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# The speed of memory errors shows the influence of misleading information: Testing the diffusion model and discrete-state models

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ABSTRACT

In this report, we evaluate single-item and forced-choice recognition memory for the same items and use the resulting accuracy and reaction time data to test the predictions of discrete-state and continuous models. For the single-item trials, participants saw a word and indicated whether or not it was studied on a previous list. The forced-choice trials had one studied and one non-studied word that both appeared in the earlier single-item trials and both received the same response. Thus, forced-choice trials always had one word with a previous correct response and one with a previous error. Participants were asked to select the studied word regardless of whether they previously called both words “studied” or “not studied.” The diffusion model predicts that forced-choice accuracy should be lower when the word with a previous error had a fast versus a slow single-item RT, because fast errors are associated with more compelling misleading memory retrieval. The two-high-threshold (2HT) model does not share this prediction because all errors are guesses, so error RT is not related to memory strength. A low-threshold version of the discrete state approach predicts an effect similar to the diffusion model, because errors are a mixture of responses based on misleading retrieval and guesses, and the guesses should tend to be slower. Results showed that faster single-trial errors were associated with lower forced-choice accuracy, as predicted by the diffusion and low-threshold models.

## 1. Introduction

When psychologists began to develop models of decision making, one of the earliest questions they investigated was whether the evidence informing decisions is continuous or discrete (e.g., Tanner & Swets, 1954). Over sixty years later, this issue is still debated in the recognition memory literature (for recent reviews, see Pazzaglia, Dube, & Rotello, 2013, and the responses by Batchelder and Alexander (2013) and Dube, Rotello, and Pazzaglia (2013)). In a recognition task, one must decide whether or not a stimulus was previously encountered in a specific context; for example, whether a word appeared in a previous study list. Researchers have explored whether information retrieved from memory is continuous or discrete by proposing specific decision models and competitively testing them in fits to recognition data. Although answering the general question remains an elusive goal, hopefully we can at least rule out some of the least promising models. Our goal is to test continuous and discrete models by evaluating the relationship between error response times (RTs) and memory strength.

Advocates of discrete models acknowledge that underlying memory strength might vary along a continuum (e.g., Kellen & Klauer, 2015; Kellen, Singmann, Vogt, & Klauer, 2015). Given the potential for confusion, we will start with an example to clarify our criteria

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for calling a model "continuous" or "discrete." In short, we make this distinction based on whether the information that determines a response has a small number or a full continuum of possible states.

To illustrate, imagine a karate instructor who is deciding which of his students will compete in an upcoming tournament. He wants to take the strongest punchers, so he purchases a force gauge and measures the punch force for each student. To decide who goes to the tournament, he sets a minimum punch strength and takes all students with force readings that exceed this criterion. If this results in too many or too few students, he can raise or lower the criterion accordingly. This situation produces a continuous model, because decisions are based on information that varies along a continuum and the instructor can make full use of this continuum in deciding which students to take.

Alternatively, imagine that the instructor does not have a force gauge, but does have boards that he could challenge the students to break. Instead of measuring punch force for each student, he first has them attempt to break a thin board with a punch, and if they succeed, then he has them attempt to break a thicker board. This situation is analogous to a discrete-state model. Note that the underlying variable is still continuous – students have a full continuum of different punch strengths – but the instructor does not have access to these continuous values to inform his decision of which students to take. Instead, his choices can only be based on where the punch strength falls in relation to two thresholds (the amount of force needed to break the thin and thick boards).[1]

Memory researchers have attempted to discriminate models assuming continuous and discrete information using confidence ratings (e.g., Chen, Starns, & Rotello, 2015; Kellen & Klauer, 2015; Province & Rouder, 2012), bias manipulations (e.g., Bröder & Schütz, 2009; Dube & Rotello, 2012; Kellen, Klauer, & Bröder, 2013), response times (e.g., Dube, Starns, Rotello, & Ratcliff, 2012; Kellen et al., 2015; Province & Rouder, 2012), forced-choice testing (e.g., Kellen & Klauer, 2011; Parks & Yonelinas, 2009), and ranking tasks (Kellen & Klauer, 2014). The results have been mixed, with different studies interpreting various findings as evidence for one perspective versus the other. Studies claiming support for continuous models have relied on results such as curved bias-manipulation ROC functions (e.g., Dube & Rotello, 2012), curved confidence-rating ROC functions for medium-strength items even when participants always give the highest confidence rating for very strong items (Chen et al., 2015), and strength effects on the probability of ranking a target item as second-most-likely to be studied in a set of words comprising one target and multiple lures (Kellen & Klauer, 2014). Studies claiming support for discrete-state models have relied on results such as higher normalized maximum likelihood values for discrete versus continuous ROC models (Klauer & Kellen, 2011), confidence rating distributions that appear to be mixtures of a limited number of evidence states (Province & Rouder, 2012), and null strength effects on RT for trials that a discrete model assigns to the same memory state (Kellen et al., 2015; Province & Rouder, 2012).

In the current paper, we test specific continuous and discrete models by evaluating the relationship between the speed of error responses in single-item recognition memory and performance on a subsequent forced-choice recognition test. Specifically, after studying a list of words, participants completed single-item test trials in which they indicated whether a word was "Studied" or "Not Studied" on the earlier list. After these trials, they completed forced-choice test trials in which they had to indicate which of two words was studied on the earlier list. All of the words in the forced choice trials were words that had already appeared in the single-item trials, and the two words in a given forced choice trial were always ones that got the same response on the earlier single-item test. On "Studied"-"Studied" (S-S) trials, both of the words were called "Studied" when they were previously tested, but only one of the words was actually on the study list. On "Not Studied"-"Not Studied" (N-N) trials, both words were called "Not Studied" when previously tested, but one of them was actually on the study list. Participants were told that every forced-choice trial had one word that they had classified incorrectly on the earlier test, and they were encouraged to correct their earlier error by choosing the word that was actually on the study list. Participants were also explicitly cautioned that all of the words in the forced-choice trials were tested before, so they had to think about whether they appeared in the study phase, not earlier on the test.

The goal of our design was to test for a relationship between the speed of error responses on the single-item trials and the probability of an accurate response when the same item reappeared in the forced-choice trials. Next, we consider predictions for our paradigm based on a popular continuous-evidence model and two versions of a discrete model.

### 1.1. Diffusion model

The diffusion model is the most thoroughly investigated continuous model for accuracy and RT (e.g., Ratcliff & McKoon, 2008; Wagenmakers, 2009). In the model, information is accumulated over time until a particular response reaches a criterion level of support (Ratcliff, 1978). In Fig. 1, information that supports a "Studied" response moves the accumulation process toward the top response criterion (or "boundary"), and information that supports a "Not Studied" response moves the process toward the bottom boundary. As shown, the evidence process can take on a full continuum of momentary values, and the decision maker can adjust the position of the response criteria along this continuum. Thus, this model meets our definition for a continuous model.

The model assumes that there are two layers of variability that can lead to memory errors. First, memory strength varies from moment to moment in the process of deciding if a single item was studied. Each trial has an average drift rate that represents the overall memory strength of the tested item; for example, if an item is strongly remembered then the process will tend to quickly move to the top boundary. The actual path of the accumulation process is quite variable around the average drift, however, so the process

[1] Of course, a model can technically assume discrete evidence states and nevertheless come arbitrarily close to mimicking a continuous model. That is, instead of having just thin and thick boards, the instructor could have 10 or 100 or 100,000 different board thicknesses, and at some point he will functionally get as much information as he would get from the full continuum of force gauge readings. Like other researchers, we use "discrete" to refer to models with a relatively small number of states. The popular discrete model that we consider has three states, as in our karate example.