Violation of Category Boundaries: a Connectionist Study with Action-based Categories

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Abstract

In this paper we describe three connectionist simulations which explore the formation of hierarchical organization of categories in the framework of an action-based theory of categorization. An organism with a visual system and a 2-segment arm has to reach different points in space depending on the object seen and on context. The context indicates whether to categorize visually perceived objects, which are all equally similar to each other, at basic or superordinate level. The results indicate that learning of hierarchical organization is easier when the actions to perform with members of basic and superordinate level categories are similar. Furthermore, learning Goal Derived categories - i.e., categories that violate categorical boundaries - is more difficult than learning Common Taxonomic categories. Thus, the results replicate empirical results with action-based categories.

Introduction

Traditionally, the mind has been viewed as a device for manipulating symbols. Accordingly, concepts or categories are viewed as static structures made up of arbitrary symbols that refer to objects and entities in the world. This view of categories implies the existence of a translation process from sensory-motor experience into amodal and arbitrary symbols.

More recently, however, there appears to be an increasing interest in embodiment in different areas of cognitive science. Many scholars share the view that cognition cannot be conceived of as separated from our bodily experiences. This implies that perception and action cannot be simply viewed as input and output devices but they are central in order to understand "higher" cognition.

Recent views of categorization conceive of concepts or categories as grounded in sensory-motor processes (Barsalou, 1999; Barsalou, Simmons, Barbey & Wilson, 2003; Glenberg, 1997; Smith, 1995; Smith & Katz, 1996; Thelen, Schöner, Scheier, & Smith, 2001). But not only categorization is action-based. If "cognition is for action", the adaptive value of categorization consists in helping to prepare for situated actions (Wilson, in press). Within an embodied perspective, concepts can be viewed directly as patterns of potential actions (Glenberg, 1997) or as represented by "perceptual symbols" which make it possible to rapidly assess the information relevant for action (Barsalou, 1999; Borghi, Glenberg & Kaschak, submitted).

The general aim of this paper is to test some claims of an action-based theory of categorization, i.e., a theory according to which categories reflect sensory-motor experiences, by using neural network simulations. The functioning of a neural network that maps sensory input into motor actions makes it clear what we mean when we say that categories are action-based and action-oriented. Neural networks are devices for transforming activation patterns into other activation patterns. There are two principles governing these transformations: as input is progressively transformed into output, the input activation patterns (stimuli) that should be responded to with the same output (action) become progressively more similar to each other (principle of categorization), while the input activation patterns that should be responded to with different outputs (actions) become progressively more different from each other (principle of discrimination). Both these principle are output-, i.e., action-based. In a neural network the properties of the input, those which distinguish one input from another input, have some control on the internal representations only in the first layers of internal units. But even at this early stage the internal representations follow the principles of categorization and discrimination which are output-based principles.

In previous work with neural network simulations we explored the strict interrelations between categorization and action. We found that the internal representations in an organism's neural network are organized in terms of macro-actions, that is, sequences of movements (micro-actions) that allow the organism to correctly respond to the perceived objects (Di Ferdinando & Parisi, in press). In other simulations we found that the network's internal representations of objects reflect the current task and not the perceptual similarity between the objects. This does not mean that perception does not play an important role in categorization: in absence of task information, in fact, perceptual similarity is the best predictor of categorization (Borghi, Di Ferdinando & Parisi, 2002; Di Ferdinando, Borghi & Parisi, 2002).

This paper goes one step further: it aims to apply an action-based theory of categorization to a specific problem in the literature of categorization, the formation of hierarchical levels, and particularly the acquisition of superordinate and basic level categories.

The term hierarchical structure is generally used to refer to the different levels of generality at which knowledge can be organized. In fact, people are able to use or refer to so-called superordinate categories (e.g., animal, furniture) or more specific or basic categories (e.g., dog, table). Basic level categories are included in superordinate categories with a class inclusion relation (Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976).

Furthermore, studies of categorization distinguish between Common Taxonomic (CT) and Goal Derived (GD) categories (Barsalou, 1985; 1991). CT categories are everyday categories, like animal and vehicle, whose members belong to the same domain and generally share some perceptual similarities. GD categories are categories whose members are assembled on the basis of some current common goal rather than of perceptual similarity. Thus, the members of GD categories do not necessarily belong to the same domain, may violate the domains boundaries, and are generally less stable in memory than CT categories. A typical example of a GD category is 'things to take to the camping-place' which can include items such as shoes, toothpaste, books, and pets.

In our simulations we address the formation of superordinate categories of both the CT and the GD type. Superordinate CT categories are formed assembling two exemplars for each of two different basic categories, while superordinate GD categories are formed assembling together one exemplar for each of four different action-based categories. An example from real life can help to clarify: the CT superordinate category of animals is formed assembling the members of, say, the 'cats' and 'dogs' basic level categories, while the GD superordinate category of birthday presents is formed putting together the members of, say, the 'cats', 'dogs', 'books' and 'jumpers' basic level categories.

The novelty in this study is that both CT and GD categories are totally action-based, i.e., the influence of perceptual similarity among the category members is ruled out. In fact, the objects to be categorized are simply filled cells in a cell matrix, and do not perceptually differ from one another.

If action influences categorization, superordinate categories should be more easily learned the more the action to perform with them is similar to the action to perform with their basic level members. This hypothesis it tested by comparing Simulation 1 and 2.

The question of whether superordinate categories are more easily learned and distinguished from basic level categories when they are formed by respecting category boundaries (CT categories) or violating them (GD categories) is tested by comparing the first two simulations with a third one. We predict that when category boundaries are violated it is more difficult to learn the task.

The Model

Imagine an organism which lives in an bidimensional environment containing 8 different objects. The organism has a simulated visual system with which it sees only one object at a time and a two-segment arm which it can move to reach some specific position in space which depends on the particular object seen and on the particular context (task). In each epoch of the organism's life the initial position of the arm is randomly selected. The organism can know the arm's position at any given time based on proprioceptive input from the arm's two segments. The organism's behavior is controlled by a nervous system, which is simulated using an artificial neural network.

The visual field is a 3x3=9 cell matrix and each object is very simple: it appears as a particular filled cell in the matrix of 9 cells. There is a total of 8 objects (in the central cell no object can appear). Notice that all objects are identical to each other, because we wanted to rule out the influence of perceptual similarity. They are only distinguished on the basis of the spatial location in the retina in which they appear.

The proprioceptive input from the arm which tells the organism the position of its arm at any given time is encoded in two further input units. This input specifies the angle of the forearm with the shoulder and the angle of the arm with the forearm.

The network architecture includes a third set of 2 input units which encode two different contexts or tasks: context A, encoded as 10, and context B, encoded as 01. The 2 context units are connected with the internal layer like the visual input units.

The network architecture is described in Figure 1.

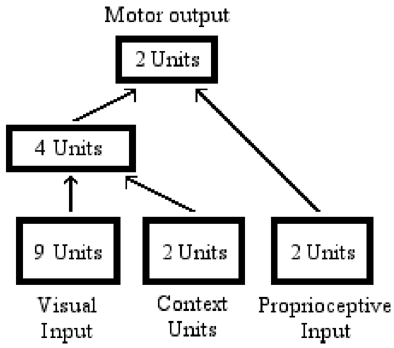

Figure 1: The neural network architecture

The organisms must respond to the input by moving the arm in such a way that the arm's endpoint (the hand) reaches some particular location in space (i.e., presses some particular button) which depends on the particular object which is presented to the organism in any given epoch and on the context. Thus they have to perform a different kind of action with the same object depending on the context. This scenario addresses a problem we encounter in real life: depending on the kind of context, we may need to categorize objects at the superordinate or at the basic level. For example, it may be useful to distinguish predators and prey when we have to decide whether to run away or not, while it may be useful to distinguish dogs and cows when we have to go hunting or to drink milk.

In our simulations, the 8 objects are grouped into 4 basic level categories, two objects for each basic level category, and into 2 superordinate categories, 4 objects for each superordinate category. In context A the organisms must use the basic level categories, i.e., they have to press one of 4 buttons depending on the object's basic level category (Figure 2). In context B the organisms have to press one of 2 buttons depending on the object's superordinate category (Figure 3).

Notice that while basic level categories are the same in all the 3 simulations, the way superordinate categories are formed varies in the 3 simulations.

All organisms live the same amount of time (number of input/output cycles of their neural network). Each individual organism is a member of a generation of 100 organisms. At the end of life the 20 individuals which perform better in the task are selected for reproduction. Five copies of the connection weights of their neural network are generated and assigned to five new individuals (offspring). The 20x5=100 offspring constitute the next generation. Reproduction is nonsexual but an average of 10% of the inherited connection weights are randomly mutated so that offspring behave similarly but not identically to their parents.

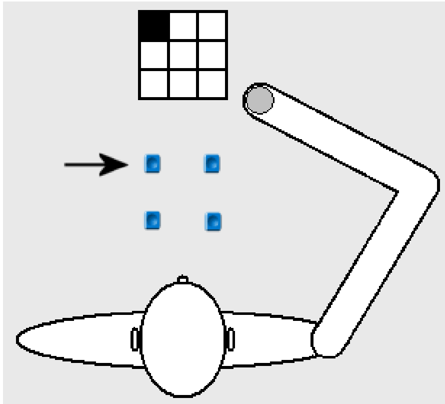

Figure 2: Context A: The organism categorizes at the basic level.

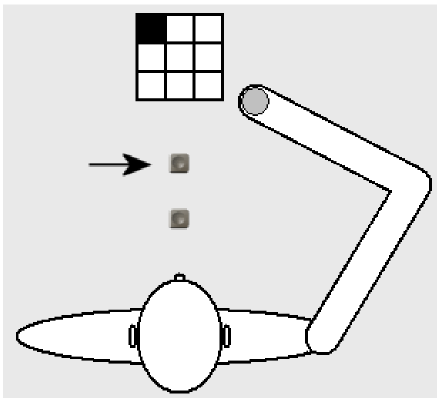

Figure 3: Context B: The organism categorizes at the superordinate level.

In order to obtain reliable results we have run each simulation with 10 different initial conditions (seeds).

The Simulations

In Simulation 1 the action the organism has to perform in response to all 4 members of a superordinate category is similar to the actions to be performed in response to the 2+2 members of its 2 basic level sub-categories and dissimilar to the actions performed in response to the 2+2 members of the 2 basic level sub-categories of the other superordinate category. Action similarity is computed in terms of physical distance of target positions.

In Simulation 1 the action to be performed at the superordinate level is to reach a button which is spatially located between the 2 buttons to be reached in response to the members of the category's 2 subcategories (Figure 4a).

In contrast, in Simulations 2 the button to be reached at the superordinate level is spatially located on the opposite side with respect to the 2 buttons to be reached when responding at the basic category level (Figure 4b).

The simulation which is critical for testing our hypothesis is Simulation 3. In this simulation the superordinate category is formed by 4 members, each of which belongs to a different basic level category (Figure 4c). This means that the location the organism has to reach while categorizing at the superordinate level, the central button on one side of the button space, is close to the location it has to reach at the basic level for 2 of the superordinate category members, while it is far for the other 2 members.

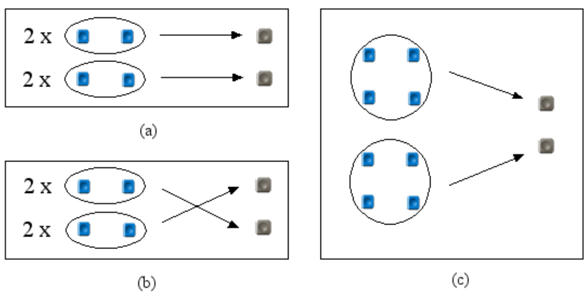

Figure 4: Locations to be reached with basic and superordinate categories: (a) Simulation 1 (CT close); (b) Simulation 2 (CT far); (c) Simulation 3 (GD).

Thus, if only action similarity influences performance, the results of Simulation 3 should be intermediate between those of Simulation 1 and of Simulation 2.

We predict, instead, that performance is influenced not only by action similarity but also by respecting vs violating category boundaries. In fact, Simulation 3 differs from both Simulations 1 and 2 because categories boundaries are violated. This means that a superordinate category (e.g., animal) is not formed by grouping together the members of 2 basic level categories (e.g., dog and robin), but by putting together the members of different basic level categories (e.g., the superordinate category 'birthday presents' is formed by 'dog', 'doll', etc.). In the literature on categorization categories which violate category boundaries are called GD or goal derived categories (Barsalou, 1983; 1985; 1991; Vallée-Tourangeau, Anthony, & Austin, 1998). Summarizing, in Simulation 3 it should be more difficult to form action-based superordinate categories in that superordinate categories are GD categories, i.e., they assemble together one member of each of the 4 different basic level categories.

Results

As predicted, organisms perform better in Simulation 1 than in Simulation 2 (see Figure 5). The performance of both the best individual and the population average in Simulation 1 is significantly better than in Simulation 2. Two sets of Anovas performed on both the average number of objects reached by the best organisms across 10 seeds and on the average performance of the population across 10 seeds every 1000 generations reached significance ($p < .01$). The results clearly indicate that, the more the actions to perform at superordinate and basic level are similar, the easier it is to learn the task.

However, Figure 5 shows also that organisms perform worse in Simulation 3 than in Simulation 1 whereas there is no difference between Simulation 2 and 3. The Anovas and the post hoc Newman-Keuls comparing the performance of the best individual and of the whole population in the three simulations every 1000 generations confirm ($p < .01$) that the performance of both the best individual and the average of the population in Simulation 3 is not significantly different from that of Simulation 2 while it differs from that of Simulation 1.

This suggests that the bad performance of organisms in Simulation 3 does not depend only on action similarity between superordinate and basic categories. If this were the case, in fact, performance in Simulation 3 should be better than performance in Simulation 2, given that, as we have seen, the average distance between the buttons to be reached with superordinate and basic categories is smaller in Simulation 3 than in Simulation 2.

Thus, our prediction is confirmed: not only action similarity has an effect on categorization but there is also an effect of violation of category boundaries.

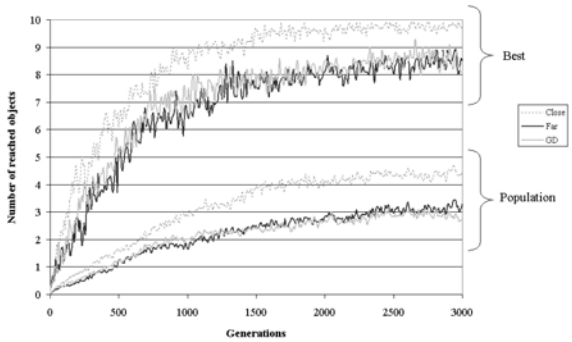

Figure 5: Number of objects reached by the best organism and the whole population in Simulation 1 (close CT), Simulation 2 (far CT), and Simulation 3 (GD). Average of 10 seeds.

In fact, with GD categories artificial organisms, like real ones (Caramelli & Borghi, under review), perform worse than with CT categories.

In order to isolate the effect of the violation of category boundaries from the effect of action similarity, we performed a control simulation in which the output of the neural network does not control the movement of the arm, but directly specifies the superordinate and basic categories to which the objects belong. More specifically, there are four output units encoding in a localistic way the four basic categories and two additional output units encoding the two superordinate categories. The task is to activate the output unit that correspond to the basic or superordinate category (depending on context) to which the object currently seen belongs.

Given that the arm has not to be moved in this simulation, the proprioceptive input is not considered.

The new neural architecture is shown in Figure 6.

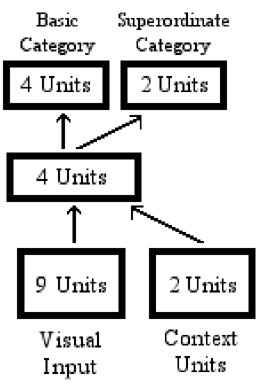

Figure 6: Control simulation. Neural network architecture.

To train the network to solve the task we used the back-propagation algorithm. Given that there is no movement of the arm, there is no difference between the condition “spatially close” and the condition “spatially distant”. We refer to both these conditions as CT (Common Taxonomic). We compared this condition with the condition GD. In this new scenario the only difference between CT and GD categories is the violation of category boundaries. Figure 7 shows that CT categories are learnt faster that GD categories, thus confirming our hypothesis.

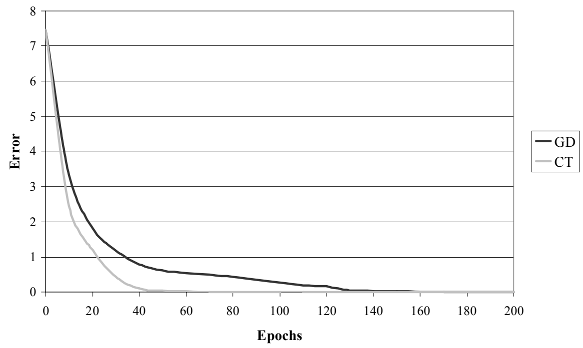

Figure 7: Control simulation. Performance with CT and GD categories.

Discussion

The goal of this study was to explore how an action-based theory of categorization can explain the formation of hierarchical levels in categories of different kind, i.e., Common Taxonomic and Goal Derived categories.

The simulations show that neural networks can learn to use different action-based categories, of superordinate and basic level, depending on the context. In fact, rather than based on perceptual similarity between category members, in our simulations categories are formed on the basis of the kind of action to be performed (see also Borghi, Di Ferdinando & Parisi, 2002; Di Ferdinando, Borghi & Parisi, 2002). The difference between CT and GD categories is captured by the fact that the CT categories are formed by assembling basic level categories, while the GD categories are formed without respecting the boundaries of basic level categories.

The first result we found was that the similarity of the action to be performed at different hierarchical levels influences categorization: in fact, the comparison between Simulation 1 and 2 showed that superordinate action-based categories are easier to form if their members have to be responded to with actions similar to those used with the members of their basic sub-categories. Consider that, in real life, action and perception are correlated, as the literature on affordances suggests (Gibson, 1979; Tucker & Ellis, 1998). By emphasizing the role of action we do not intend to reduce the importance of perception and perceptual similarity (Goldstone, 1994), and our results do not allow us to do this.

The results also show that neural networks have more difficulties in learning superordinate GD categories, i.e., categories which violate basic level category boundaries, than superordinate CT categories that do not violate such boundaries. In general, in the literature of categorization it is argued that GD category are less stable in memory than CT categories (Barsalou, 1991). This instability is considered to be due to the less frequent use of these categories which in turn is due to the perceptual dissimilarity between the category members. The novelty in our study is that the categories we use are completely action-based - thus the influence of perceptual similarity is ruled out. Using only action-based categories our study suggests that the instability of GD categories may depend on the frequency with which an action is performed with a certain category member, i.e., on the existing consistency between the canonical actions we perform with an object and the action we are required to perform in a new context.

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