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Michael J. Kahana (ed.), Anthony D. Wagner (ed.)

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CHAPTER

## 30 Discrimination, Recognition, and Classification

Michael L. Mack, Thomas J. Palmeri

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### Abstract

Retrieval processes provide ways of using memory. This chapter describes three important ways of using memory, with a focus on using memory to make decisions about visual objects. Discrimination is deciding if an object is distinct from another object experienced at the same time or moments ago, recognition is deciding if an object is the same as an object experienced some time in the past, and classification is deciding what kind of object something is. All three require comparing the representation of a currently perceived object with representations retrieved from memory to drive a decision process. The chapter discusses the component mechanisms for discrimination, recognition, and classification as formally instantiated in computational models and also discusses relationships between model mechanisms and brain mechanisms as revealed by neuropsychology and brain imaging.

**Keywords:** [dimensions](#), [features](#), [similarity](#), [exemplars](#), [prototypes](#), [decision-making](#), [evidence accumulation models](#), [computational modeling](#), [dissociations](#), [neuroimaging](#)

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## Introduction

Imagine your morning routine ends with a walk through the park on your way to the lecture hall for class. One morning, as you reach the park's central esplanade, a happy dog barrels toward you, stopping just short of crossing your path. You can *discriminate* one dog from another dog: Is that the same dog that moments ago ran around a park bench to reach you? You can *recognize* the dog: Is that the dog you saw in this same park last week? You can *classify* the dog: You know it is a dog. You also know it is an animal. Is this dog, in particular, a border collie or another kind of herding dog?

These thoughts are examples of common types of memory decisions we make about our everyday experiences (Figure 30.1). They all involve some kind of comparison of a current perceived experience—in this chapter, we focus on visual experiences with objects—with some form of representation of past experiences retrieved from memory that provide evidence to drive a decision process. *Discrimination*<sup>1</sup> is deciding whether the current object is distinct from an object experienced moments ago. *Recognition*<sup>2</sup> is deciding whether the current object is the same as one experienced some time in the past. *Classification* is deciding what kind of object something is. Kinds can range in abstraction (Rosch et al., 1976) from the highly specific identification of a particular individual (*my dog Max*) to a subordinate type (*yellow Labrador retriever*), to a basic kind (a dog), to a superordinate class (*an animal, a living thing*). ↵



**Figure 30.1** Example discrimination, recognition, and classification decisions for a single visual object.

Source: Photograph by Sebastian Lehmann.

On the surface, these seem like very different memory decisions dependent on very different retrieval processes. Discrimination retrieves a specific immediate past experience, whereas recognition can involve a sense of familiarity with a host of past experiences.<sup>3</sup> Discrimination involves a specific individual, whereas classification involves generalization over a broad category. Recognition is memory based on episodic experiences, whereas classification reflects semantic knowledge about a category. Indeed, as we review in

the following sections, certain theories of discrimination, recognition, and classification have viewed these as distinct memory processes relying on distinct forms of memory representation. But when performance in these memory tasks is formalized in computational models that instantiate memory representations and mechanistic processes in mathematics and simulation, we can see many more similarities in representations and processes than might be apparent otherwise.

Discrimination, recognition, and classification are all broad topics for discussion. Other chapters in this volume discuss recognition memory (e.g., Chapters 31 and 32), and entire volumes have been devoted to classification and concepts (e.g., Murphy, 2004) and formal models of classification (e.g., Pothos & Wills, 2011). We focus on formal models to illustrate the representations and component processes involved in discrimination, recognition, and classification in precise mechanistic detail; to describe ways in which these might share aspects of representation and process; and to highlight the inferential power of computational modeling approaches (e.g., Farrell & Lewandowsky, 2018; Hintzman, 1990). We highlight specific examples of neural evidence using a model-based cognitive neuroscience approach (e.g., Forstmann & Wagenmakers, 2015; Palmeri et al., 2017; Turner et al., 2017), with other chapters in this volume discussing the neural basis of memory more generally (e.g., Chapter 4, 5, and 35).

## Modeling Discrimination, Recognition, and Classification

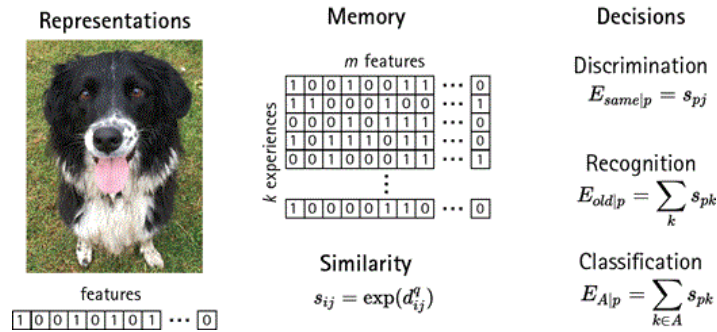
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### Components of Models

At a minimum, any model of discrimination, recognition, or classification requires at least three key components to be specified: the perceptual representation of an object;<sup>4</sup> the memory representations that this perceptual representation is to be compared to; and the decision process that uses the evidence from the comparison to determine same versus different (discrimination), old versus new (recognition), and one category versus other categories (classification).

#### p. 873 **Perceptual Representations**

Many models assume that objects are represented as multidimensional arrays of discrete features or continuous dimensions (Figure 30.2). For example, the dimensions of an object representation might correspond to its shape (square vs. triangle), color (black vs. white), and size (large vs. small) (e.g., Nosofsky, Gluck, et al., 1994); so [1 2 2] would then correspond to the perceptual representation of a small white square.



**Figure 30.2** An example modeling framework that accounts for discrimination, recognition, and classification decisions. Objects are composed of multiple features that are represented as vectors of feature values. In this depiction, features are assumed to be present or absent (i.e., a value of 1 or 0); however, features can also have continuous values. These representations of experiences are stored in a memory matrix, with each row representing a memory trace consisting of features from a prior experience. A similarity measure can be used to query the match between a current object,  $p$ , and a memory trace. Similarity is often formalized as the exponential of a Minkowski distance. These model components can be leveraged to make decisions about discrimination, recognition, and classification.

Source: Photograph by Anna Blumenthal.

In a model, the values along particular dimensions for particular objects might simply correspond to the direct physical manifestation of objects realized in an experiment or by previous psychophysical studies that carefully map physical properties of objects onto psychological representations. Alternatively, the values along dimensions for particular objects could be determined by techniques such as multidimensional scaling (MDS; e.g., Nosofsky, 1992a; Shepard, 1980), in which a matrix of similarity ratings between all possible pairs of objects is obtained and used to construct a multidimensional psychological space, with individual objects represented as points in that space. Objects are positioned within that space so that distances between objects are proportional to their judged dissimilarity. MDS can confirm that physical manipulations of dimensions correspond to expected psychological dimensions of simple objects (e.g., Nosofsky, 1991a; Nosofsky & Palmeri, 1997) or can be used to reveal multidimensional representations for more complex objects (e.g., Nosofsky et al., 2018; Palmeri & Nosofsky, 2001).

Multidimensional arrays can also be simulated to capture the statistical similarity structure of objects used in an experiment without any particular simulated array meant to correspond to any specific item from an experiment. For example, multidimensional arrays simulating individual objects could be samples from a multivariate normal distribution (e.g., Ross et al., 2014). Multidimensional random samples could be drawn in such a way to reflect statistically experimental factors such as between-item similarity, within- and between-category similarity (e.g., Hintzman, 1986; Nosofsky, 1988), and the relative frequency of individual features (e.g., Shiffrin & Steyvers, 1997). In a simulation, although a model may not predict at the level of individual items, it may predict at the level of factors such as relative item similarity, category typicality, category similarity, and frequency that are reflected in the sampled multidimensional item arrays.

All of the above simulate perceptual dimensions without instantiating a model of perception itself. Whereas people in an experiment view images of objects, the models view multidimensional arrays, not images. Researchers have also explored using models of object recognition and computer vision as a perceptual front end to create within the simulation perceptual representations directly from the same images used in experiments with human participants (e.g., Annis et al., 2022; Mack & Palmeri, 2010; Ross et al., 2014; Sanders & Nosofsky, 2018).

## Memory Representations

Certainly the simplest model assumption is that an experienced perceptual representation gets stored as a complete memory representation. Although many failures of memory can be attributed to failures of retrieval, many models also assume that storage is imperfect and that there is some parameterized probability that features in the perceptual representation are encoded as part of a memory representation (e.g., Hintzman, 1988; Shiffrin & Steyver, 1997). Models can also assume that memory representations decay in strength over time (e.g., Estes, 1994; Nosofsky & Palmeri, 1997) and that the quality of memory representations can vary across individuals due to brain damage at one extreme (e.g., Nosofsky & Zaki, 1998) to cases of domain expertise at the other extreme (e.g., Annis & Palmeri, 2019).

Although memory for individual episodic experiences is commonly modeled as the storage of individual episodic representational arrays in memory (e.g., Hintzman, 1988; Shiffrin & Steyver, 1997), models vary in how knowledge about categories and other forms of semantic knowledge are represented in memory. Models that are *instance-based* or *exemplar-based* assume that abstract knowledge for purposes of classification emerges from retrieval of the very same episodic experiences that underlie recognition memory (e.g., Hintzman, 1986, 1988; Jacoby & Brooks, 1984; Logan, 1988; Nosofsky, 1988). Other models assume that knowledge about a category is inherently abstract and that memory representations responsible for classification involve the abstraction of a prototype (e.g., Posner & Keele, 1968; Smith & Minda, 2002), that classification involves learning simple rules combined with memory for exceptions to those rules (e.g., Nosofsky, Palmeri, et al., 1994; Palmeri & Nosofsky, 1995; Sakamoto & Love, 2004), or that semantic knowledge is stored in more complete representational arrays in memory from those that encode incomplete episodic experiences (e.g., Shiffrin & Steyvers, 1997).

Finally, especially in the case of models of recognition memory, it is common to assume that a representational array, whether for a probe item or a stored memory, includes not only the perceptual features of the object but also features associated with the context in which an object was experienced (e.g., Hintzman, 1988; Murdock, 1982; Shiffrin & Steyvers, 1997; see also Chapters 31 and 38).

## Similarity

To discriminate, recognize, or classify an object, its perceptual representation needs to be matched with retrieved memory representations. Common to many models of discrimination, recognition, and classification is that this match is based on similarity.<sup>5</sup>

If objects are represented as multidimensional arrays of discrete features or continuous dimensions, there are many natural ways to formalize mathematically the similarity between two representational arrays. If representational arrays are vectors of unit length  $\hookrightarrow$  (or if the length is proportional to the strength rather than the content of the representation), then cosine similarity, which is the dot product of the two vectors normalized by their length, is a possible measure. If the vectors contain discrete features, then the contrast model (Tversky, 1977), which is a weighted sum of both common and distinct features, is a possible measure (see also Nosofsky, 1991a). A match can also be based on likelihoods as part of a Bayesian decision process (e.g., Anderson, 1990; Nosofsky, 1990; Shiffrin & Steyvers, 1997).

If objects are represented as points in a multidimensional psychological space, then a simple, and arguably most common, assumption (see Figure 30.2) is that similarity,  $s_{ij}$ , between two objects,  $i$  and  $j$ , is a decreasing function of distance,  $d_{ij}$ ,

$$d_{ij} = \left( \sum_{m=1}^M w_m |i_m - j_m|^r \right)^{1/r}$$

where  $M$  is the number of dimensions in the representational array,  $i_m$  is the value of object  $i$  along dimension  $m$ , and  $r$  reflects the distance metric. The familiar Euclidean distance metric results when  $r = 2$ , and a city-block distance metric results when  $r = 1$ ; it is common to assume the Euclidean metric for integral dimensions and city-block for separable dimensions (Garner, 1974; Shepard, 1987).<sup>6</sup> Dimensions are weighted,  $w_m$ , according to their relative diagnosticity for the current task demands (Nosofsky, 1984; see also Carroll & Wish, 1974; Kruschke, 1992; Lambert, 2000); the importance of these weights is highlighted later.

Similarity is a decreasing function of distance, with the most common general form being

$$s_{ij} = \exp\left(-d_{ij}^q\right)$$

where  $q = 1$  gives an exponential function and  $q = 2$  a Gaussian function. Shepard (1987) described the exponential ( $q = 1$ ) as a law of generalization based both on empirical data and Bayesian principles; cases in which a Gaussian ( $q = 2$ ) provides a better account than an exponential (e.g., Nosofsky, 1986) may reflect the presence of sensory-perceptual noise (e.g., Kahana & Sekuler, 2002) when stimulus differences approach just-noticeable differences (e.g., Ennis, 1988).

### Evidence for Discrimination, Recognition, and Classification

For a given task, we can define the evidence ( $E$ ) in favor of one decision over other decisions as a function of the similarity between the representation of the probe object  $p$  and representations in memory.

For discrimination, we are asking if probe  $p$  is the same as item  $j$  that was just experienced. So the evidence for a “same” response ( $E_{same|p}$ ) can be defined most simply<sup>7</sup> as

$$E_{same|p} = s_{pj}$$

For recognition memory, it is common to assume that the evidence for an “old” response ( $E_{old|p}$ ) is based on the overall familiarity of probe  $p$ , formalized mathematically in its simplest form as the summed similarity between  $p$  and all items in memory (with a match of context cues used to limit the relevant stored memories to a particular list or other such experimental context defining the appropriate recognition decision):

p. 876

$$E_{old|p} = \sum_k s_{pk}$$

where  $k$  indexes all instances in memory. Evidence of this sort is an example of a *global matching* model of recognition (e.g., see Chapter 31; see also Gillund & Shiffrin, 1984; Hintzman, 1988). Such familiarity-based matching process is often, but not always, one of the components of dual-process models of recognition memory (e.g., see Chapter 32).

For classification, evidence that probe  $p$  belongs to category  $A$  ( $E_{A|p}$ ) depends on the similarity between probe  $p$  and the memory representation of category  $A$ .<sup>8</sup> If knowledge about a category is represented in terms of stored exemplars, we can compute the evidence based on the nearest neighbor to probe  $p$  (most similar stored exemplar of category  $A$  to probe  $p$ ), average similarity of probe  $p$  to stored exemplars of category  $A$  (e.g., Reed, 1972), or summed similarity of probe  $p$  to stored exemplars of category  $A$ . Summed

similarity is the most common (and most successful) variant assumed by the exemplar-based *generalized context model* (GCM; (Nosofsky, 1984, 1986; see also Medin & Schaffer, 1978):

$$E_{A|p} = \sum_{k \in A} s_{pk}$$

where  $k$  indexes all instances of category  $A$  in memory. Alternatively, if knowledge about a category is represented in terms of an abstracted prototype, then the evidence that probe  $p$  is a member of category  $A$  is simply given by the similarity between probe  $p$  and the stored prototype for category  $A$ ,  $P_A$ .

### Decision Rules

The evidence is used to make a decision, responding “same” or “different” in a discrimination task, “old” or “new” in a recognition task, “category A” or “category B” in a classification task.

In the case of discrimination and recognition, a simple deterministic decision rule would be to respond “same” (or “old”) if the evidence ( $E_{same}$  or  $E_{old}$ ) is greater than some criterion ( $k_{same}$  or  $k_{old}$ ),

$$E > k$$

and respond “different” (or “new”) otherwise. Of course, the criterion (or the evidence) could be noisy, in which case the decision rule would be

$$E > k + \varepsilon$$

where  $\varepsilon$  is a sample from a normal distribution with mean 0 and standard deviation  $\sigma$ . Decisions about discrimination and recognition are based on whether the match (discrimination) or familiarity (recognition) are sufficiently strong (relative to some criterion).

In the case of classification, a relative decision rule is needed instead. An object  $p$  is classified as a member of category  $A$  if its summed similarity to exemplars of category  $A$  ( $E_A$ ) is greater than its summed similarity to exemplars of category  $B$  ( $E_B$ ), again allowing for there to be noise in the decision rule (or evidence):

$$E_A > E_B + \varepsilon$$

There can also be response bias ( $\beta$ ) (see Nosofsky, 1991a) irrespective of the relative evidence:

p. 877

$$E_A > E_B + \beta + \varepsilon$$

In the extreme, as  $\beta$  grows larger and larger, the likelihood of ever responding category  $A$  grows smaller and smaller. Of course, discrimination and recognition decisions can also be biased, but, mathematically, adding a bias term would be non-identifiable (any bias parameter would be additive with the criterion parameter).

In the case of deterministic decision rules, the probability (or frequency) of responding (“same,” “old,” “category A”) would need to be determined by Monte Carlo simulation (or by a mathematical derivation of the long-term probability given the specified deterministic decision rule).

Models can also be specified using a probabilistic decision rule. For discrimination, the probability of deciding “same” given a probe  $p$  is

$$P_{same}(p) = \frac{E_{same|p}}{E_{same|p} + k_{same}}$$

For recognition, the probability of deciding “old” given a probe  $p$  is

$$P_{old}(p) = \frac{E_{old|p}}{E_{old|p} + k_{old}}$$

For classification, the probability of deciding “category A” given a probe  $p$  is

$$P_A(p) = \frac{\beta_A E_{A|p}}{\beta_A E_{A|p} + \beta_B E_{B|p}}$$

Again, whereas the response biases ( $\beta_A$  and  $\beta_B$ ) are explicit for classification models (because of the relative decision rule), they are implicit (not uniquely identifiable) within the values of the criteria for discrimination and recognition models.

And whereas discrimination and recognition are inherently two-choice decisions, classification can be multichoice. In that case, the decision rule for classification can be extended to

$$P(p) = \frac{\beta_A E_{A|p}}{\sum_{K \in R} \beta_K E_{K|p}}$$

where  $K$  is the set of possible categories under consideration (see Palmeri, 1997).

A range of decision rules from probabilistic to deterministic can be formalized by raising the evidence to a power (Ashby & Maddox, 1993)

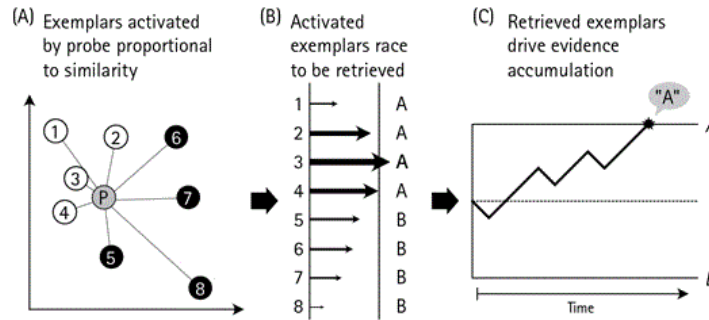
$$P(p) = \frac{(E_{A|p})^\gamma}{(E_{A|p})^\gamma + (E_{B|p})^\gamma}$$

(leaving out the bias terms for simplicity), with  $\gamma = 1$  giving the probabilistic decision rule and  $\gamma \rightarrow \infty$  giving a deterministic decision rule without noise. Ashby and Maddox (1993) demonstrated formally the mathematical relationships between the probabilistic decision rule and the deterministic decision rule.<sup>9</sup> Although there are cases in which humans (and animals) engage in probability matching in ways that suggest a purely probabilistic decision rule, in most cases of object classification, humans (and animals) tend to respond more deterministically than predicted by a purely probabilistic decision rule.

p. 878

These deterministic and probabilistic decision rules only predict response probabilities. To extend these frameworks to response times as well as response probabilities, the evidence is used to drive an accumulation process (see Chapter 33). The first such model of classification was the *exemplar-based random walk* (EBRW) model (Figure 30.3; Nosofsky & Palmeri, 1997, 2015; Palmeri, 1997), which combined elements of the exemplar-based GCM model of classification (Nosofsky 1984, 1986), the instance theory of automaticity (Logan, 1988), and a random walk model of decision-making (e.g., Busemeyer, 1985; Link, 1992; Ratcliff, 1978).





**Figure 30.3** The EBRW model was the first classification model to formalize how similarity processes acting on multidimensional memory representations can account for both response probabilities and response times. (A) In EBRW, a probe item (P) activates stored exemplars (1–8) proportional to their similarity. (B) This similarity drives a race between activated exemplars to be retrieved from memory. (C) Retrieved exemplars then drive an evidence accumulation process toward a decision.

Adapted from Nosofsky et al. (2014), Figure 7.

Time enters into EBRW in two ways. First, following instance theory, repetitions of the same item are assumed to create new memory representations of that item. When a probe  $p$  is presented, instances race to be retrieved from memory. Based on instance theory, more repetitions of the same item in memory mean that the winner of the race for retrieval will get faster with more experience. This property allows instance theory, and hence EBRW, to predict speed-ups with experience (see also Palmeri & Cottrell, 2009; Palmeri et al., 2004). One thing that distinguishes EBRW from instance theory is that memory retrieval rates depend on the similarity between probe  $p$  and stored exemplar  $j$ . If retrieval times are exponentially distributed, then it can be shown that the probability of retrieving exemplar  $j$  (relative to all stored exemplars of category A and category B) is given by

$$P(\text{retrieve } j) = \frac{s_{pj}}{\sum_{k \in A} s_{pk} + \sum_{k \in B} s_{pk}}$$

and the probability of retrieving any exemplar from category A is simply

$$P(\text{retrieve } A) = \frac{\sum_{k \in A} s_{pk}}{\sum_{k \in A} s_{pk} + \sum_{k \in B} s_{pk}}$$

which is the GCM.

p. 879 Rather than base a decision on a single retrieval (like GCM), EBRW assumes that each retrieval drives a random walk decision process.<sup>10</sup> Like other evidence accumulation models (see Chapter 33), EBRW assumes that evidence is accumulated toward an upper boundary associated with a category A decision and a lower boundary associated with a category B decision (for a generalization to multiple categories, see Palmeri, 1997). This accumulation over time is the second way time enters the EBRW. If a category A exemplar wins the retrieval race, the random walk takes a step toward the A threshold ( $\theta_A$ ); if a category B exemplar wins, it takes a step toward the B threshold ( $\theta_B$ ). Which threshold is hit first determines both what response is made (A or B) and when it is made (like other evidence accumulation models, EBRW also assumes non-decision time associated with perceptual processing and motor execution).

Interestingly, if the response thresholds are set equal to one another ( $\theta_A = \theta_B = \theta^*$ ), it can be shown (Nosofsky & Palmeri, 1997) that predicted response probabilities from EBRW are

$$P(A|p) = \frac{\left(\sum_{k \in A} s_{pk}\right)^{\theta^*}}{\left(\sum_{k \in A} s_{pk}\right)^{\theta^*} + \left(\sum_{k \in B} s_{pk}\right)^{\theta^*}}$$

which is identical to the  $\gamma$  decision rule outlined previously.

Although the EBRW was originally developed to account for response probabilities and response times in classification tasks, its principles have been extended to account for a range of speeded discrimination and recognition paradigms as well (e.g., Annis et al., 2022; Annis & Palmeri, 2019; Mack & Palmeri, 2010; Nosofsky, Cao, et al., 2014; Nosofsky & Palmeri, 2015). Further extensions of these models consider the dynamics of how object features are sampled and how these representational dynamics influence the time course of discrimination, recognition, and classification (e.g., Cohen & Nosofsky, 2003; Cox & Criss, 2020; Lamberts, 2000). Notably, EBRW has been recently leveraged to identify trial-by-trial brain activation associated with speeded classification (Heffernan et al., 2021).

## Relations Between Discrimination, Recognition, and Classification

Having outlined a formal mathematical framework for modeling discrimination, recognition, and classification in the same language, we now highlight a few examples of work examining relationships between these memory retrieval processes. As noted elsewhere, the literature on each of these processes is vast, so the following discussion is only illustrative rather than exhaustive.

### Relations Between Identification and Classification

Classification involves knowledge in memory generalized over a broad category of objects—for example, deciding that some object is a kind of thing called a “dog” and not a “cat.” Identification involves knowledge in memory about a specific individual object—for example, deciding that some object is an individual named “Brownie” and not “Max” or “Chelsea.” Identification is like discrimination (which is why we discuss identification here) in that they both involve a specific individual, whereas classification involves generalization over a class.

An early theory of identification bears important similarities to the class of theories described previously. The *similarity choice model* (SCM) of identification (Luce, 1963; Shepard, 1957) assumes that identification confusion, the probability of identifying stimulus  $i$  with the label associated with stimulus  $j$ , is given by

p. 880

$$P((S_i)) = \frac{\beta_j s_{ij}}{\sum_k \beta_k s_{ik}}$$

The evidence that stimulus  $i$  should be given the label associated with stimulus  $j$  is given by the similarity between  $i$  and  $j$ , just like the evidence for a same–different discrimination described previously. The primary difference is that in identification, relative evidence is required to decide on a particular label to apply to an object, whereas in discrimination, absolute evidence is required to decide if an object is the same as or different from a previous object.

One early hypothesis assumed that similarity between objects was invariant over task demands. In that case, the object similarities that would govern identification of a unique individual should also govern

classification as a member of a broad category. In its simplest form, the identification confusions of objects within a category should simply sum together to predict the probability that an object is classified as a member of that category. But this *mapping hypothesis* (Nosofsky, 1986) between identification and classification fails (e.g., Shepard et al., 1961; see also Nosofsky, 1984). Classification performance cannot be predicted from identification performance if object similarities are assumed to be invariant across tasks. Indeed, Shepard et al. (1961) suggested from these failures that classification must involve some form of abstract knowledge learning, such as rule formation (see Nosofsky, Palmeri, McKinkley, 1994), whereas identification involves some form of stimulus–response association learning.

Nosofsky (1984, 1986) instead allowed for similarities to vary across tasks in a principled way. Whereas the locations of objects in multidimensional space would remain invariant across tasks, the weights applied to psychological dimensions, the  $w_m$  terms included in the distance metric described previously, could vary across tasks (see also Kruschke, 1992). In particular, dimensions that were diagnostic for classification (or identification or recognition) would receive large weights, whereas dimensions nondiagnostic for the task would receive small weights, thereby stretching the psychological space along diagnostic dimensions and shrinking the space along nondiagnostic dimensions. When attention weights are added to the modeling framework, classification can indeed be predicted from identification (Nosofsky, 1984, 1986, 1987). The same object representations, memory representations, and kinds of processes can govern identification and classification.

### Relations Between Recognition and Classification

Many classic theories argued that recognition and classification depend on distinct memory systems. Recognition is *episodic*, whereas classification is *semantic* (Tulving, 1972, 2002). Recognition is *declarative*, whereas classification is *non-declarative* (Squire & Zola, 1996). Some of these claims are based on neuropsychological and (more recently) brain imaging results (but see the section titled “Neural Evidence”), but certain empirical results also suggested dissociations between recognition and classification.

In experiments in which participants learn novel objects belonging to novel categories and are tested both on their classification of old and new objects and on their recognition memory for old and new objects, there is often little correlation between classification confidence and recognition memory performance (e.g., Anderson et al., 1979; Hayes–Roth & Hayes–Roth, 1977; Metcalfe & Fisher, 1986). Intuitively, it seems reasonable to presume that if memory for specific exemplars drove both classification and recognition, then objects classified with high confidence should also be well recognized. A failure to find a correlation between classification and recognition seems problematic for a single-system exemplar model.

p. 881 Yet exemplar models account quite naturally for these observed cases of a lack of correlation (e.g., Nosofsky, 1988, 1991b, 1992b). Although according to models such as the GCM, both classification and recognition are assumed to be based on similarity to the same stored exemplars in memory, classification depends on the relative summed similarity to exemplars in one category versus another category, whereas recognition depends on the absolute summed similarity to all exemplars in memory. An object could be similar to many stored exemplars, causing it to be recognized as “old,” but those similar exemplars could belong to different categories, making classification confidence low; alternatively, an object could be dissimilar to most stored exemplars, causing it to be recognized as “new,” but it could be similar to only exemplars in one category, making classification confidence quite high.

## Effects of Learning and Expertise on Discrimination, Recognition, and Classification

Learning, experience, and expertise affect perceptual representations that aid discrimination, enhance perceptual and memory representations that aid recognition, and build representations that enable increases in performance at classification at various levels of abstraction (e.g., Gauthier et al., 2009; Palmeri et al., 2004).

Early in learning to classify objects, people may be given explicit rules (e.g., Palmeri, 1997; Palmeri & Nosofsky, 1995) or generate rules on their own (e.g., Ashby et al., 1998; Nosofsky, Palmeri, McKinley, 1994). Imperfect category rules can be supplemented with exceptions stored in memory (e.g., Davis et al., 2012a, 2012b; Nosofsky et al., 2004; Nosofsky & Palmeri, 1997; Sakamoto & Love, 2004). According to instance theory (Logan, 1988) and EBRW (Nosofsky & Palmeri, 2015; Palmeri, 1997), performance in a task such as classification involves a race between applying a categorization rule and retrieval of memories for past experiences performing the classification. Early in learning, the rule tends to dominate performance because it wins the race. Assuming that memory storage is obligatory (Logan, 1988) and that additional stored memories speed up the memory retrieval process, later performance, after some experience, is based on memory retrieval (Palmeri, 1997; see also Johansen & Palmeri, 2002), leading to automaticity and expertise (Palmeri et al., 2004; see also Chapter 72).

Often accompanying classification learning of new object categories are changes to the perceptual representations of objects that belong to those learned categories as revealed by changes in discrimination performance. In addition to the kind of dimensional stretching of diagnostic psychological dimensions during object classification, as reflected by changes to the  $w_m$  parameter in the formula for the distance metric, there can often be longer term changes in perceptual discriminability along those diagnostic dimensions. As a consequence of learning novel categories, people show increased perceptual discrimination for basic form and color dimensions (e.g., Goldstone, 1994), as well as along more complex dimensions of complex objects (e.g., Folstein et al., 2012; Goldstone & Steyvers, 2001) that are relevant to learned categories.

Finally, learning and expertise with object classification can affect recognition memory for objects in an expert domain. Real-world perceptual expertise in a domain—for example, for birds, vehicles, or medical images—is often accompanied by increases in visual short-term memory (e.g., Curby et al., 2009) and long-term memory (e.g., Evans et al., 2011; Herzmann & Curran, 2011). Annis and Palmeri (2019) observed increases in short-term and long-term memory for birds as a function of perceptual expertise at classifying birds and via an extension of EBRW showed that these increases in memory performance were best explained by a combination of an increase in the quality of the perceptual representations of birds and the memory strength for bird memories as a function of real-world expertise (see Chapter 72).

In the above discussion, we intentionally focused on one particular family tree of computational models (SCM, GCM, and EBRW) because they allowed us to illustrate potential theoretical connections between discrimination, recognition, and classification. Of course, there are other theoretical perspectives in this active area of research. Some past debates—for example, between exemplar models (Nosofsky & Smith, 1992) and decision boundary models—have given rise to more nuanced contrasts between exemplar (McKinley & Nosofsky, 1995) and exemplar-like models (e.g., Ashby & Waldron, 1999) that make similar predictions about behavior but differ in their relations to neural processes (e.g., Ashby & Rosedahl, 2017). Object classification can be based on rules rather than similarity (e.g., Ashby et al., 1998; Erickson & Kruschke, 1998), perhaps supplemented by similarity to stored exemplars, especially those that represent exceptions to classification rules (e.g., Nosofsky, Palmeri, et al., 1994; Palmeri & Nosofsky, 1995). Or they can be based on representations that can approximate rules, prototypes, or exemplars in a more flexible manner (e.g., Love et al., 2004), or can reflect a combination of rules and exemplars whose combination might vary as a function of experience and expertise (e.g., Johansen & Palmeri, 2002; Palmeri et al., 2004). To the extent that representations supporting classification are more abstract than experienced exemplars, then multiple memory systems could be implicated in recognition and classification.

## Neural Evidence

The modeling framework detailed above highlighted one particular theoretical view that there is a common mechanistic substrate for discrimination, classification, and recognition through flexible retrieval of memory representations. Early patient and neuroimaging work, some of which we note below, supported a different view that there are multiple distinct learning and memory systems supported by separable neural mechanisms. More recent work leveraging sophisticated model-based cognitive neuroscience approaches has demonstrated common neural substrates for component processes involved in discrimination, recognition, and classification. Rather than a comprehensive review of the rich literature on related neuroscience research, we highlight these studies that integrate computational and neuroscientific methods.

## Neural Representations, Similarity, and Attention

The computational framework we describe is based on feature-based representations of experiences and similarity processes that compare current experiences to stored representations to make discrimination, recognition, and classification decisions. Neural evidence for these mechanisms has existed for as long as the field has studied the brain. For example, seminal neurophysiological studies in monkeys showed that firing rates for neurons in inferotemporal cortex exhibit sensitivity to features diagnostic for newly learned classification (Freedman et al., 2003; Sigala & Logothetis, 2002) while retaining coding for item-specific features (Op de Beeck et al., 2001). Similarly, early studies leveraging functional magnetic resonance imaging (fMRI) in humans demonstrated that activation of brain regions along the ventral visual pathway discriminates between categories of visual content (Epstein & Kanwisher, 1998; Gauthier et al., 1999; Kanwisher et al., 1997) and does so according to a gradient of feature similarity (e.g., Gauthier et al., 1997).

The advent of multivariate techniques that enable researchers to quantify patterns of neural activity across cell populations and multiple voxels provided the opportunity to more precisely assess the content of neural representations when making different types of decisions. For example, real-world categories of visual content are distinctly represented in  $\hookrightarrow$  activation patterns across ventral visual cortex (e.g., Connolly et al., 2012; Haxby et al., 2001; Kriegeskorte et al., 2008) and the medial temporal lobe (MTL; e.g., LaRocque et al., 2013; Liang et al., 2013). Work specifically targeting the contribution of visual and semantic features to

neural representations for naturalistic and novel visual objects has converged on two central findings: (a) The more features two objects share, the more similar their neural representations; and (b) there exists a gradient of feature type along the ventral visual pathway with more visual features dominating representations in occipital and posterior temporal regions and more conceptual features dominating medial and anterior temporal regions (Clarke & Tyler, 2014; Davis & Poldrack 2014; Erez et al., 2016; Martin et al., 2018). Interestingly, item- and category-specific patterns of activation elicited when viewing or encoding visual content are also present during memory retrieval (Chadwick et al., 2016; Kuhl et al., 2012; Mack & Preston, 2016; Polyn et al., 2005; Staresina et al., 2012; Tompary et al., 2016), a finding consistent with the proposal for a common neural substrate underlying classification and recognition.

Model-based cognitive neuroscience approaches (e.g., Forstmann & Wagenmakers, 2015; Palmeri et al., 2017; Turner et al., 2017), in which latent representations and processes from computational models are leveraged to interrogate brain function, have recently significantly advanced our understanding of the neural underpinnings of discrimination, recognition, and classification. One such study (Mack et al., 2013) looked to neural representations of fMRI activity present during classification as evidence to adjudicate between exemplar- and prototype-based models of classification. The logic followed that the evidence guiding classification decisions ( $E_{A|p}$ ) would be evident in neural activation patterns. Given the differences in the nature of their underlying representations, exemplar and prototype models predict unique signatures of classification evidence. Thus, the better correspondence between neural activation and a model's latent quantity of classification evidence, the better that model formalizes the representations and processes of classification. This approach showed that in a classic classification task using what is known as the "5-4" category structure (Medin & Schaffer, 1978), almost all participants were better fit by a classification model using exemplar representations rather than prototype representations.

These findings were extended (Bowman & Zeithamova, 2018) with a classification task defined by category structures that encourage more abstract or prototype-like representation (Zeithamova et al., 2008), finding stronger evidence in neural activation for classification evidence as predicted by a prototype model. Interestingly, both studies demonstrated that attention to different stimulus features as predicted by the computational models was consistent with the similarity between neural representation in multiple brain regions associated with visual processing (lateral occipital and parietal cortices), memory (hippocampus and MTL cortex), and decision-making (ventromedial and rostralateral prefrontal cortex) (see also Davis et al., 2017). In other words, the similarity of activation patterns for different objects during classification behavior matches the attention-weighted similarity computation formalized in computational models. These highlighted studies offer compelling neural evidence for the model mechanisms outlined in the prior section, specifically multidimensional representations based on feature combinations, feature-based attention that distorts and shapes representations (e.g., Goldstone & Styvers, 2001; Nosofsky, 1986), and similarity-based processes (Shepard, 1987). And, collectively, this work supports the notion that the nature of memory representations underlying any given type of discrimination, classification, or recognition decision is adaptive with regard to prior experience and current task goals (Anderson, 1990; Love et al., 2004; Love & Gureckis, 2007; Mack et al., 2016). In fact, emerging evidence from neural firing and synchrony in monkey lateral prefrontal cortex suggests both specific exemplar-like and generalized prototype-like representations are available through separable neural circuits during classification decisions (Wutz et al., 2018).

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The library of cognitive neuroscience research on discrimination, classification, and recognition is vast, and we have highlighted only a fraction of relevant findings. By focusing on both seminal studies that first established how neural evidence supports flexible decisions based on memory representations and more recent studies that integrate computational modeling with neuroscience methods, we hope to provide the interested reader with helpful entry points into the rich literature.

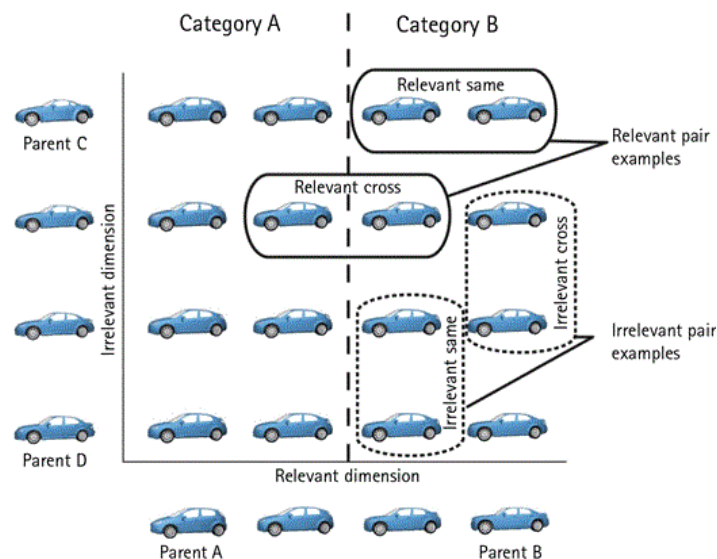
## A Common Neural Framework

In the following sections, we specifically highlight cognitive neuroscience studies that have assessed the central proposal outlined above—namely that discrimination, recognition, and classification share a core set of computational mechanisms and representations.

### Discrimination and Classification

A fundamental prediction of common mechanisms and representations for discrimination and classification is that memory representations and similarity computations that support successful classification should impact discrimination performance. In terms of the model framework proposed here, the same representations driving decision evidence to classify an object ( $E_{A|p}$ ) are at play in discriminating between that object and one seen just before it ( $E_{\text{same}|p}$ ). Simply stated, learning that two objects belong to different categories should change the perception of these two objects such that they appear more different even in perceptual tasks not related to classification. This increase in discrimination due to classification learning is known as *acquired distinctiveness* and has been a guiding hypothesis in many behavioral (e.g., Goldstone, 1994; Goldstone & Styvers, 2001; Notman et al., 2005; Op de Beeck et al., 2003) and neural (e.g., De Baene et al., 2008; Folstein et al., 2013; Jiang et al., 2007; Li et al., 2007; Sigala & Logothetis, 2002) studies.

Although initial attempts to obtain neural evidence of acquired distinctiveness resulted in mixed findings, one notable study by Folstein and colleagues (2013) provided a compelling demonstration of a neural link between classification and discrimination. Participants first learned to classify complex visual objects—cars—carefully constructed from a morph space of three-dimensional car models into two categories (Figure 30.4). After successfully learning to classify the cars, participants performed a visual discrimination task during fMRI scanning in which they determined whether or not two sequentially presented cars were positioned in the same location on the screen. Critically, car pairs were composed of the same car or two different cars that varied along a feature dimension that was either relevant or irrelevant for the classification task. This paradigm was designed to reveal fMRI adaptation (Grill-Spector et al., 2006), an effect in which the second presentation of a visual stimulus results in lower activation because it is engaging the same population of neurons. The logic followed that if classification shapes neural representations such that features relevant for classification are selectively enhanced with richer representations, pairs of objects that differ along these classification-relevant features will exhibit less or no adaptation. In contrast, object pairs that differ along irrelevant features will have more overlap in neural representation, resulting in greater adaptation effects. Indeed, this was exactly what was found: Regions within the ventral visual stream, including fusiform gyrus and occipital regions, showed greater sensitivity to cars varying along classification-relevant features. This neural acquired distinctiveness was mirrored in behavior: Participants were better able to discriminate small variations in cars that differed along relevant versus irrelevant features. <sup>↳</sup> These findings demonstrate an important link between the neural substrate of discrimination and classification. Learning to classify visual objects changes their neural representations, and these learning-related changes impact the neural representations and behavior during subsequent discrimination tasks.



**Figure 30.4** Illustration of the morph space from Folstein et al. (2013). Two sets of parent car models were first morphed to create two perceptual dimensions (parent A to B and parent C to D). The full morph space was then created by factorially blending these two perceptual dimensions. Participants learned to classify the cars into two categories defined by the vertical dashed line. After classification learning, participants then performed an unrelated perceptual task in which pairs of morph cars were presented in sequence. Relevant pairs varied along the perceptual dimension relevant for the classification learning, and irrelevant pairs varied along the other dimension. Folstein et al. (2013) found that relevant pairs were associated with a greater release from repetition suppression than irrelevant pairs in subregions of lateral occipital and ventral temporal cortex. These findings suggest that neural representations of the car stimuli were shaped by classification learning selectively to the dimension relevant for classification.

Adapted from Folstein et al. (2013), Figure 1.

### Classification and Recognition

Some of the earliest work on the neuroscience of classification and recognition was conducted with individuals who had amnesia (Knowlton & Squire, 1993; Squire & Knowlton, 1995). This work demonstrated that despite catastrophic memory loss due to damage to key memory structures in the MTL, individuals with amnesia were capable of learning new classification tasks. The compelling results stood in the face of the formal theoretical relationship between recognition and classification (e.g., Love & Gureckis, 2007; Nosofsky, 1988) by positing distinct neural mechanisms (Squire & Zola, 1996), a theoretical stance supported by fMRI evidence that distinct brain regions are recruited in service of the two tasks (Reber et al., 2003). However, it has been demonstrated that global similarity models that leverage common representations and computations for classification and recognition can successfully account for patient data in both types of tasks (e.g., Love & Gureckis, 2007; Nosofsky & Zaki, 1998; Palmeri & Flanery, 1999; Palmeri & Flanery, 2002). Moreover, neuroimaging research from the past decade suggests that in addition to its role in memory, the MTL is in fact a critical player in classification (Bowman & Zeithamova, 2018; Davis et al., 2012a, 2012b; Mack et al., 2016, 2018; Poldrack et al., 2001; Seger et al., 2015; Zeithamova et al., 2008). Here, we highlight two studies that target a common mechanistic account of classification and recognition through an integrated approach combining computation models with neuroimaging.

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As detailed in the section titled “Modeling Discrimination, Recognition, and Classification,” decisions of classification and recognition rely on the same underlying evidence (i.e., summed similarity of the current stimulus to stored memory representations) compared to a task-specific criterion. Notably, this criterion is



expected to qualitatively vary between classification and recognition (Nosofsky et al., 2012). For example, to make successful recognition decisions while minimizing false alarms to stimuli that are related but nonetheless novel, the current stimulus must match a specific prior experience to a high degree, thus necessitating a high criterion. In contrast, a classification decision relies on the relatively lax criterion of sufficient similarity to prior experiences with no need for exact matches. It follows that such differences in criterion may lead to different activation profiles across brain regions, despite the same computations and representations guiding decisions in the two tasks. Nosofsky et al. (2012) tested this hypothesis by manipulating the criterion used by participants for recognition and classification during fMRI scanning. After matching criterion settings across the tasks, they found no discernable differences in brain activation. Moreover, an exemplar-based model of the two tasks accounted for both classification and recognition behavior. Finally, model-based predictions of criterion settings across the tasks corresponded with individual differences in activation in both the frontal eye field and anterior insula, two brain regions implicated in perceptual decision-making tasks. Thus, these findings support a common computational mechanism for classification and recognition with neural engagement that varies according to task demands.

A complementary study by Davis et al. (2014) examined a common role for similarity-based comparisons to memory representations in recognition and classification. Specifically, they hypothesized that if the same representations and similarity-based computations underlie decision evidence for classification and recognition, similarity between neural representations elicited during these two tasks should predict recognition and classification behavior. By analyzing activation patterns in the medial temporal lobe during classification and recognition, it was demonstrated that global neural pattern similarity (i.e., the summed similarity between the activation pattern for the current stimulus and all other stimuli) predicted both confidence in recognition memory decisions (e.g.,  $E_{old|p}$ ) and a latent model measure of classification evidence (e.g.,  $E_{A|p}$ ). These findings suggest that not only is MTL function important for classification and recognition but also MTL-based representations operate according to the formal principles of the computational framework that accounts for both classification and recognition.

## Conclusion

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Discrimination, recognition, and classification span a wide range of behaviors with seemingly distinct psychological and neural mechanisms. However, converging behavioral and neural evidence motivated by a rich theoretical history, the highlights of which were covered in this chapter, suggests that these different types of decisions may arise from common representations and processes, or at least that a common set of computational principles may govern forms of representations and kinds of processes, even if those representations and processes may be distributed across different brain areas (Bowman & Zeithamova, 2018; Zeithamova et al., 2019). The central component of this integrative framework is the flexible retrieval of memory representations. Whether deciding if the object in front of you is the same as what you experienced just moments ago, is a specific kind of animal, or is familiar based on a host of past experiences, the same memory representations serve as evidence for your final decision. Looking forward, we expect that future research will elaborate on this common framework by targeting how factors of experience impact decisions across these different types of flexible retrieval. For example, how does perceptual expertise that relies on extensive semantic knowledge (e.g., expert bird watchers) impact memory for experiences related and unrelated to that expertise (e.g., Annis & Palmeri, 2019)? And, what are the neural mechanisms that support flexible encoding and retrieval of memory representations across changing task goals (e.g., Bowman & Zeithamova, 2018; Davis et al., 2017; Mack et al., 2016, 2020).

Finally, it is worth noting the value of computational modeling in arriving at the field's current understanding of discrimination, recognition, and classification. Only by formalizing the computations and

representations implicit in verbal descriptions of these different decisions has it been possible to disconfirm some theories and strongly support others. Moreover, the recent boom in model-based and computationally sophisticated neural approaches to investigating discrimination, recognition, and classification has significantly broadened the theoretical scope and impact of findings. Such an approach offers the unique opportunity to localize quantitatively defined model representations and computations to specific brain regions (e.g., Davis et al., 2012a; Kragel et al., 2015; Mack et al., 2016) and to adjudicate among competing formal theories with brain measures (e.g., Bowman & Zeithamova, 2018; Davis et al., 2012b; Mack et al., 2013). Indeed, it is compelling and persuasive evidence to demonstrate that the neural representations of stimuli match one model's representational predictions more than another (e.g., Mack et al., 2013) or that trial-by-trial fluctuations in neural signal from a specific brain region correspond with the dynamics of a latent model component (e.g., Davis et al., 2012a). A promising avenue for future work will be a focus on how individuals or patients differ in terms of computational model predictions (e.g., differences in feature dimension attention weights) and how these model-based quantities are linked to individual differences in neural function and representation.

This integrative approach also promises to motivate the development of more comprehensive mechanistic theories that bridge levels of analysis to account for both behavior and brain function. For example, one exciting new direction in the field (Gureckis & Love, 2007; Mack et al., 2018) is a theoretical push to marry the computational framework we have highlighted here with the brain-based accounts of episodic memory, such as the influential complementary learning systems theory (McClelland et al., 1995; Norman & O'Reilly, 2003; Schapiro et al., 2017). This work extends the perspective of common functions and representations underlying classification and recognition behavior to formalize how functions of memory encoding (e.g., pattern separation in the hippocampus) may form distinct exemplar-like representations of our experiences. Such representations can then be flexibly retrieved for a variety of decisions through selective attention and goal-based strategies ascribed to cortex (e.g., Hutchinson et al., 2014; Mack et al., 2020) and potentially leveraged to support the formation of representations in other brain regions.

Looking forward, key questions remain: How is selective attention tuned to diagnostic feature dimensions, and how are these weights applied across changing task demands? How does learning shape the nature of representations necessary for classification, and what impact does this have on recognition? How does recent experience interact with prior knowledge in making flexible discrimination, classification, and recognition decisions? Future research that integrates computational theory with brain measures will undoubtedly answer these questions to shed light on the cognitive and neural dynamics underlying how we perceive, learn, and remember.

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## Notes

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1. Here, we focus on deciding whether one object and another object are the same or different (or, more generally, whether one stimulus and another stimulus are the same or different), discriminating one object from another, sometimes classically characterized as an AX discrimination task. An ABX discrimination (or AXB discrimination) task presents three objects and asks the observer if X is the same as A or the same as B; even more complex variants of discrimination tasks have been used. Whereas discrimination involves deciding whether two objects are the same or different, “detection” involves deciding whether an object is present or absent (in a background of internal or external noise). Relations between discrimination and other concepts in psychology (e.g., classical and operant conditioning) are beyond the scope of this chapter and this volume.
2. “Recognition” typically has a specific meaning in the memory literature as deciding whether a current experience (here, an object) is *old* (seen before) or *new* (not). In the vision science literature, by contrast, “object recognition” often refers broadly to the array of processes involved in creating a visual representation of an object (Palmeri & Gauthier, 2004; Palmeri & Tarr, 2008). Here, we use “recognition” exclusively in the sense of memory and refer to perceptual processes involved in creating a representation of an object using other terms.
3. Of course, recognition can involve the recollection of a specific past experience as well as an overall sense of familiarity.
4. Recall that our focus is on discrimination, recognition, and classification of *visual objects*.
5. There are models and theories of classification that are not based on similarity, or at least not entirely, and are dependent on more abstract knowledge representations such as rules (e.g., Nosofsky, Palmeri, et al., 1994), causal relations (e.g., Rehder, 2003), or theories (e.g., Murphy, 2004; Murphy & Medin, 1985). We focus on similarity-based models of classification to highlight the relationships between these models and models of discrimination and recognition.
6. As the name suggests, integral dimensions are often said to be perceived unitarily, as part of an integrated whole, such as the hue, saturation, and brightness of colors. Separable dimensions, by contrast, are often said to be perceived, attended, and processed independently, such as the shape and color of objects.
7. Most accounts of discrimination bypass the important question of how the right memory representation of the first object is retrieved so it can be compared with the second object, or there is the tacit assumption that the context is so overwhelming that memories from objects on other discrimination trials do not intrude (but see Cohen & Nosofsky, 2000).
8. Again, we are focusing on similarity-based models of classification here. Classification based on abstract rules or knowledge would involve very different mechanisms.
9. Although theoretically the form of a category representation (exemplar vs. prototype) and the nature of the decision rule (deterministic vs. probabilistic) are conceptually independent, it has been shown that considering both factors is critical for contrasting alternative models. For example, Nosofsky and Zaki (2002) showed that certain instantiations of a prototype model are sufficiently flexible to allow for a range of probabilistic versus deterministic decision rules to be embedded within them non-identifiably, whereas an exemplar model must have the probabilistic versus deterministic nature of the decision rule expressed explicitly.
10. As the time for each step and the size of each step go to 0 (appropriately) in the limit, a discrete random walk approaches a continuous diffusion process (Feller, 1968).

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