

**Computational Modeling and What It Can Tell You  
About Behavior**

Contributors: Deon T. Benton & David H. Rakison

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## Abstract

Connectionist models represent powerful learning tools for understanding learning and development in infants and young children. In this case, we discuss two such models and how they have provided key insights into how infants and young children form perceptual object categories and how they come to represent objects in the world. Limitations of these specific models, the appeal of the connectionist modeling approach, and directions for future research are also discussed.

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## Learning Outcomes

By the end of this case, students should be able to

- Summarize key developmental findings of the two case studies described in this case and discuss what problems these findings posed to developmental scientists
  - Describe what “connectionist” models are and how, in what ways, and to what extent they have been applied to the developmental case studies discussed in this case
  - Clearly and succinctly explain the strengths and weaknesses of connectionist models, especially as they pertain to the two developmental case studies described in this case
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John Connor: Can you learn stuff you haven't been programmed with ... .?”

The Terminator: My CPU is a neural-net processor; a learning computer.

Terminator 2: Judgment Day

Computational models—in this case a neural-net processor—are not yet sufficiently accomplished or complex to take over the world or bring about Armageddon, but they have been instrumental to scientists because they provide insight into the nature of the learning process and how knowledge ultimately is acquired. Such computer models—including neural net processors and Bayesian and dynamic systems models—have been particularly useful to developmental psychologists because they can clarify otherwise opaque existing verbal theories and patterns of findings by providing new insights into the nature of the learning mechanism (or set of mechanisms) that underpins those theories, findings, and behaviors.

These computer models serve a further special purpose in developmental science because they permit theories to be instantiated in concrete and mathematical terms and can extend the explanatory scope of—and thus improve upon—these theories through the generation of testable predictions. A number of computational modeling techniques have been used to

explore learning and development, from Bayesian approaches that have attempted to model behavior as a rational decision-making process (Gopnik et al., 2004) to dynamic systems approaches that view behavior as embedded in the body and emergent (e.g., Smith & Samuelson, 2003). However, the approach that we focus on in this case is connectionist or parallel distributed processing (PDF) modeling. We focus on this approach for two reasons: First, many, if not the majority of, models of development have been connectionist in design (Shultz, 2003). Second, connectionist models—perhaps more so than any other approach—have simulated effectively a wide range of developmental findings (McClelland et al., 2010; for a review, see Yermolayeva & Rakison, 2014). In this case, we will introduce two key behavioral findings in the developmental literature—one that pertains to infants and the other to young children—and describe how developmental researchers have used connectionist models to gain insight into the mental representations and learning mechanisms that underpin those findings. The phenomena that we will discuss in particular include (a) that 3- to 4-month-old infants will form a perceptual category for cats that excludes dogs but form a perceptual category for dogs that includes cats, and (b) that the ability to represent absent objects tends to emerge earlier on tasks that require looking than on otherwise identical tasks that require reaching and action. We will conclude with a discussion of the limitations of this approach with respect to the two findings just mentioned, discuss what is the appeal of the connectionist modeling approach, and suggest directions for future behavioral and modeling research.

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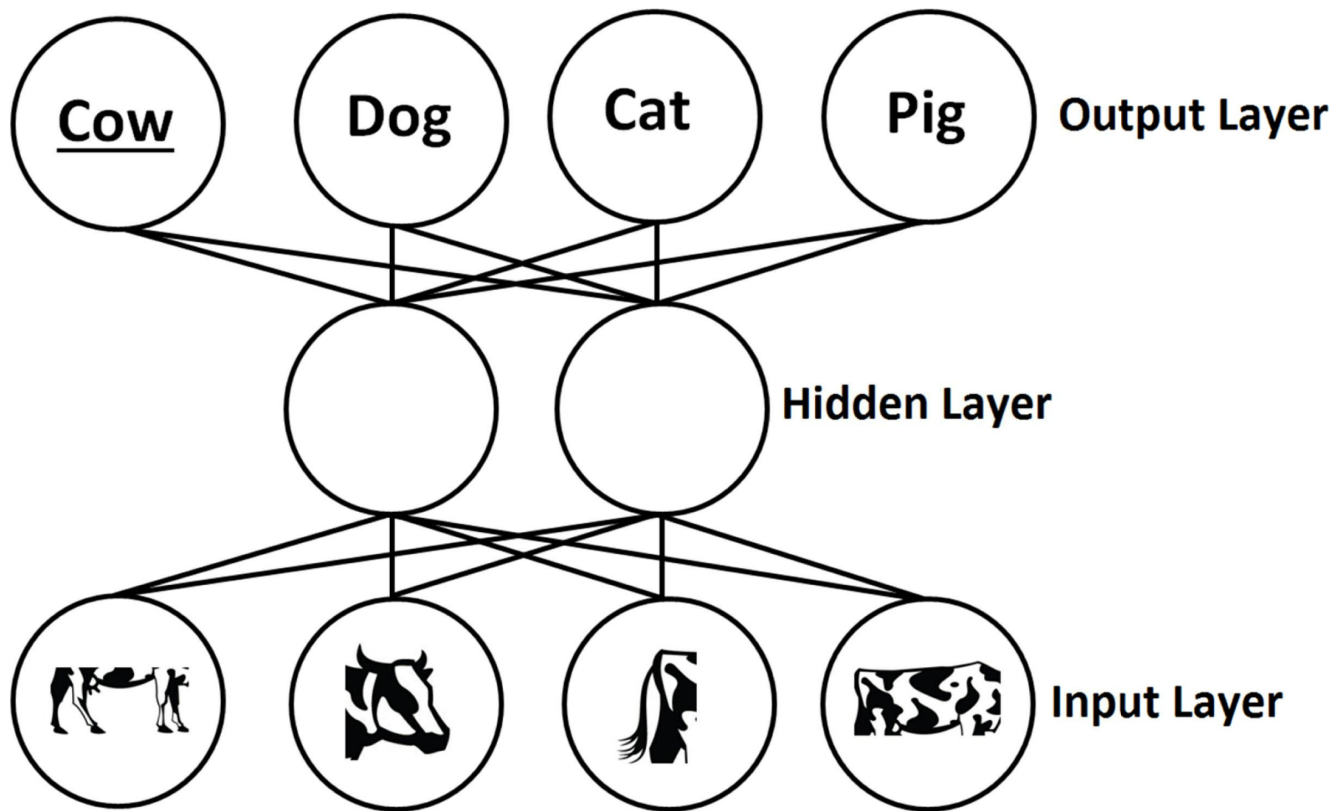
### The Connectionist Approach

Connectionist models constitute a class of “neural-net processors”—that is, “learning computers” that process information in human-like ways and that draw inspiration from the neural structure of the human brain—that provide insight into important issues that pertain to learning and change that have been observed in the developmental literature. These models have been especially popular among developmental psychologists precisely because (a) they are inspired by how the human brain processes information and thus are biologically plausible, (b) they are suited to address important developmental issues such as those discussed in this case, and (c) they make minimal assumptions about the “starting state” of the infant, and thus, knowledge is not assumed to be innate but instead is acquired gradually through learning.

These systems are generally organized into distinct layers: an input layer akin to human sensory mechanisms, a middle or “hidden” layer akin to the processing of the human brain, and an output layer akin to behavior. Each layer consists of simple neuron-like processing units or nodes that turn “on” or “off” in the presence of different input (see [Figure 1](#)). These units can represent either the features of a particular object (e.g., color, shape, size) or the whole object and whether those features or objects are present (i.e., the unit is “on”) or absent (i.e., the unit

is “off”). The concept of cow, for instance, may either be represented by a collection of “on” units that correspond to the distinct features of the cow (e.g., legs, eyes, udders) or by a single active unit that would represent the entire cow. A key feature of these models is that knowledge about concepts, objects, and events is stored in the set of connection “weights.” These weights connect the nodes in each layer to each other and can be modified or adjusted—based on some pre-specified learning rule—to reflect the current learning demands, to simulate long-term learning in the real world or short-term learning on a particular task, and to enable the model to produce desired behavior in response to incoming information (e.g., to generate the word “cow” when presented with cow features; see Yermolayeva & Rakison, 2014 for an extensive review of connectionist models).

**Figure 1. Depiction of a standard three-layer connectionist neural network.**



Note: The input layer is connected to the hidden layer—in which “internal representations” are formed—which in turn is connected to the output layer. Each layer consists of processing nodes or units that make use of signals that can turn units “on” or “off” in subsequent layers. In this example network, the features of a common cow are distributed across the four input nodes. This example network is tasked with the job of activating the node that corresponds to the word “cow” (i.e., the left-most node).

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#### Evidence for Perceptual Categorization and a Computational Model

The ability to form categories—to place things into groups based on, among other things, similarity (e.g., cats), a rule (e.g., blue objects), or even a principle (e.g., morally right things)—is a fundamental cognitive ability that has been an attractive topic to developmental scientists. Much of this research has demonstrated that the ability to form categories of animals, furniture, vehicles, and people emerges during the first two years of life. For example, Younger, Cohen, and colleagues (Younger, 1990; Younger & Cohen, 1986; Younger & Gotlieb, 1988) have demonstrated that in the first year of life infants can form novel categories for artificial (“made-up”) animal stimuli. Across a variety of experimental paradigms, this line of research has shown that 10-month-old infants are sensitive to, and can encode, correlated features to form perceptual categories (that rely only on surface features such as shape, color, and parts). And research by Arterberry and Bornstein (2001) showed that 3-month-olds can form categories of animals that include novel animals but exclude a novel vehicle as well as a category of vehicles that includes a novel vehicle but not a novel animal when the exemplars of these categories are presented as dynamic point-light displays alone. Thus, infants’ initial representations for objects and entities in the world are constructed based on the associative relation between perceptual, surface, and dynamic features of objects.

The findings we focus on here are drawn from a seminal study by Quinn, Eimas, and Rosenkrantz (1993). The study used the familiarization procedure in which infants are repeatedly shown the same stimulus—or various stimuli from the same category—and then tested with a new stimulus from a new category and a new stimulus from the familiarization category. In this study, 3- to 4-month-old infants repeatedly were shown different pictures of either dogs or cats presented two at a time side-by-side. Following this familiarization period, infants were shown a picture of a new member of the familiar category paired (e.g., a novel cat if previously shown cats) with a novel member of a novel category (e.g., a dog if previously shown cats). Infants’ preference for either picture was tested by measuring relative looking time to each one.

It was hypothesized that if infants formed a category of the familiar stimuli, they would look longer at the member of the novel category than that from the familiar category. Thus, infants familiarized to pictures of cats were expected to look longer at test at a novel dog than a novel cat, whereas infants familiarized to pictures of dogs were predicted to look longer at test at a novel cat than a novel dog. Somewhat surprisingly, Quinn et al. (1993) found that although infants familiarized to pictures of cats looked longer at a novel dog at test than a novel cat—which suggested that they had formed a category for dogs that excluded a novel cat—infants familiarized to pictures of dogs looked equally long at test at a novel dog and a novel cat. This result presented an interesting phenomenon to developmentalists because it was unclear why

infants would show such an asymmetry when they form categories of cats and dogs. In other words, why would infants form categories that include some species but exclude other ostensibly related species? Quinn et al. (1993) speculated that the asymmetry resulted from greater variability among the dog features (e.g., face, shape, and body dimensions) than among the cat features, which subsequently caused the dog features to overlap the cat features. Thus, a novel cat—for a novice learner like a 3- to 4-month-old—is a plausible member of the category of dogs, but a novel dog is unlikely to be a plausible member of the category of cats.

This explanation was neither tested in the original study by manipulating the variability of the cat and dog feature stimuli nor was it instantiated formally in a computer model. Computational models can be informative in such cases because they can help to reveal why, for example, 3- to 4-month-old infants categorized cats and dogs differently in Quinn et al. (1993) as well as generate novel, testable predictions about category performance with other stimuli. Connectionist models are ideal to elucidate the role of features (e.g., facial and body dimensions) on infants' categorization behavior because a principal goal for these models is to learn how one or more features are related to other features (e.g., things with cat facial dimensions are likely to have cat body dimensions). Quinn and colleagues (e.g., French, Mareschal, Mermillod, & Quinn, 2004; Mareschal, French, & Quinn, 2000) used computational (connectionist) models to explore the original finding from Quinn et al. (1993), to extend this finding, and to generate predictions about whether infants' ability to categorize cat and dog stimuli is affected by modifications to the features of the original cat and dog stimuli presented in Quinn et al. (1993).

These models were trained on six instances of a given category (e.g., six dogs or six cats), which was consistent with the familiarization procedure used with infants. However, unlike infants, cats and dogs were presented to the model as 10 different measured traits (e.g., ear length, nose length, body length, all of which were measured from the original pictures used in Quinn et al., 1993) along 10 "nodes" such that when the features were combined they represented a particular cat or a particular dog. The task for the model during training was to take those input "images" and recreate them as output. The training stimuli used in these modeling experiments were either the same as those in Quinn et al. (1993) to explore the original asymmetry (Mareschal et al., 2000) or were stimuli in which either the cat or dog features were made to be more similar to the dog or cat features (French et al., 2004). The models were then presented with novel stimulus novel dog and cat at test, and its ability to recreate those stimuli as output was tested. The network was said to have included a novel member of the familiar category into the category it formed during training if it successfully

recreated that novel member. Thus, a model was said to have formed a category of cats that included a novel cat but excluded a novel dog following training with cats if it recreated the image of a novel cat but not the image of a novel dog. In contrast, the models were said to have formed a category of cats that included a novel cat and a novel dog if it recreated the novel cat and dog test stimuli.

In addition to replicating the original asymmetry found with 3- to 4-month-old infants, the model revealed—and subsequent experiments with 3- to 4-month-old infants confirmed (e.g. French et al., 2004, Exp. 1)—that the asymmetry could be reversed when the cat features varied more than the dog features; that is, when the cat features varied more than the dog features and the model (or infant) was trained on cats, it perceived a novel dog to be a plausible member of the category of cats as evidenced by its ability to recreate the novel dog stimulus. The model results revealed in addition—and subsequent experiments with 3- to 4-month-olds also confirmed (e.g. French et al., 2004, Exp. 4)—that the asymmetry could be eliminated altogether when the features of the cat and dog stimuli did not overlap. In the absence of such overlap, the model created a category for dogs that included a novel dog but excluded a novel cat following training on dogs and a category for cats that included a novel cat but excluded a novel dog following training on cats. Together, the model results highlight that young infants rely on perceptual features to categorize cats and dogs, which has implications for broader category learning. This insight into infants' ability to learn about cats and dogs—and more generally to form categories—would not have been generated without the implementation of a computer model. More generally, these results highlight the crucial role of computational models in clarifying how, and in what ways, infants' categorization of stimuli can be expected to change when the features of those stimuli are modified.

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### **Representing Absent Objects and a Computational Model**

Connectionist models have not only been used to explore the basis of category acquisition in young infants, but they have provided key insight into why infants succeed on certain tasks earlier than on other tasks when both tasks are designed to tap the same knowledge. Tasks on object permanence—the knowledge that objects continue to exist even when hidden from view—represent one such case in which infants succeed on one kind of task that tests this knowledge but fail on related tasks that test the same knowledge (for a review, see Munakata, McClelland, Johnson, & Siegler, 1997). Developmentalists have used a variety of different tasks to assess infants' and children's object-permanence abilities, but the two tasks we focus on here are the A-not-B task that was developed by Piaget (1954) and the “rotating-screen” task that was first introduced by Baillargeon, Spelke, and Wasserman (1985). These tasks are discussed because it was only when this work was implemented as a computational model that

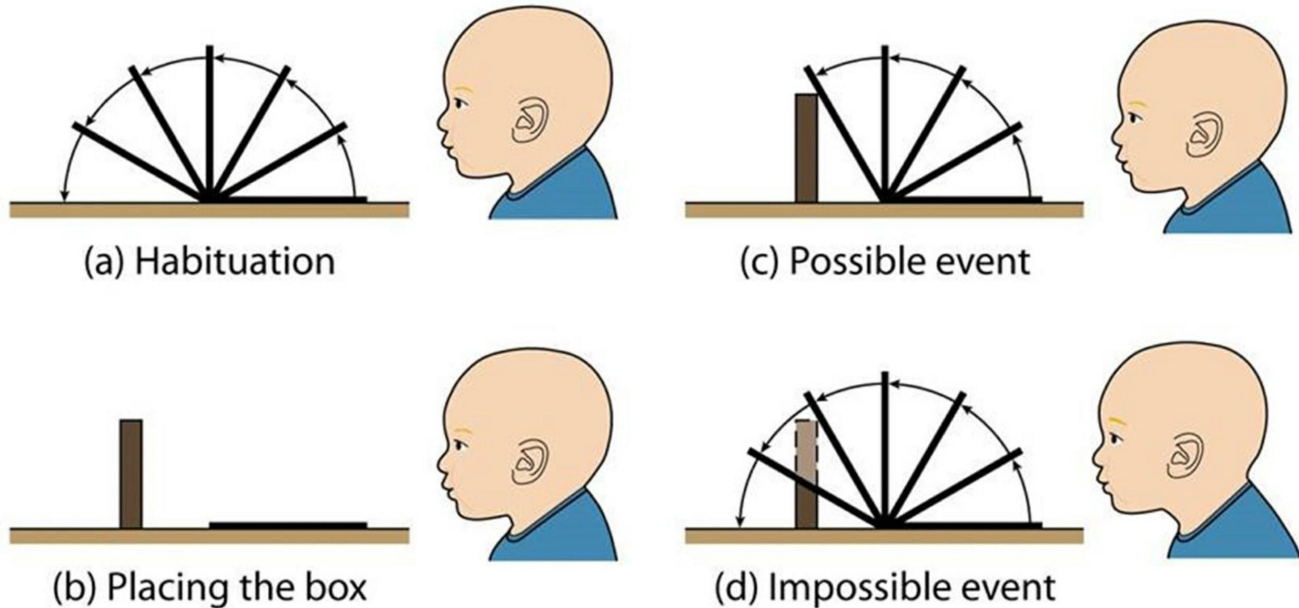
it was possible to explain why infants succeed on the former task but not on the latter task until later in development.

In Piaget's traditional A-not-B task, an experimenter hides an attractive toy or object in location A beneath a distinctive cover or cloth. The infant or child is then encouraged to retrieve the hidden object, and this process is repeated several more times. The experimenter then hides the toy in plain view in a new location, location B, and again the infant is encouraged to retrieve the hidden object. Research that has used this paradigm has shown that 8-month-olds tend to search in the initial location (A) for the object, and they search at the correct location (B) by 12 months of age if the delay between hiding and search is relatively short (Bigelow, MacDonald, & MacDonald, 1995; Diamond, 1985; Piaget, 1954) and by 10 months of age if infants are allowed to stand (e.g., Smith & Thelen, 2003).

In contrast to traditional A-not-B studies that require children to engage in manual search, others have used infants' pattern of looking to assess whether they can "search" for and represent hidden objects. For example, in Baillargeon and colleagues' rotating-screen task, 3.5- to 5-month-olds were habituated—that is, repeatedly shown a stimulus until looking time decreased to a preset criterion—head-on to an event in which a screen rotated continuously through a 180° arc in a manner that resembled the movement of a drawbridge (see [Figure 2](#)). A box was then placed behind the rotating screen—while the screen lay flat against the floor of the habituation stage—and infants were shown an impossible and a possible test event. In the possible test event, the screen rotated approximately 120° until it made contact with the box behind it. In the impossible event, the screen rotated 180°—as it did during habituation—and appeared ostensibly to rotate through the box that was placed behind it. In the studies that use this task, it was reasoned that if infants represented the box even when hidden by the screen—that is, if infants demonstrated object permanence—they should look longer at the impossible test event than the possible test event because the screen should not rotate through the solid object that was located behind it.



**Figure 2. Example of the rotating drawbridge mechanism and the habituation and test events that Baillargeon (1987) used to assess infants' ability to represent objects that were hidden from view: (a) Habituation, (b) placing the box, (c) possible event and (d) impossible event.**



This is exactly what was found with 4.5-month-olds (Baillargeon, 1987), 5-month-olds (Baillargeon et al., 1985), and a subset of 3.5-month-olds (Baillargeon, 1987). Baillargeon used these findings and those from similar such studies (e.g., Baillargeon, 1991; Baillargeon, DeVos, & Graber, 1989; Baillargeon & Graber, 1988) to conclude that object permanence emerges by, at the very latest, 3 to 4 months of age (e.g., Baillargeon, 2008). The findings from the traditional A-not-B studies and those from Baillargeon and colleagues, too, presented an interesting phenomenon to developmentalists because it was unclear why infants showed evidence of object permanence earlier in tasks that required looking than in tasks that required reaching and action when both tasks assessed knowledge about hidden objects.

What, then, accounts for these discrepant findings? It has been posited that the reason infants succeed on visual tasks—such as Baillargeon et al.'s (1985) rotating-screen task—earlier than they do on motor tasks—such as the physical search A-not-B task—is because the latter task requires infants to engage in means-end action sequences. This ability, which includes actions such as pulling a cloth to retrieve a hidden object or toy, does not emerge until around 12 months of age. The crux of the argument is that such action sequences require that infants have a sufficiently strong internal representation of the hidden object that can be maintained through reaching and pulling; a weaker internal representation of the object is required to

respond to the possibility of event sequences (e.g., the impossible and possible events in the rotating screen study). On these accounts—as well as related ones that attribute the discrepancy to factors such as a lack of motivation to reach or failure to distinguish present objects from absent ones (for a review, see Diamond, 1991)—infants' earlier success on visual tasks than on motor tasks results not from a lack of the concept of object permanence but from ancillary deficits.

In contrast, other accounts have maintained that the ability to represent hidden or absent objects is not present from birth but rather emerges through infants' interactions with objects (e.g., Morton & Munakata, 2002; Munakata, 1998; Munakata, McClelland, Johnson, & Siegler, 1997). According to this account, object permanence is not thought of in absolute all-or-none terms, but rather knowledge about present and absent objects is assumed to be graded—that is, it is represented by different “strengths”—and gradually emerges as infants gain experience with objects in the real world. In this way, success (or failure) on different versions of the A-not-B task depends only on whether those tasks require more or less graded knowledge about present and absent objects. This means that infants may succeed on visual versions of the A-not-B task earlier than on motor versions of the same task because a weak internal representation may be sufficient to produce longer looking to impossible events on visual tasks but be insufficient to prevent infants from searching at the incorrect location on motor tasks because motor tasks require both a visual and motoric response.

Of these competing accounts, only the latter account has been instantiated in the context of computational (connectionist) model to explore the mechanism that causes infants to show object permanence earlier on some tasks than on others. This is because these models make it possible to explore how, and in what ways, graded changes in the underlying weights support success on visual and manual object-permanence tasks. For example, Munakata et al. (1997) developed computational models that were trained either to predict the reemergence of occluded objects or to learn to “reach” for hidden objects similar to what was done in Piagetian A-not-B tasks. In particular, the model consisted of a prediction system (i.e., looking) and a reaching system. The model's goal in the looking system was to maintain a representation of an object as it traveled back and forth behind an occluder that was located at center screen and to predict or “gaze” at where the object would appear next from frame to frame. In contrast, the goal of the reaching system was to predict the location of the model's next “reach” across frames. Thus, if an object was initially stationed at Position 0 in the model's visual field, the model had to predict that the object would appear next at Location 1. Furthermore, if the occluder was at Position 5 and the object was at Position 4, the model had to predict both that the object would next appear at Location 5 and be able to represent that object even though it

was now hidden by the occluder and not presented to the model. Given that no actual reaching or looking occurred in the model, the difference between the two systems was that learning was initiated later for the reaching system than for the corresponding looking system. The decision to delay learning in the reaching system relative to that in visual system also enabled Munakata et al. (1997) to account for the finding that success on reaching tasks generally develops later than on looking tasks.

Finally, the model consisted of a set of “hidden” units that corresponded to the model’s internal representation of the object. The purpose of these internal-representation units was to enable the model to develop sufficiently strong internal representations of the object as it moved across the screen that would support its “looking” and “reaching” behaviors. Munakata et al. (1997) then examined the model’s ability to represent occluded objects at test by examining the internal representation that the models formed for the absent object. It was reasoned that the pattern of activity that corresponded to the object when hidden by the occluder would be easier to visualize as the model’s representation (i.e., weights) of that object strengthened during the course of training.

The simulation results revealed that (a) the ability to represent occluded objects in the prediction “visual” system emerged earlier than the ability to reach for the same objects in the reaching system, a result that was consistent with the results of Baillargeon et al. (1985) and Piaget (1954); (b) that successful reaching required a stronger internal representation than what was required to support looking to surprising events; and (c) that rather than being present from the outset of training (or correspondingly from birth in infants), the concept of object permanence emerged gradually as the model gained experience with objects that came in and out of view. These findings from the model are important for a number of reasons. First, they suggest that earlier success on visual tasks than on reaching tasks can be explained by the gradual strengthening of internal representations (e.g., memory) of hidden objects. Second, they imply that object permanence may emerge from interactions with occluded objects rather than being present from birth or shortly thereafter. Finally, they indicate that arguments in which later success on manual versions of the A-not-B tasks are attributed to ancillary deficits may perhaps be premature and unnecessary. The results of the model demonstrated that this discrepancy may result from the gradual strengthening of knowledge (i.e., weights) that ultimately may support inferences about occluded objects in looking and reaching tasks.

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#### **Limitations of the Quinn and Munakata Connectionist Models**

Despite the importance of the findings discussed above on our understanding of how infants

and children categorize objects and represent those objects, the models of Quinn and colleagues and Munakata et al. (1997) suffer from several limitations that are worth discussing. First, although the models of Quinn and colleagues provided a plausible mechanistic account of perceptual category acquisition in infants, no attempt was made explicitly to model the development of such category acquisition, that is, Quinn et al. did not use the model to examine how category acquisition changes from month to month or from year to year (cf. Johnson & Quinn, 2000). This limitation is important to address not least because it is needed to provide a coherent account that describes how category acquisition changes over developmental time. Although Quinn and colleagues did not explicitly model development, doing so is relatively straightforward in connectionist models; for example, some models can be made to learn slower than others or older models are given more “experience” with the input than younger models.

Second, despite the fact that some think that the mechanism that underpins learning and cognition is associative (e.g., Benton & Rakison, 2017; Gomez, 2002; Newport & Aslin, 2004; Rakison & Lupyan, 2008; Rovee-Collier, 1999; Yermolayeva & Rakison, 2016), others have taken a starkly different perspective to argue that humans use Bayesian inference and mental “graphs” to learn and make rational inferences about objects and entities in the world (e.g., Gopnik et al., 2004). The rationale for this latter approach is that because there is evidence that infants and children can perform actions that they have not seen performed and can make inferences based on indirect relations between objects and events, cognition must be supported by more advanced learning abilities and mechanisms. The goal for future behavioral and computational research will be to examine whether, to what extent, and under what conditions cognition is associative, Bayesian, or some combination of the two.

Third, compared to the real-world learning experience of infants and children, the models of Quinn and colleagues and Munakata et al. (1997) were trained and tested in relatively restricted environments. That the training experience of the models presumably did not match that of infants and children in the real world—where the training experience was more restricted in the former than in the latter case—is potentially problematic because it limits the extent to which the model’s findings can be generalized and used to explain category formation and object-permanence abilities in the real world and limits how well the models can learn when exposed to a wider range of experiences. Such restricted training can even lead to “catastrophic interference,” whereby old information is “forgotten” at the expense of newly learned information. A future goal for modelers and developmentalists will be to make their models more realistic by exposing them to a wider range of experiences that more closely match those of human infants, children, and adults. Nonetheless, despite these limitations, the models

presented in the preceding sections are important because they provide insight into how infants form categories and how they come to represent hidden objects in tasks that require looking and reaching.

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### **The Appeal of the Connectionist Modeling Approach**

Before closing this case, it is worth discussing briefly what is the appeal of connectionist models and why have they been so popular. These models have been criticized by some for being black boxes because their behavior is often difficult to describe in concrete terms (e.g., Klahr, 2004) and for sometimes failing to integrate new and old experiences (French, 1999). Nonetheless, they exhibit several desirable properties that have contributed to their continued popularity and widespread use in cognitive sciences (Yermolayeva & Rakison, 2014).

One such desirable property is the ability to sustain damage—in the form of removing weights or units from different parts of the systems—and still be able to produce accurate or near-accurate behaviors and patterns of responses. This is viewed as desirable property because the human brain and cognitive system—on which PDP connectionist models are loosely based—can also sustain damage in one area that may have little to no effect on other areas and thus little to no effect on behaviors that are associated with those unaffected areas. Thus, it is possible to gain insight into how brain damage in humans influences behavior and processing in undamaged areas of the brain by studying the role of such damage in connectionist PDP systems (e.g., Plaut, 1995).

Connectionist models are also desirable because they exhibit the ability to generalize learned experiences to new ones. This particular property is possible in connectionist systems because incoming input patterns are processed through the same set of intermediary weights. Thus, two patterns that are similar will tend to produce similar output patterns and responses because these patterns interact with the same underlying weight structure. This feature has important ramifications for theories about learning and the application of that knowledge to new situations in the real world.

Still another desirable property of these models is their ability to simulate developmental change. Because learning in these systems often depends on choices about what network architecture is used or what learning rate is employed, it is possible to be explicit about plausible mechanisms of change, to investigate developmental change in systematic ways, and to generate predictions about developmental change that can improve existing theories of cognitive development. In general, connectionist models provide a valuable tool for investigating challenging aspects of cognition, for understanding and clarifying how knowledge

is learned and extended, and for providing explicit, testable predictions that have important implications for purported mechanisms of developmental change.

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### Conclusion

The aim of this case was to introduce the connectionist framework and to discuss how it has been applied to clarify exciting yet somewhat paradoxical developmental findings, such as asymmetrical category learning of cats and dogs in young infants and the observed tendency of infants to show success earlier on some tasks than on others despite identical required prerequisite knowledge. The modeling results presented above suggested that the gradual strengthening of knowledge combined with an associative learning system that internalizes structure and regularity in the real world can explain these findings without recourse to inborn knowledge or ancillary-deficit accounts. Connectionist models thus represent powerful, albeit underutilized, tools to explain and elucidate unclear findings, provide clear predictions about change that can be tested empirically, disentangle competing theoretical accounts and refine existing verbal theories, create a unified framework—that makes minimal assumptions about initial knowledge or the shape that the knowledge takes—that explains and accounts for learning in and across different content domains, and lead to new directions for developmental research. Connectionist models play a vital role in science and represent a tool—among many others—that can and should be exploited better to characterize early learning and change and to address key questions that have heretofore evaded developmental scientists.

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### Exercises and Discussion Questions

1. Based on what you know about connectionist models from the reading, identify *at least one* other conflicting finding in the developmental literature (or in a literature with which you are familiar) and describe how this approach can be extended to clarify and provide insight into those findings.
2. The case discussed and described how connectionist models can help to elucidate unclear findings. Discuss how and in what ways these and other unclear findings can lead to “better” models. In other words, how can existing findings help computational modelers to develop models that do a better job at capturing real-world phenomena?
3. How important is it for developmental scientists to work closely with computational modelers? What advantage does this have in helping researchers better to understand how humans form concepts, represent objects, and think and reason about the world?
4. We opened the case by quoting an interaction between John Connor and The Terminator. In your opinion, will connectionist models (or any other model type with which you may be familiar) become advanced enough to form human relationships, feel pain, and show

empathy toward others like The Terminator? If so, how and why? If you disagree, why not?

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### Further Reading

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