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# An Exemplar-Based Random Walk Model of Perceptual Categorization

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**Abstract**

The Exemplar-Based Random Walk (EBRW) model (Nosofsky & Palmeri, 1997; Palmeri, 1997) incorporates elements of Nosofsky's (1986) generalized context model (GCM) of categorization and Logan's (1988) instance theory of automaticity. The model assumes that categories are represented in terms of stored exemplars. Exemplars are represented as points in a multidimensional psychological space with similarity a decreasing function of distance in the space. During categorization, exemplars race to be retrieved from memory with rates determined by their similarity to the presented object. Memory retrieval drives a random walk decision process. The model accounts for categorization response times and accuracies in a variety of tasks. Moreover, it accounts for the development of automaticity in categorization and for categorization in cluttered environments.

Recent years have seen tremendous progress developing powerful psychological theories of perceptual categorization. However, as competing theories have become increasingly sophisticated it has become increasingly difficult to contrast their predictions – theories which differ rather markedly in their assumptions about category representations and decision processes can nevertheless make strikingly similar predictions of categorization response probabilities.

One fundamental limitation of most current theories is that they offer no account of the time course of categorization judgments. Therefore, one aim of recent theoretical work has been to develop dynamic theories which can account for categorization response times (RTs) as well as categorization accuracies. In addition to addressing the need to develop more complete theories of categorization, examination of response times may prove to be fertile territory for testing the representational and processing assumptions of various theories.

In this article, I describe a recently developed model of categorization, the Exemplar-Based Random Walk (EBRW) model (Nosofsky & Palmeri, 1997; Palmeri, 1997). The model assumes that categories are represented in term of the individual instances which have been experienced; in this way, it differs markedly from theories of categorization which posit that prototypes, rules, or other forms of abstract knowledge underlie categorization. Categorization decisions are determined by the similarity between a presented item and stored category exemplars. In this article, I begin by providing an overview of the EBRW and describing several successful applications of the model. I then describe some recent extensions of the model to categorization tasks involving multiple objects in the visual field.

## Theoretical Background

The EBRW (Nosofsky & Palmeri, 1997; Palmeri, 1997) combines elements of the Generalized Context Model (GCM) of categorization (Nosofsky, 1986) and the Instance Theory of automaticity (Logan, 1988). The theoretical claim of the EBRW is that both categorization and automaticity are manifestations of the same exemplar-based memory retrieval processes. Below, I briefly discuss these two models and then describe the EBRW in some detail.

### The Generalized Context Model (GCM)

The GCM (Nosofsky, 1986) is an exemplar-based model of categorization. The model assumes that people represent categories in memory in terms of fairly detailed information about specific instances (exemplars) they have experienced. When judging whether an object is a member of some category, a person compares the object with similar stored exemplars. The object is classified according to its relative similarity to the objects in the various categories. The GCM stands as one of the most successful theories of categorization in the field today. Not only has the GCM accounted for fundamental categorization phenomena, but it has provided an integrated theory of recognition memory, stimulus identification, and typicality judgments. However, although powerful in its ability to predict accuracy in a wide variety of tasks, the GCM is limited in providing no account of how processing unfolds over time – that is, the theory cannot predict the amount of time it takes to make a categorization response.

### The Instance Theory of Automaticity

According to Logan's (1988) instance theory, automaticity in some aspect of cognition reflects shifts from algorithmic or strategic processes to memory-based processes. People are assumed to start with some set of general algorithms, strategies, or rules that solve a particular task, such as categorization. Every time some cognitive skill is performed, a trace of the instance of that action is stored in memory. When a new object is encountered to be categorized or judged in some way, a race ensues between

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the strategy and retrieval of previously stored instances. Initially, performance is governed solely by strategic processing. Memory retrieval is assumed to get faster as more repetitions of a particular instance are stored whereas the time for strategic processing is assumed to remain constant. Soon, memory retrieval begins to dominate the race over strategic processing. In essence, novices must solve the task using explicit strategies whereas experts simply remember what they did before. Qualitative changes in performance are due to shifts from strategic processing to memory retrieval. Quantitative changes in processing speed, often characterized by a power law of practice, are due to more instances being added to memory (Logan, 1992). However, although elegant in its simplicity, and powerful in its predictions, instance theory is limited by not taking into account graded similarities among exemplars and not allowing for response competition to emerge.

## The Exemplar-Based Random Walk Model

The EBRW combines elements of the GCM and instance theory. It embeds a dynamic similarity-based memory retrieval mechanism within a competitive random walk decision process. The EBRW is one of the first models to make quantitative predictions of both categorization response time (RT) and accuracy. It is also unique in providing a unified account of a variety cognitive tasks.

Following the GCM, exemplars are represented as points in a multidimensional psychological space. Typically, this psychological space is derived through multidimensional scaling or other techniques (Shepard, 1980). Similarity between objects is a decreasing function of distance in the space. Distance between exemplars *i* and *j* is given by

$$d_{ij} = \left[ \sum_{m=1}^{M} w_m \left| x_{im} - x_{jm} \right|^r \right]^{1/r}, \qquad (1)$$

where $x_{\mathrm{im}}$ is the psychological value of item *i* along dimension *m*, *M* is the number of psychological dimensions, and *r* determines the distance metric. The $w_{\mathrm{m}}$ are selective attention weights that stretch the psychological space along diagnostic dimensions and shrink it along nondiagnostic dimensions. Similarity between exemplars *i* and *j* is an exponentially decreasing function of psychological distance,

$$\eta_{ij} = \exp(-\kappa \cdot d_{ij}), \qquad (2)$$

where $\kappa$ is a sensitivity parameter that scales the psychological space (Shepard, 1987).

One advantage of assuming a multidimensional scaling theory of similarity, rather than simply allowing similarities to be free parameters, is that it is possible to relate performance in various tasks using the same stimuli. Following GCM, whereas psychological similarities may not remain invariant across tasks, the underlying

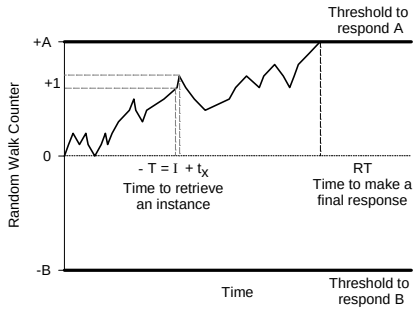


**Figure 1**. Schematic illustration of the random walk process in the EBRW.

multidimensional psychological space is assumed to remain invariant. However, it may be subject to differential stretching or shrinking along certain psychological dimensions according to their diagnosticity within some particular task (Kruschke, 1992; Nosofsky, 1986).

Following instance theory, memory retrieval is a race process; because of the statistical properties of race models, retrieval speeds up as more repetitions are stored. However, unlike instance theory, according to EBRW, when an item is presented, all exemplars race to be retrieved with rates proportional to their similarity to the presented item. Specifically, the race times are exponentially distributed with rates determined by similarity (see also Bundesen, 1990). The probability density that *j* completes its race at time *t*, given presented item *i*, is given by

$$f(t) = \eta_{ij} \exp(-\eta_{ij} \cdot t) \qquad (3)$$

The first exemplar to complete its race is retrieved and the category label is extracted. Those items most similar to the presented item are most likely to be retrieved.

The result of this race feeds a random walk. As shown in Figure 1, the random walk has a counter that records the amount of evidence for a Category A or Category B response. The counter begins at zero. If the winning exemplar is a member of Category A then the counter is increased by one; if it is a member of Category B, then the counter is decreased by one. A response is made when the counter exceeds the A threshold or falls below the B threshold. The time to take each individual step is given by

$$\Delta T = \alpha + t_x, \qquad (4)$$

where $t_x$ is the winning retrieval time and $\alpha$ is a constant term associated with each step of the random walk. Nosofsky and Palmeri (1997) presented detailed analytic derivations for both response probabilities and response times. Palmeri (1997) extended the model to situations involving more than two response categories.

## Tests of the EBRW

What follows is a brief description of several experiments and theoretical analyses which have been performed to test predictions of the EBRW.

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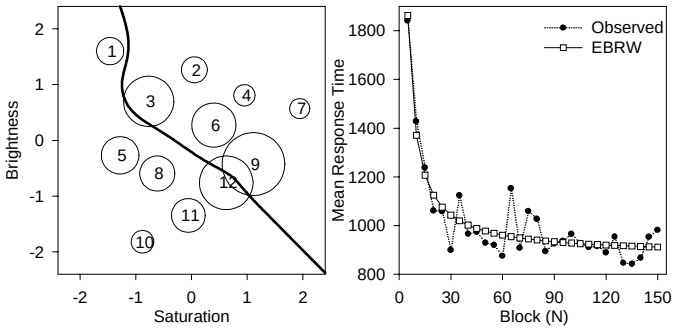


**Figure 2**. The left panel displays the MDS solution for color stimuli from one subject; circle size is linearly related to categorization response time. The right panel displays observed and predicted RTs as a function of practice for one subject.

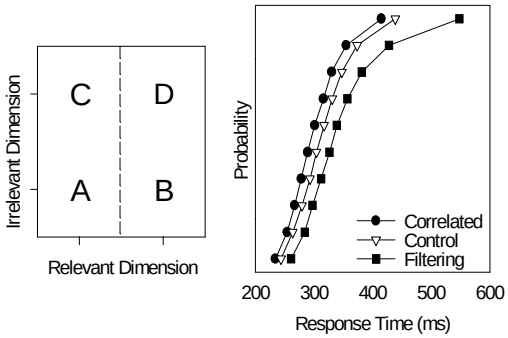


**Figure 3**. The left panel displays the stimulus configuration used in the Garner experiments. The right panel displays observed RT distributions.

## Categorization Response Times

In one experiment, over five days of training, subjects learned to classify a set of twelve colors varying in saturation and brightness. On each trial, one of these colors was randomly selected, the subject classified it as an A or a B as quickly as possible without making errors, and then corrective feedback was given. Over an additional three days, subjects made pairwise similarity ratings of the colors for purposes of multidimensional scaling.

Data were analyzed separately for each individual subject. Figure 2 displays the multidimensional scaling solution for the twelve colors for one particular subject. Stimuli in the upper right portion of the figure belonged to Category A. RTs are proportional to the size of each circle. RTs were highly systematic: In general, those stimuli close to the boundary were classified more slowly than those objects far from the boundary. The EBRW successfully predicted the observed RT data for all three subjects. The model predicts RTs to vary according to the relative similarity of an item to exemplars of each category. Basically, if an item is similar to exemplars from one category, then any one of those exemplars will be rapidly retrieved, meaning that the random walk will rapidly accumulate information. If an item is similar to items from both categories, however, then exemplars from either category could be retrieved, causing the walk to wander between the two response boundaries, leading to fairly slow responses. The EBRW also predicted the power law speedup as a function of training (see Figure 2). As more instances of a stimulus are stored, memory retrieval speeds up (Logan, 1988), speeding up the random walk.

## Garner Speeded Classification

This study investigated a classic set of speeded classification results initially provided by Garner and colleagues (see Garner, 1974). Three basic classification tasks have been defined (see Figure 3): control (e.g., A vs. B), filtering (e.g., A and C vs. B and D), and correlated (A vs. D). In the control task, only a single dimension is relevant; in the correlated task, the second dimension is redundant, so attending to it facilitates classification relative control; in the filtering task, the second dimension must be ignored, so attending to it interferes with classification relative to control. For stimuli composed of relatively integral dimensions (e.g., saturation and brightness of colors, or pitch and loudness of tones) the correlated task is faster than the control task, and the control task is faster than the filtering task.

Although fundamental, widely cited results, until only recently, formal accounts had not been provided to explain these patterns of results (see Ashby & Maddox, 1994; Nosofsky & Palmeri, 1997, in press). According to EBRW, correlated is faster than control largely because the stimuli associated with the two different responses are less similar in correlated (A vs. D) than in control (A vs. B). When stimulus A is presented, stimulus D in the correlated task will be retrieved less often than stimulus B in the control task. Control is faster than filtering largely because there are more repetitions of each item in the control task than in the filtering task. In control, half of the exemplars stored in memory are A's. Therefore, when an A is presented, these identical items will be retrieved fairly quickly, leading to a rapid accumulation of information. In contrast, in filtering, only one fourth of stored exemplars are A's.

Not only are the mean RTs ordered, but as shown in Figure 3, we have found that the RT distributions are strictly ordered as well (correlated < control < filtering). EBRW successfully predicts this strict ordering. Note that whereas orderings of distributions implies orderings of means, the converse is not true. In fact, another model of categorization RT, the decision boundary model (Ashby & Maddox, 1994), successful predicts orderings of mean RTs but cannot predict the observed orderings of RT distributions (Nosofsky & Palmeri, in press; Palmeri, in preparation).

## Categorization and Automaticity

Building on the instance theory of automaticity, EBRW accounts for both qualitative and quantitative changes that take place during the automatization of cognitive skills.

Categorization is just one aspect of cognition which can become automatized. In much the same way that exemplar memories underlie the development of automaticity in making categorization judgments, the EBRW extends Logan's (1988) insights that exemplar memories underlie the development of automaticity of various cognitive skills.

This close theoretical relationship between categorization and automaticity has only recently been recognized. One reason for this late recognition is that research on automaticity and research on categorization have had quite distinct histories. Whereas categorization has often been studied in conjunction with concept formation and memory, automaticity has traditionally been viewed as a special topic in the study of attention. Another possible reason is methodological. Most automaticity studies involve extended training whereas most categorization studies involve much less training. In addition, whereas automaticity studies have generally neither manipulated nor measured the similarities between objects, similarity manipulations are a defining characteristic of most categorization studies.

In recent research mirroring the structure of many categorization tasks, I tested for generalization once automaticity was achieved by presenting new objects of varying similarity to training objects (Palmeri, 1997). The task was to judge the numerosity of configurations of dots. On each trial, a dot pattern with between 6 and 11 dots was presented and the subject judged numerosity as quickly as possible without making errors. The same set of patterns were repeatedly presented for thirteen sessions. Not surprisingly, as shown in the left panel of Figure 4, RTs increased linearly as a function of numerosity during session 1. However, as training increased, the slope of this RT function gradually decreased. By the thirteenth session, RTs were essentially flat as a function of numerosity.

Following training, new transfer patterns that were moderate similarity, low similarity, and unrelated to the old training patterns were presented. As shown in the right panel of Figure 4, consistent with an instance-based theory, old patterns were judged as quickly as were patterns at the end of training, unrelated patterns were judged as slowly as were patterns at the start of training, and distorted patterns were judged with intermediate speed according to their level similarity to old patterns.

These observed data were well accounted for by the EBRW. Following instance theory, it is assumed that people begin with the explicit counting rule they are given for making responses. The speed of counting dots does not change with practice, at least not for adult subjects. What does change, however, is that particular instances of the dot patterns are repeatedly stored in memory. The algorithmic counting process and memory retrieval race to complete, with the winner driving the response. Early in training, explicit counting dominates, leading to increasing RTs as a function of numerosity. Later in training, retrieval of

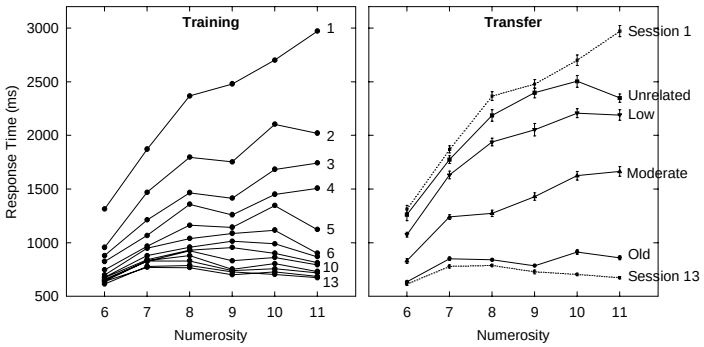


**Figure 4**. Both panels display RTs as a function of numerosity. The left panel displays training data from sessions 1-13. The right panel displays transfer data for old patterns and new various levels of distortion.

instances begins to dominate, leading to flat RTs as a function of numerosity. New patterns presented during transfer retrieve instances according to their similarity. Unrelated patterns retrieve stored patterns very slowly, so responses to them are based on explicit counting, leading to slower RTs and steep slopes. Similar patterns retrieve stored patterns more readily, leading to a mix of counting and retrieval, leading to faster RTs and flatter slopes.

I also examined the effects of similarity on learning by manipulating the within- and between-category similarity of the patterns (Palmeri, 1997). Consistent with the predictions of the EBRW, increasing within-category similarity speeds the development of automaticity in making numerosity judgments (as signaled by flat slopes) and speeds responses. Similarly, increasing between-category similarity slows the development of automaticity and slows responses.

These phenomena are not limited to numerosity judgments. In many cases people are initially provided rules for deciding category membership. Automaticity in making categorization judgments may often reflect a shift from explicit rule application to automatic retrieval of past instances from memory (see Palmeri, 1997).

## Categorization in Cluttered Environments

In a typical perceptual categorization task, a subject names some object presented in the center of the visual field. In typical visual selective attention and visual search tasks, the subject judges whether or not some particular object is present in a cluttered visual field, or names some object while trying to trying to ignore others in the visual field. Despite obvious parallels between these two fundamental cognitive operations, traditionally they have remained both empirically and theoretically distinct.

An unique insight by Bundesen (1990) was that aspects of visual object identification and visual attention can be understood within a common theoretical framework: In essence, identification and attentional selection both involve making perceptual categorizations. Bundesen formalized his ideas in the Theory of Visual Attention (TVA). TVA shares

several fundamental elements with both instance theory and GCM. Therefore, it logically shares basic elements with the EBRW as well. TVA is briefly described below along with an extension called CODE TVA (Logan, 1996) and an extension is proposed linking them with the EBRW. An application to a classic paradigm is then described.

## The Theory of Visual Attention (TVA)

TVA assumes that decisions are driven by perceptual categorizations of the form "object x in the visual field belongs to category C." TVA is formalized as a race process: All possible categorizations of objects in the visual field race to enter short term memory (i.e., receive attention) with rates determined by (a) the strength with which object *x* is associated with category *C* (similarity), (b) a bias to categorize objects in the display as members of category *C* (response bias), and (c) a bias to select object *x* to be categorized (stimulus bias). Formally, the rates of categorizing *x* as a member of *C*, $v(x, C)$, is given by

$$v(x,C) = \eta(x,C)\beta_C\alpha_x \qquad (5)$$

where $v(x, C)$ is the similarity of object *x* to category *C*, $\beta_C$ is the response bias for category *C*, and $\alpha_x$ is the stimulus bias for object *x*. The response biases ($\beta$) change the probability that a given category is selected without influencing the probability that any specific object is selected. Stimulus biases ($\alpha$) change the probability that a specific object is selected without influencing the probability that it is categorized in any specific way. In many applications, increasing the number of stimuli in the display decreases the stimulus bias for all items.

TVA is generally neutral with respect to the representations of categories and how the $\eta(x, C)$ terms are calculated. However, Bundesen seems to have a prototype theory in mind when he says “every perceptual category is supposed to be associated with a template.” In most applications, the $\eta$ terms are simply free parameters adjusted to fit a particular set of experimental results.

Bundesen (1990) demonstrated success of TVA in a diverse set of phenomena including stimulus identification, whole report, visual cueing, and visual search.

## The CODE Theory of Visual Attention (CTVA)

Logan (1996) extended TVA by combining it with the COntour DEtector (CODE) theory of grouping by proximity (van Oeffelen & Vos, 1982). An object is represented by a unimodal distribution of features in space. Multiple objects in the visual field give rise to overlapping distributions. The probability density of object presence at a given point in space is equal to the sum of all of the distributions at that point in space. The resulting CODE surface has a topography of hills (objects) and valleys (no objects). Perceptual groups are created by applying a threshold which cuts across this CODE surface. Any connected regions above the threshold are considered a perceptual group. Setting the threshold low clusters all objects in the visual field into one common perceptual group. Setting the threshold high clusters each object into its own perceptual group. The location of this threshold is largely assumed to be under the control of higher-level processes.

CODE provides inputs to TVA. In Bundesen's model, the entire visual field is sampled. By contrast, in CTVA, any given perceptual group can be selected (attended to) and only features within that perceptual group are passed on to TVA for selection. Because the distributions of features overlap, any selected perceptual group will contain features from each object in the visual field weighted by the amount of its distribution which falls within the selected perceptual group. Hence, in CTVA, the rates are given by

$$v(x,C) = c_x\eta(x,C)\beta_C\alpha_x \qquad (6)$$

where $c_x$ is the amount of the distribution for object *x* which falls within the selected perceptual group. Logan also extended TVA by configuring it as a counter model rather than a race model whereby $K_C$ categorizations of type *C* are required before a response of “C” can be made.

Logan (1996) demonstrated success of CTVA in a variety of visual search tasks, highlighting those in which stimulus proximity was manipulated.

## EBRW Model of Visual Attention

Although unquestionably powerful theories, TVA and CTVA are incomplete in several respects. This work aims to develop a more powerful theory by merging elements of TVA and CTVA with the EBRW. To account for effects of grouping, the front-end to the EBRW is a CODE surface.

First, TVA and CTVA are generally silent with respect to how stimuli are represented, how similarities are computed, and how categories are represented. The EBRW provides both a rich multidimensional scaling theory of object representations and similarity – objects are represented as points in some multidimensional psychological space with similarities a decreasing function of inter-point distances in that space – and a rich theory of category representations – categories are represented in terms of stored exemplars. Similarities ($\eta$ terms) in the EBRW, rather than being free parameters as in TVA and CTVA, are given by Equation 2. Distances in psychological space can be estimated using data from an independent task such as similarity judgments or identification confusions. The rate of categorizing *x* as a member of *C*, $v(x, C)$, is given by Equation 6. Note that when a single item is displayed the model reduces to the EBRW model presented in the beginning of this paper. As noted earlier, one advantage of relying on a MDS theory of similarity, is that it is possible to relate performance in visual attention tasks to performance in other categorization or identification tasks using the same stimuli.

Second, TVA and CTVA provide only preliminary accounts of practice effects in visual selective attention tasks. The EBRW gives a natural account of the effects of experience because it is derived from the instance theory of

automaticity (Logan, 1988; Palmeri, 1997). According to instance theory and the EBRW, every experience with some object is obligatorily stored as a separate exemplar in memory. Therefore, the rate of categorizing *x* as a member of *C*, $v(x, C)$, increases with increasing experience with members of category *C*. The effects of this experience on performance in some task depends in large part on the consistency of the training (see Schneider & Shiffrin, 1977).

Finally, the decision components in TVA (a first-instance race process) and CTVA (a counter process with an absolute threshold) fail to account for "response competition" effects that arise when objects are similar to exemplars from more than one category. Such effects can readily be accounted for by random walk models, such as the EBRW, but are problematic for simple race models, such as TVA, and counter models, such as CTVA (see Nosofsky & Palmeri, 1997, and Palmeri, 1997).

Below I describe one application of the EBRW to the classic flanker paradigm originated by Eriksen and Eriksen (1974). The flanker task involves categorizing an object at a fixed location while attempting to ignore other objects in the visual field. In other work, I have successfully fitted the EBRW to visual search tasks in which target-distracter similarity is systematically manipulated. Visual search tasks involve judging the presence or absence of members of a given category in a field of objects belonging to a distracter category. Space considerations prohibit me from discussing this work within this paper.

## Applications to the Flanker Task

A classic paradigm for investigating selective attention and response selection is the flanker task (Eriksen & Eriksen, 1974). The subject's task is to respond on the basis of the category of a central item flanked by distracters. For example, the letters H and K would require one response and the letters S and C would require another. The distracting flankers could be compatible, associated with the same response as the target, incompatible, associated with a different response, or neutral, associated with neither response. Examples of displays are shown below:

| | | | |
|---|---|---|---|
| Compatible | K | H | K |
| Neutral | V | H | V |
| Incompatible | S | H | S |

The task is to ignore flankers and categorize solely on the basis of the central letter. The target always appeared in the central location. The distance between the target (T) and the flankers (F) was manipulated. As shown in Figure 5, a strong response compatibility effect was observed, with compatible flankers facilitating responses and incompatible flankers inhibiting responses relative to neutral flankers. A strong distance effect was also observed, with the

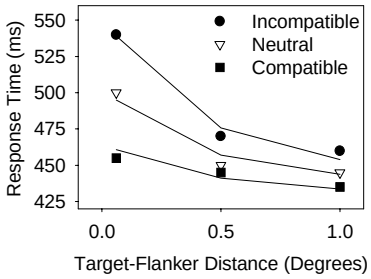


**Figure 5**. RTs as a function of T-F distance in the Eriksen and Eriksen (1974) flanker task. Symbols are observed data, lines are EBRW predictions.

compatibility effects diminishing as T-F distance increased. Following Logan (1996), the distance effects arise largely from CODE surface processing within CTVA. Assuming a three-item flanker task, the target and two flankers give rise to a CODE surface with three peaks. A threshold is applied at the local minima of the CODE surface, yielding three perceptual groups. Since the target location never changes, subjects select the middle perceptual group, which contains information from the target and the two flankers. However, the contributions of the two flankers relative to the target is a function of the T-F distance. When the distance is small, the relative contribution from the flankers is considerable; when the distance is large, the relative contribution from the flankers is small (see Logan, 1996). Therefore, the magnitude of the response compatibility effect due to the presence of flankers decreases with distance.

Not only does the magnitude of the compatibility effect decrease with distance, but RTs in all three conditions decrease with target-flanker distance as well. When target-distracter distance is large, the threshold applied to the CODE surface is low enough so that most of the target distribution is contained within its perceptual group. That is, $c_x$ is quite large. Increasing $c_x$ increases $v(x, C)$, causing faster retrieval times, leading to faster RTs.

Finally, we must account for the compatibility effect itself. Assume that H is the target. The evidence for an H-K response versus an S-C response in each condition is

| | H-K | S-C |
|---|---|---|
| Compatible | $c_x^T \eta_T + 2c_x^F \eta_T$ | $c_x^T \eta_D + 2c_x^F \eta_D$ |
| Neutral | $c_x^T \eta_T + 2c_x^F \eta_N$ | $c_x^T \eta_D + 2c_x^F \eta_N$ |
| Incompatible | $c_x^T \eta_T + 2c_x^F \eta_D$ | $c_x^T \eta_D + 2c_x^F \eta_T$ |

where the $c_x$ terms give the relative contribution of the central target item (T) and the two flankers (F), $\eta_T$ is the evidence that a letter belongs to its own response category, $\eta_D$ is the evidence that a letter belongs to the other response category, and $\eta_N$ is the evidence that a neutral letter belongs to a response category, ($\alpha$ and $\beta$ terms are set equal to 1). EBRW was fitted to the data; the excellent fits are given by the solid lines in Figure 5 (these fits were obtained with $\eta_T$ equal to 1.0, and both $\eta_D$ and $\eta_N$ equal to 0.1). By contrast, with these same parameters, CTVA is unable to predict the response compatibility effects. In fact, CTVA erroneously

predicts the RTs to be ordered compatible < incompatible < neutral. The random walk seems the natural vehicle for implementing the response competition which has long been thought the primary source of the compatibility effects in this paradigm. To my knowledge, no other computational model has been able to predict all aspects of the Eriksen and Eriksen (1974) data quite as well.

## Discussion

Most aspects of categorization predicted by EBRW are founded on the similarity relations between stimuli. Slow responses are usually a result of response competition which occurs when stimuli are similar to exemplars from multiple categories. Because of the perceptual nature of most of the paradigms we have addressed, a distance-based model of similarity has been sufficient. Although apparently simple on the surface, this is a fairly sophisticated and powerful theory of similarity (Nosofsky, 1991).

Although this work makes significant progress toward developing a comprehensive theory of perceptual categorization, there are important aspects of similarity and categorization which EBRW does not address. First, to the extent EBRW addresses learning, the process is incomplete. EBRW assumes that each instance of an item is stored as a separate exemplar. Power law decreases in RT as a function of learning emerge because of the race process for retrieving items from memory (Logan, 1988; Palmeri, 1997). However, another aspect of category learning which EBRW largely neglects is changes in attention to psychological dimensions which results in changes in similarities between stimuli. An important characteristic of GCM is that people learn to selectively attend to those dimensions which are most diagnostic for solving a given problem. One natural approach is to recast EBRW in a connectionist framework. In the same way that ALCOVE (Kruschke, 1992) is a connectionist version of GCM, allowing predictions of the time-course of category learning, dynamic versions of ALCOVE can be developed which incorporate critical elements of EBRW. Basically, rather having selective attention weights be free parameters of the model, connectionist principles in ALCOVE allow them to be acquired via error-driven learning mechanisms.

Second, not only does EBRW assume relatively static stimulus similarities during category learning, it also assumes static stimulus similarities during a single categorization trial. Using response-signal techniques, Lamberts (1995) demonstrated that similarity changes systematically within the course of a categorization decision: Early in processing, similarity is determined largely by dimensional salience; later in processing, similarity in determined largely by dimensional diagnosticity. Further work is needed to determine how best to modify the EBRW to account for such results.

## Acknowledgements

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