# Human and Optimal Valuation in a Sequential Decision-Making with Uncertainty Task

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Many sequential sampling models suggest decisions rely on the accumulation of evidence over time until reaching a particular threshold. These models can often account for variations of speed and accuracy in perceptual tasks by manipulation of this threshold. But how does this threshold get determined in real-world decisions? It has been hypothesized the threshold maximizes some reward function, possibly incorporating measurements of both speed and accuracy (Gold & Shadlen, 2003). This approach has produced a family of models that accurately describes behavior for two-alternative forced choice (TAFC) tasks. (Bogacz, et al., 2006) However, it has been unclear what the optimal threshold becomes when additional perceptual information can be obtained at a cost.

We present a model of optimal sequential decision-making in a task that extends the traditional TAFC by adding the option of additional information. In the task, the observer receives a sample from two overlapping distributions.

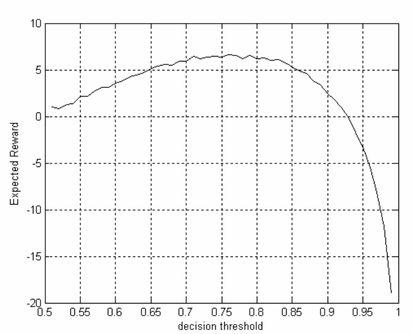


Figure 1: The expected reward given the posterior probability of one distribution is over a threshold. This curve is for correct classification = 6, incorrect -99, each sample -5 points.

The observer can either use the sample to guess the distribution or choose another sample. A reward structure determines point values for correct and incorrect answers along with the cost of each additional sample. Thus, the task is to weigh the current evidence against the value of acquiring additional samples. The model adapts the drift-diffusion model (Ratcliff & Rouder, 1998) for sequential decisions using a Partially Observable Markov Decision Process. The optimal decision is defined by computing the expected rewards for a particular threshold (figure 1). This model provides a method for evaluating the cost structures that humans may impose on judgment tasks along with understanding the decision maker's sensitivity to different reward structures.

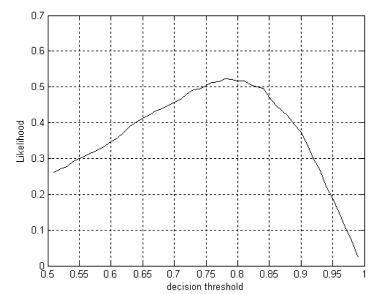


Figure 2: Threshold likelihood as a function of decision threshold for ones subject's 1500 trials in the reward structure in figure 1.

In addition to discussing these issues, we use the model to understand the effects of imperfect integration (memory limitations), variable signal strengths, and variations in the reward structure for human behavior (figure 2) and optimal behavior.

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