PF was inhibited (as described above), and looking was released. Thus, the dynamic model showed habituation in looking time, just as infants do.

Perone and Spencer (2013) tested whether the dynamic model could account for the developmental changes infants show in habituation tasks: faster habituation rates and the ability to make finer-grained distinctions with age. To simulate development in the visual-cognitive system of the dynamic model, they implemented the Spatial Precision Hypothesis (SPH). The SPH posits that the strength of excitatory and inhibitory connectivity within and between layers increases over development (see Simmering & Schutte, 2015, for review). Implementing the SPH in the context of the habituation task led to faster, more stable WM formation and more robust novelty detection. This led to quick habituation and improved discrimination with age, just as infants show. The dynamic model's performance highlighted the link between visual exploration and learning. For example, spontaneous long looks helped WM form, which led to fast habituation. Conversely, spontaneous short looks led to slowed memory formation. This provides an explanation for how individual differences in visual exploration can structure learning. This highlights the importance of simulating real-time behavior in a model to understand how the cognitive system functions and develops.

Visual Paired Comparison

The visual paired comparison (VPC) paradigm is commonly used to study visual recognition and categorization processes during infancy. VPC differs from the habituation paradigm in a critical way: it introduces competition. Infants are presented with pairs of stimuli and can freely look back and forth between them. This context yields a rich set of looking measures, including shift rate (gaze switches per second of looking), look duration (mean duration of each look), peak look (longest look), and preferences (proportion of looking to one item greater than chance). Infants' recognition memory is assessed via pairing a previously seen, familiar item with a novel item. A preference for the novel item is evidence of both (1) recognition of the familiar item and (2) discrimination between the familiar and novel items (as illustrated in Fig.1). With age, infants exhibit faster shift rates, shorter look durations, shorter peak looks, more fine-grained discrimination, and stronger novelty preferences. These looking behaviors develop more slowly in at-risk populations, such as preterm infants (e.g., Rose, Feldman, & Jankowski, 2001).

The dynamic model can adapted to VPC by equipping it with a fixation system that looks at left and right locations (see Fig.1), compared to the single item/fixation location used for habituation. The dynamics of the visual-cognitive system are otherwise identical to the model simulations of habituation from Perone and Spencer (2013). Perone and Spencer (2014) asked whether this same model and developmental mechanism could account for the range of behavioral changes infants show over development in VPC. They probed this by testing infants' looking behavior and discrimination abilities between 5 and 10 months of age, then simulating the paradigm in the dynamic model. They found that infants exhibited faster shift rates, shorter look durations, and shorter peak looks with age. They also found that infants were able to make discriminations along a continuous metrically organized dimension by 7 months of age. The model exhibited the same behavioral pattern over development for precisely the same reasons as it did in the habituation paradigm: faster, more robust memory formation.

Perone and Spencer (2014) also analyzed individual differences. In particular, individual differences in looking during the learning phase of VPC predicted their discrimination abilities during the testing phase. This pattern was found in the dynamic model's performance as well. But where did these individual differences come from? There were no parameter changes to simulate "individuals" in the model; rather, the individual differences in patterns of performance were *emergent.* The structure of looking behavior that builds memory representations and supports discrimination in the dynamic model emerged autonomously. This parallels the insight gained from the simulations of habituation: infants' exploratory behavior in the task influenced the formation of memory, which in turn shaped their subsequent looking behavior. Although the processes at work in the habituation and VPC are generally considered similar, what infants remember in each paradigm is different (Oakes & Ribar, 2005). This is the first theory to formally account for how the same learning process unfolds in both contexts.

Capacity Limits over Development

One of the hallmarks of WM is its limited capacity. Visual working memory (VWM) in particular is limited to only three or four items in adults (Luck, 2008). The majority of

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work characterizing VWM capacity limits have focused on children and adults, with the change detection task being a common approach, shown in Figure 2A. In this task, a small number of simple items (e.g., colored squares) is shown briefly, followed by a brief blank delay, then a test array in which either all of the items remained the same or one has changed. Capacity estimates from this task (using a formula proposed by Pashler, 1988) have shown a gradual increase from early childhood through adolescence (Simmering, 2016; Simmering & Perone, 2013). Studies with infants, however, present seemingly contradictory results, with estimates of capacity reaching adult-like levels within the first year of life (e.g., Oakes, Ross-Sheehy, & Luck, 2006; Ross-Sheehy, Oakes, & Luck, 2003). One way to address this apparent discrepancy across tasks and age groups is through the dynamic model framework presented here.
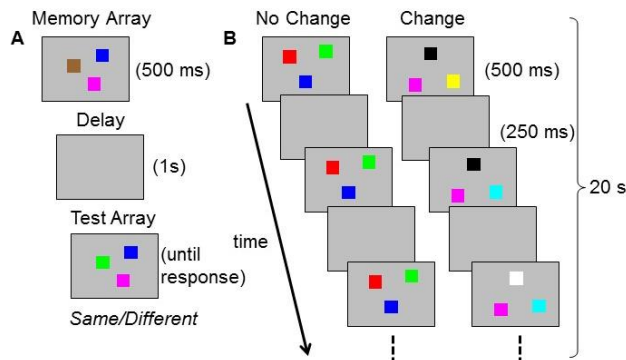

Figure 2. Sample trials from two tasks used to estimate VWM capacity: (A) change detection used with children and adults and (B) change-preference used with infants.

The task used to estimate capacity during infancy, shown in Figure 2B, is a variant of VPC called the change preference paradigm. Infants are presented with the same number of colored squares is presented on each of two displays. The squares briefly appear and disappear repeatedly throughout each trial; across these presentations, the colors in the "no-change" display remain the same; on the other "change" display, one color changes following each blank delay. Infants' fixation is tabulated over the course of the trial, and compared to chance (i.e., equal looking to both displays). Capacity is estimated from the highest set size (i.e., number of colors per display) at which infants show a reliable preference for the "change" display. The rationale behind this interpretation is that if infants can remember the colors within a display, the "change" display will appear novel and therefore support a looking preference. Ross-Sheehy et al. (2003) estimated capacity to be only one item at 6 months, but three to four items at 10 months. Oakes et al. (2006) then showed that the capacity increase from one to three items occurred between 6 and 7 months of age.

How can the change preference task yield a VWM capacity of 3-4 items at 10 months but the change preference task only yield a capacity of 1-2 items at 3 years? Perone et al. (2011) situated the dynamic model in the change preference

paradigm and showed that the SPH could account for the age-related changes in capacity estimates during infancy. One intriguing finding from these simulations was that a robust preference in the model did not depend on holding all of the items in memory: that is, a preference for set size three did not necessarily reflect that three items could be held in WM. Perhaps this means that the items required to be remembered to yield different estimates differs across tasks. Simmering (2016) probed this possibility by situating the dynamic model in *both* the change preference and change detection task. In order for the dynamic model to simulate performance in the change detection task, it must be equipped to give the "same" or "different" responses required by the task. This type of response system can be implemented by building from the mechanisms of recognition and familiarity inherent in the model's visual-cognitive system (see Fig.1): peaks in WM indicate familiar items whereas peaks in PF indicate novel items. Thus, a simple system in which activation from WM projects to a "same" decision node, and activation from PF projects to a "different" decision node, can use these signals to general a discrete response on each trial (see Johnson & Simmering, 2015, for further discussion).

Model simulations revealed that the two tasks used to estimate capacity showed different relationships between the underlying memory representations and the behavioral measures used to estimate it (Simmering, 2016). In particular, while simulations of the infant task suggested that behavioral estimates may over-estimate the number of items held in memory (Perone et al., 2011), simulations of adults' performance in change detection indicated it under-estimated the number of items held in memory (Johnson, Simmering, & Buss, 2014). Simmering (2016) bridged these results from infancy and adulthood by testing young children in both types of capacity tasks, then directly comparing performance across tasks and simulating results within a unified model. Simulations showed that developmental changes in both tasks could be accounted for within the same model through strengthening connectivity. Furthermore, although the tasks yielded different estimates of capacity between 3 and 5 years of age – at least six items in the looking task versus only two to three items in the change detection task – the common underlying processes were evident in correlations across tasks. Motivated by the common processes that support the detection of novelty across the two tasks in the model, Simmering (2016) found that children's preference scores in the looking task were significantly correlated with their hit rates (i.e., proportion correct on change trials) in change detection. This relationship across tasks was not evident from considering only the capacity estimates from each task, but rather depended on a systematic understanding of how cognition and behavior relate.

Spatial Cognition and Development

The preceding sections showcased the use of the same model and developmental mechanism to adapt across contexts and development for visual (featural) memory processes. In this section, we illustrate that the same model

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can be adapted to account for performance in four spatial cognition tasks– (1) perseverative reaching in the Piagetian A-not-B task, (2) A-not-B-type biases in a sandbox task, (3) reference-related biases in spatial recall and (4) similar biases in position discrimination. Moreover, we show that developmental change across all of these domains was explained with the SPH.

A-not-B Tasks

Beginning with the A-not-B task (cf. Thelen, Schöner, Scheier, & Smith, 2001), weaker connectivity to simulate early infancy (8-10 months) led to perseverative reaching because the peak representing the second (B) location was not strong enough to overcome the history of reaches at the first location (A). With stronger connectivity to capture development, this peak could be maintained accurately through the delay to support accurate reaching as seen in older infants (10-12 months).A similar interaction between memory for the current target and prior reaches can be seen in older children's performance in a sandbox version of the A-not-B task (e.g., Schutte, Spencer, & Schöner, 2003; Spencer, Smith, & Thelen, 2001). Children between the ages of 2 and 6 years show recall responses that are biased toward previously-remembered locations, with a developmental change in the spatial spread of this influence – younger children's performance is biased over larger separations than older children's (Schutte et al., 2003). This metric change in the influence of reaching history in the task has been simulated first through changes in the spread of activation within the three-layer architecture (Schutte et al., 2003) and later through changes in only the strength of connectivity (Simmering et al., 2008; see Simmering & Schutte, 2015, for further discussion). By showing that the SPH can account for changes in infants' performance in the canonical A-not-B task as well as the metric changes during early childhood, this model architecture brought together previously disconnected age groups and tasks into a unified framework.

Spatial Recall & Discrimination

Young children's performance in spatial recall tasks also shows influences of the spatial structure of the space, in addition to prior history of reaches. Specifically, young children recall locations as closer to the midline symmetry axis of the task space, whereas older children and adults recall locations further from midline and the edges of the task space (see Spencer, Simmering, Schutte, & Schöner, 2007, for review). These effects can be simulated in the same three-layer architecture through the coordination between perceptual and memory processes in the sandbox or "spaceship" tasks. As connectivity strengthens over development, the representation of information in both perception and memory lead to the transition in bias (Schutte & Spencer, 2009, 2010). These processes operate continuously through time, and can be detected even in the brief delay of position discrimination tasks, linking together previously disconnected areas of research (Simmering & Spencer, 2008).

Implications and Future Directions

We presented a unified theory of working memory development that spans an impressive number of domains and periods of development. Importantly, this was only possible by using a concrete tool – a computational model – to tackle the difficult challenge of explaining cognition across domains and development. There are a number of implications of this work. First, our theory indicates that cognitive processes are not domain specific. Instead, the same general visual-cognitive system can account for multiple neurocognitive processes by organizing itself differently in different contexts with different behavioral demands. These include infant habituation (looking), visual working memory capacity (same/different judgments), and spatial recall (position estimation). Second, our theory indicates that the developmental mechanisms that drive change across domains are not unique. We showed that the SPH could account for changes in performance across multiple domains and radically different periods of development. Last, our account raises the intriguing possibility that we can target basic visual-cognitive processes to strengthen early in development, which may have an impact across many domains and over a long period of time.

One long-term goal of employing such a computational framework is to make further connections across age groups and domains, and to provide a mechanistic account of how behavior emerges in specific task contexts. Such examples can already be found in the domains of executive function (e.g., Buss & Spencer, 2014; Perone, Molitar, Buss, Spencer, & Samuelson, 2015) and word learning (e.g., Samuelson, Schutte, & Horst, 2009; Samuelson, Smith, Perry, & Spencer, 2011). By connecting the same real-time processes of encoding, maintaining, and comparing visual inputs with the longer time-scale of learning in contexts that connect to verbal labels, we can test how far relatively simple cognitive mechanisms can go toward explaining complex behaviors (cf. Smith, Jones, & Landau, 1996).

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