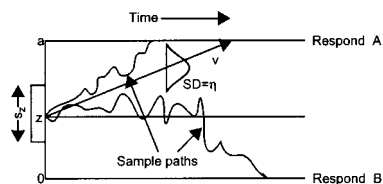




# Putting noise into neurophysiological models of simple decision making

TO THE EDITOR—In neurophysiology and cognitive psychology, considerable progress has been made in understanding the decision processes involved in simple cognitive tasks. Reddi and Carpenter's LATER model<sup>1</sup> assumes that decision time reflects the gradual accumulation of evidence from a stimulus, with a response generated only when the total amount of evidence exceeds some critical amount. The model has received support from single-cell recording data showing that populations of monkey frontal eye field cells exhibit buildup activity before a decision requiring an eye movement, and that decision time is predictable from the buildup activity. The model was applied to response time data collected from a two-choice task with human subjects, predicting the empirically observed shapes of response time distributions. However, the model has no mechanism for producing errors. This means it cannot



**Fig. 1.** An illustration of the diffusion model showing sample paths. The diffusion model assumes that information from a stimulus, represented by the mean drift rate  $v$ , is variable and is accumulated over time from the starting point  $z$  toward one or the other of the two response boundaries,  $a$ , for response A, or  $0$ , for response B. The two sample paths each have mean drift rate  $v$  and correct response A, and within-trial variability causes one process to reach the correct boundary,  $a$ , but the other to reach the incorrect boundary,  $0$ . The shape of response time distributions arises from the geometry of the diffusion process in a manner similar, but not identical, to LATER: as drift rate is incrementally decreased, increases in response time become larger, producing an increase in positive skew. Speed-accuracy tradeoffs are modeled by boundary settings: moving the boundaries apart gives greater accuracy and slower response times; moving the boundaries closer gives more errors and faster response times. Variability in drift rate and in starting point across trials give rise to slow and fast errors, respectively<sup>4</sup>.

account for accuracy rates or error response times, both of which are measured in two-choice experiments.

In cognitive psychology, there has been a history over the last 40 years of modeling simple two-choice decision processes<sup>2</sup>. Successful models such as the diffusion model<sup>3,4</sup> assume the same gradual accumulation of evidence as the LATER model, but also include an additional crucial feature: the accumulation of information within a trial is assumed to be noisy. This allows the models to explain how error responses come about and also to predict accuracy, error response times, the shapes of response time distributions, and the effects of speed versus accuracy instructions.

To support LATER, the distribution of an inverse transformation of response times was shown to be normal, so that if cumulative frequency on a  $z$ -scale (cumulative normal scale) is plotted against  $1/RT$ , then the result is a straight line. An approximately linear cumulative normal- $1/RT$  function is produced when the transformation is applied to most distributions that are consistent with response time distributions (for example, inverse Gaussian, exGaussian<sup>5</sup>). LATER predicted the point at which the linear functions from two experimental conditions intersect, one condition in which subjects were instructed to respond as quickly as possible, and the other, as accurately as possible.

The diffusion model (Fig. 1) produces these same regularities. To show this, simulated data were generated from the diffusion model with parameter values chosen to produce accuracy rates and response times the same as those in Reddi and Carpenter's experiments, consistent with the ranges of values in published fits<sup>6,7</sup> (Fig. 2).

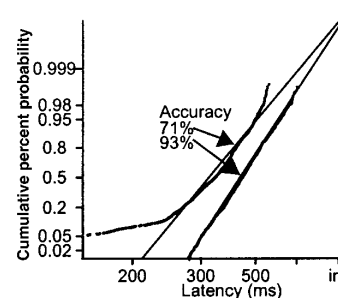
The simulated data mimic those presented in support of LATER: First, the two distributions converge at the same point at infinite time. The diffusion model predicts this because as response boundaries increase, the distributions skew a lot and shift a little, exactly what is required to produce convergence. Second, an assumption (Fig. 2) about anticipations produces

the straggling left tail for the speed condition. Third, the model produces accuracy values that match data to within 1 percent while also producing the linear functions and convergence at infinite time. Fourth, the effects of speed-accuracy instructions are well modeled with changes only in response boundaries.

Stochastic decision models, like the diffusion model, developed in psychology can account for all the dependent measures collected in two-choice experiments. The models also suggest ways of interpreting neurophysiological data in terms of variability in processing (neural noise<sup>8</sup>), competition between responses, and differences in difficulty of choices as indexed by accuracy and response time. The results from LATER and the diffusion model show the possibility of convergence and useful cross-fertilization.

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**Fig. 2.** Simulated data for 1000 responses. Boundary separation  $a = 0.10$  in the accuracy-stressed condition and  $0.04$  in the speed-stressed condition, with starting point halfway between;  $T_{er} = 300$  ms (encoding and response output time);  $\eta = 0.08$ ;  $s_z = 0.02$ ;  $v = 0.3$ . Accuracy was  $0.712$  in the speed condition and  $0.935$  in the accuracy condition, matching the experimental data. In the experimental speed condition, many responses were identified as anticipations. To model these, 500 responses picked randomly from a uniform distribution, range 100 to 550 ms, were added to the speed condition correct responses. The cumulative correct response time distributions plotted on a normal probability scale against  $1/RT$  produce a plot that mimics plots from LATER.

