TESTING A DYNAMIC NEURAL FIELD MODEL OF CHILDREN'S CATEGORY LABELLING

KATHERINE E. TWOMEY

University of Liverpool
Liverpool, UK.

JESSICA S. HORST

University of Sussex
Sussex, UK

Recently, Dynamic Neural Field models have shed light on the flexible and dynamic processes underlying young children's emergent categorisation and word learning (DNF; e.g., Spencer & Schöner [1]). DNF models are a distinct class of neural network in which perceptual features can be represented topologically and time continuously, complementing existing connectionist models of cognitive development by building category representations that are available for inspection at any given stage in learning. Recent research in infant categorization and word learning has demonstrated that young children's ability to learn and generalise labels for novel object categories is profoundly affected by the perceptual variability of the to-be-learned category. We have captured these data in a DNF model of children's category label learning. Given a known vocabulary, our model exploits mutual exclusivity via simple associative processes to map novel labels to novel categories, and is able to retain and generalize these newly-formed mappings. The model was used to generate the testable prediction that children's generalizations of novel category labels should be contingent on the number and closeness of objects' perceptual neighbours. We present a replication of this prediction, via an empirical study with 30-month-old children. In line with the model, children were only able to generalize novel words to completely novel objects when those objects were central to the just-encountered category, rather than peripheral. This empirical replication demonstrates the predictive validity of DNF models when applied to cognitive development. Further, the data suggest that children's ability to categorise and learn labels is not a conceptually-based, stepwise phenomenon, but rather a graded, emergent process. As such, these data add weight to associative, dynamic systems approaches to understanding language learning, categorisation, and cognition more generally.

1. Introduction

The puzzle of how young children learn to categorise and label objects is well-known. Born into an enormously rich perceptual environment, from an early age children parse objects into categories and treat exemplars from a single category equivalently. By 18 months, children have begun to label these categories (e.g., Houston-Price, Plunkett, & Harris [2]), reliably inferring the referents of novel words despite the proliferation of potential referents [3]. This ability to form a quick, initial hypothesis about a word's meaning is known as fast mapping [4]. Several theoretical accounts of categorisation and word learning have been offered, from low-level associative learning (e.g., Smith [5]) to *a priori* conceptual primitives (e.g., Carey [6]).

Word learning and fast mapping have latterly been the focus of a variety of computational models (e.g., Colunga & Smith [7]; Gliozzi, Mayor, Hu & Plunkett [8]; McMurray, Horst & Samuelson [9]; Samuelson, Smith, Perry & Spencer [10]). Although inspired by an abundance of experimental literature, these simulations go a step further: unlike cognitive change in children, changes in a model's cognitive structure can be observed as they develop over time. Thus, computational models have made novel predictions about the cognitive structures underlying a variety of behaviours, across development [11].

Importantly, however, these predictions must be empirically tested if a model's explanation for a behavior is to be taken seriously. The current paper presents just such a test. Twomey & Horst [12] describe a Dynamic Neural Field model (for an invaluable introduction and review see Spencer, Thomas, & McClelland [13]) which has successfully replicated data from an empirical study examining the effect of variability on 30-month-old children's category label learning. The current paper presents a novel prediction generated by the model (Simulation) and an empirical replication of that prediction (Experiment).

2. Simulation

2.1. *Dynamic Neural Fields.*

Dynamic Neural Fields (DNFs [1]) are emergentist models of changes in neural activation in response to external stimuli. In contrast to their connectionist cousins (e.g., McClelland, et al. [14]), DNFs simulate neural structure and time continuously, with representations distributed across fields. DNFs are topologically functional, such that similarity on a given metric is represented by distance on a given axis.

Consisting of one or more input fields, DNF models initially receive input in the form of a modeller-defined increase in activation at a certain location in the field. These inputs represent responses to stimuli. Over time, the dynamics of the DNF allow peaks of activation to emerge in the thanks to locally-excitatory and both locally- and globally-inhibitory neural interactions; that is, activation spreads from a given location to its neighbours, whilst activation at more distant locations is suppressed. These peaks are taken to represent associations between stimuli.

Input fields are coupled reciprocally to memory fields, which are functionally similar to Hebbian weight changes in connectionist models. When a peak forms at a given location in the input field, activation spreads to the Hebbian field, where it decays slowly. The Hebbian field therefore helps new peaks form at the locations of previous peaks, simulating learning of associations over time.

2.2. *Categorisation by shared features.*

Existing empirical and behavioural research demonstrates that children can categorise based on co-occurrence of perceptual features such as shape, colour and texture [15, 16, 17, 12]. More recently, connectionist models have simulated the developmental differentiation of children's categories based on the assumption that categories are scaffolded from coherent covariation of perceptual features [18]. Taken together, evidence from empirical and computational studies suggests that exemplars that share perceptual features are perceived as perceptually similar by young children (see also, Sloutsky & Fisher [19, 20]).

That children can extend known category labels to novel exemplars is not in dispute [21, 22, 23, 24]. However, the number of features shared between even perceptually very similar items seems likely to affect label extension. We hypothesised that when taught a novel label for a novel category in a simulated fast mapping task, our model would generalise that label to new category members that shared many – but not few – features with previously-encountered exemplars.

2.3. *Method*

2.3.1. *Architecture*

The model is an adaptation of Faubel & Schöner's [25] simulation of dynamic feature binding and consists of a two-dimensional input field, representing perceptual similarity on one axis and labels on the other, as depicted in Figure 1 (see also Twomey & Horst [12]). Simultaneous presentation of inputs along the label and perceptual similarity axes may give rise to a peak at their intersection, representing an association between these two inputs—in behavioural terms, an association between a label and an object.

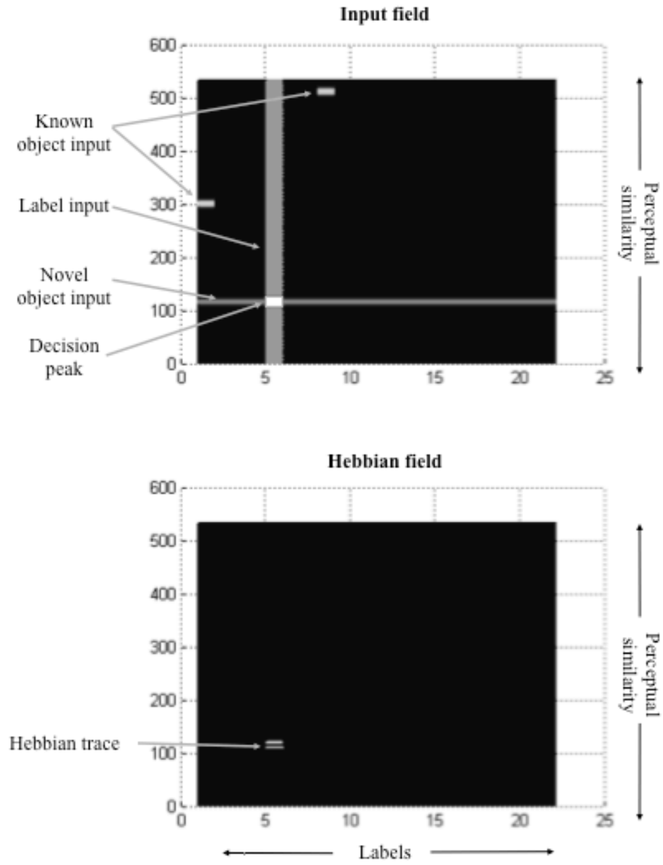


Figure 1. Architecture of the Dynamic Neural Field model. Lighter regions indicate activated locations of the field. Dark regions indicate locations at resting level.

Because activation from these peaks is stored in the Hebbian field, during the familiarisation phase the model learns which labels are associated with which objects.

2.3.2. *Stimuli.*

"Novel" object stimuli consist of input ridges along the perceptual similarity axis, which are generic along the label axis; that is, on the first presentation of a novel object, a peak can form at the intersection of that input and any location on the label axis, reflecting the fact that children in fast mapping tasks do not know the name of the novel objects they encounter. "Known" object stimuli consist of peaks of activation at locations in the input field representing the previously learned intersection between a label and an object. Label stimuli consisted of a ridge of activation along the label axis and could therefore be associated with any position along the feature axis. Exact locations of object inputs along the feature and label axes are given in Table 1.

	Referent Selection						Extension			
	Known object 1		Known object 2		Novel category exemplars		*Few*		*Many*	
	Object	Label	Object	Label	Object	Label	Object	Label	Object	Label
Category "*hux*"	40	21	470	13	113	5				
	30	1	510	8	115	5	119	5	114	5
	450	16	230	7	117	5				
Category "*cheem*"	150	9	60	4	263	11				
	80	18	360	2	265	11	269	11	264	11
	380	15	170	14	267	11				
Category "*doff*"	210	3	320	12	413	17				
	340	20	20	6	415	17	419	17	414	17
	490	19	190	10	419	17				

Table 1. Locations along feature and label axes of inputs to the model. Inputs representing extension exemplars with many shared features are closer to exemplars seen during referent selection than inputs representing extension exemplars with few shared features.

2.3.3. *Design and Procedure.*

Our model simulates the empirical fast mapping paradigm, in which children are presented with multiple referent selection trials consisting of an array of two known objects and one novel object, and asked to retrieve the novel object in response to the novel label ("Can you show me the *blicket*?"; e.g., Horst & Samuelson [26]). The specific design of the empirical task discussed here is described in detail in section 1.2.1.3. In line with this empirical task, the model is presented with an initial referent selection phase, during which it is familiarised with three novel categories (each consisting of three exemplars) and three novel labels, presented in blocks of six trials per category. Each block consists of three known and three novel trials. Each novel exemplar serves once as the target (on a novel trial), and once as a competitor (on a known trial). The model is therefore presented with a total of 18 referent selection trials.

A single referent selection trial consists of an initial presentation of two known object peaks and a single novel object ridge. Then, the model is given a label input ridge, reflecting the experimenter's request for the novel object. This ridge crosses either a known object location (on known trials) or the novel object location and a known object location (on novel trials). A peak of activation may develop at one of these intersections, simulating the child's choice, which may or may not be correct.

Immediately following referent selection the model is given five trials in which no stimuli are presented, reflecting the delay between referent selection and test in the empirical task, and allowing the stored memory traces to decay. Importantly, however, these memory traces do not decay entirely during this delay. Any remaining activation in the memory field may therefore influence peak formation (or "object choice") during the test trials. Following the delay the model receives three retention trials, identical to referent selection, except that object stimuli consist of three novel object ridges, one from each previously-encountered category. The model receives a different, previously-encountered novel label on each retention trial. Thus, the model can only accurately respond if the memory trace associating novel objects to novel labels is sufficiently robust. Finally, the model is presented with three extension trials to test label generalisation. At this stage, the model receives completely novel stimuli that share either *many* or *few* features with just-encountered exemplars. The model was run 24 times per condition.

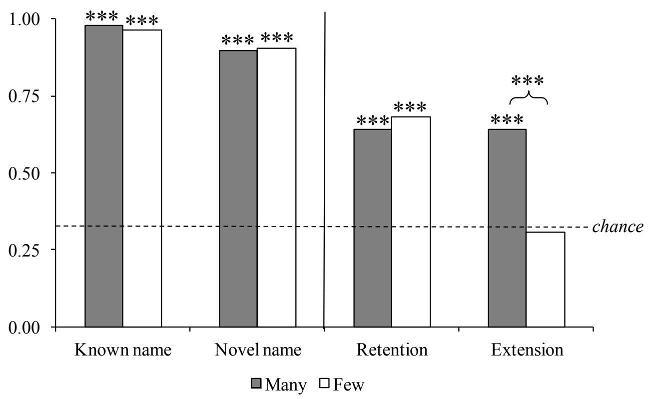


Figure 2. Simulation results. *** p <.001. Chance = 0.33, all tests two-tailed.

2.3.4. *Results and Discussion*

Results from the simulation are depicted in Figure 2. During referent selection the model mapped known and novel labels to the correct referent at levels greater than expected by chance (0.33, all ps <.001, all t-tests two-tailed). At test, the model retained novel labels at above-chance levels in both conditions, *many:* $t(23) = 5.46$, p <.001, $d = 1.12$, *few:* $t(23) = 4.76$, p <.001, $d = 0.97$ (note that no difference was anticipated between conditions for retention, as stimuli presented during referent selection and retention are identical across conditions). In contrast, however, the model extended novel labels in the *many* condition,

$t(23) = 5.44$, $p < .001$, $d = 1.12$, but did not extend novel labels in the *few* condition, $t(23) = -0.45$, *ns*., $d = -0.09$. An independent samples *t*-test confirmed a significant difference between conditions for extension, $t(46) = 4.17$, $p < .001$, $d = 1.23$. Thus, as predicted, the model generalised novel names only to objects that shared many features with the categories encountered during referent selection.

3. Experiment

Using the same architecture and procedure as a previous, successful DNF simulation of 30-month-old children's behaviour in a fast mapping task (Twomey & Horst, 2011), the DNF model predicts that children will extend previously fast-mapped novel names to completely novel exemplars that share many – but not few – features with previously-seen novel exemplars. The current experiment tests this prediction empirically with 30-month-old children using a design identical to the model. Importantly, the stimuli used during referent selection were identical across conditions until the extension trials when children were presented with exemplars that shared either many or few shared features with just-seen novel exemplars.

3.1. *Method*

3.1.1. *Participants.*

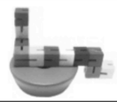
40 typically developing, monolingual, English-speaking 30-month-old children (23 girls, M = 29m, 0d, SD = 43.34d; range = 24m, 11d - 32m, 17d) with a mean productive vocabulary of 521 words (SD = 128.92 words, range = 263 - 662 words) and no family history of colourblindness participated. Half of the children were randomly assigned to the *many shared features* condition, and the other half were randomly assigned to the *few shared features* condition. Children's ages and productive vocabularies did not differ between conditions. Data from 10 additional children were excluded from analyses due to fussiness (7), experimenter error (2) and illness (1). Parents were reimbursed for travel expenses and children received a small gift for participating.

3.1.2. *Stimuli.*

Known objects consisted of eighteen toys from categories familiar to 2-year-old children, for example a plastic toy apple and a metal toy bus. Novel objects are depicted in Figure 3 and consisted of fifteen toys from three categories not familiar to 2-year-old children. Novel exemplars from a given category shared basic shape but differed in overall number of shared features, based on evidence that preschool children can differentiate shape components in 3D objects (or "geons" [27, 28]) and categorise solid objects on the basis of shared shape [29, 30, 22]. Thus, within each novel category, exemplars shared more or fewer perceptual features (geons, colour) with other exemplars of that category. Test objects, depicted in the final two columns of Figure 3, were designed to share either *many* or *few* features with objects encountered during referent selection. To ensure that the *many*- and *few-shared-features* test objects were indeed appropriately similar or dissimilar to the objects encountered during referent selection, we conducted a Multidimensional Scaling Analysis (MSA; for discussion see Abecassis *et al.* [27]), calculating object similarity based on shared colour, geons and labels. The MSA confirmed that the *many* objects were more similar to the referent selection objects than the *few* objects[a]. Finally, novel category labels were the arbitrarily assigned nonsense words *hux, doff* and *cheem* (see also Twomey & Horst [12]).

3.1.3. *Procedure and design.*

Before the experiment began the parent was asked to complete a vocabulary checklist [31]. Parents were also shown colour photographs of all stimuli to ensure that they were appropriately familiar or novel. All children were familiar with all known objects, and no children were familiar with any of the novel objects.

Label	Referent Selection			Extension	
				Few	*Many*
hux					
doff					
cheem					

[a] To further confirm that the stimuli presented to the children reflected the stimuli presented to the model, 20 adults from the university community were asked to rate each object for similarity to the object shown in the second column of Figure 3 on an 11-point Likert scale. Scores reflected the distances between the model stimuli, and a subsequent re-run of the simulation with stimuli positioned at the exact locations dictated by these similarity scores generated the same pattern of results.

Figure 3. Novel objects used in the empirical study.

The experiment began with three warm-up trials to familiarise children with the task. Stimuli were presented on a transparent plastic tray divided into three equal sections. Three known objects, chosen at random from the known objects used during the referent selection phase, were presented to the child on the tray in pseudorandomly-determined position (i.e., left, middle or right). First, the experimenter held the tray stationary on the table and silently counted for three seconds to allow the child to look at the objects (see Horst & Samuelson [26]). Then, the experimenter asked the child to select one of the objects ("Which one's the cow? Can you show me the cow?"). All objects were labelled twice, with up to two more labelling instances when children needed encouragement. No object was labelled more than four times. The experimenter then slid the tray towards the child and allowed the child to point to or hand her one of the objects. Children were heavily praised for correct responses, and prompted to choose again for incorrect responses.

Referent selection trials immediately followed warm-up trials and proceeded in an identical manner, except that children were given no feedback following their choices. Each child encountered three novel categories (each consisting of three exemplars) and three novel labels, presented in blocks of six trials per category. Each block consisted of three known and three novel trials. Each novel exemplar served once as the target (on a novel trial), and once as a competitor (on a known trial). The children were therefore presented with a total of 18 referent selection trials, followed immediately by a five-minute delay.

After the delay, children were presented with a new warm-up trial to re-engage them with the task. Three retention trials immediately followed the warm-up trial and were identical across conditions. Retention trials proceeded in an identical manner to referent selection trials, except that children were presented with three novel exemplars on each trial: one previously-encountered exemplar from each novel category. Extension trials proceeded in an identical manner to the retention trials. Children were presented with three completely novel exemplars, one from each novel category. In the *many* condition, children were presented with the exemplars that shared many features with those encountered during referent selection. In the *few* condition, children were presented with the exemplars that shared few features with those encountered during referent selection.

3.2. *Results and Discussion*

Results from the empirical study are depicted in Figure 4. During referent selection children mapped both known and novel labels to the correct referent at levels greater than expected by chance (0.33; both *p*s <.001, all *t*-tests 2-tailed). At test, children retained novel labels at above-chance levels in both conditions, *many shared features:* $t(19) = 2.82$, $p < .05$, $d = 1.29$, *few shared features:* $t(19) = 2.20$, $p < .05$, $d = 1.01$. In contrast, children extended novel labels in the *many* condition, $t(19) = 3.74$, $p = .001$, $d = 1.72$; but did not extend novel labels in the *few* condition, $t(19) = 0.88$, *ns*., $d = 0.31$. An independent samples *t*-test of extension between conditions approached significance, $t(38) = 1.85$, $p = .071$, $d = 0.60$. Thus, children's overall pattern of responding reflected the overall pattern generated by the model.

These data support "correlated features" accounts of categorisation, for example the classic Younger & Cohen studies [15, 32]. In these studies, 10-month-old infants were sensitive to correlations between configural and perceptual attributes in novel 2D animal stimuli (see also Plunkett, Hu & Cohen [33]; Rakison & Cohen [34]; Younger & Cohen [32]; Younger, Hollich, & Furrer [35]). The current study demonstrates that older children can also generalize labels systematically based on correlations between perceptual features such as geons and colour. Importantly, the empirical data replicate the simulated data, indicating that the DNF model constitutes an informative simulation of young children's category label learning.

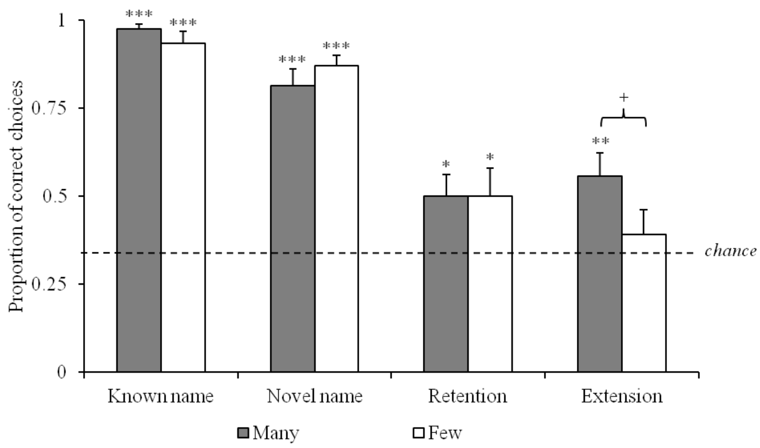


Figure 4. Children's proportion of correct choices. Dotted line represents chance (.33). Error bars represent one standard error. *** $p < .001$, ** p .001, * $p < .05$, + $p = .071$.

4. General Discussion

This paper presents an experimental replication of predictions generated by a computational model of young children's word learning and categorisation.

Based on a Dynamic Neural Field model of children's word learning via mutual exclusivity [12], we simulated children's behaviour in a fast mapping task to examine the nature of children's noun extensions after familiarisation with an object category. The model predicted that children would extend labels only to novel exemplars that shared many features with the familiarised category, and these predictions were borne out empirically.

In line with earlier applications of DNFs to developmental phenomena such as the A-not-B error [36], spatial binding of objects to labels [10] and the shape bias [37], this model successfully simulates apparently complex behaviour using simple low-level associative processes. Importantly, during referent selection the model maps novel words to novel referents without any preprogrammed "reasoning" ability. Rather, category label learning emerges from the online interaction between inhibitory processes and previously-learned items.

Dynamic Neural Field models are theoretically situated in Dynamic Systems theory, in which complex yet stable behavioural and cognitive systems emerge *ad hoc* from the interaction between components available at a given time (for example, the body, perceptual input, and the task environment) in the context of nested timescales of learning (for example, lifetime experience with categories and labels, exemplars and labels encountered earlier in the experiment, and the exemplar and label present on a given trial). Thus, these data add weight to the growing body of work demonstrating that cognition, behaviour and the environment are inextricably coupled and inseparable from their temporal context, contributing to our understanding of young children's categorisation, as well as to a new conception of developing cognition as an emergent dynamic system.

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