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A Dynamic and Stochastic Theory of Choice, Response Time, and Confidence

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Abstract

The three most basic performance measures used in cognitive research are choice, response time, and confidence. We present a diffusion model that accounts for all three using a common underlying process. The model uses a standard drift diffusion process to account for choice and decision time. To make a confidence judgment, we assume that evidence continues to accumulate after the choice. Judges then interrupt the process to categorize the accumulated evidence into a confidence rating. The fully specified model is shown to account qualitatively for the most important interrelationships between all three response variables found in past research.

Keywords: diffusion; random walk; confidence; cognitive model; judgment.

Introduction

The three most important measures of cognitive performance are choice, decision time, and confidence. Signal detection theory (Green & Swets, 1966) was originally designed to explain choices and is able to also account for confidence ratings. A great limitation of this model, however, is its inability to explain decision time. Random walk/diffusion theory was introduced for this purpose (Link & Heath, 1975; Ratcliff, 1978). This theory provides an elegant explanation for both choices and response time. A great limitation of random walk/diffusion theory, up till now, is its inability to account for confidence ratings. To date only the Poisson race model has successfully accounted for all three variables (Van Zandt, 2000; Vickers, 1979; Vickers & Packer, 1982; Vickers, Smith, Burt, & Brown, 1985b).[1] The purpose of this paper is to develop a generalization of the random walk/diffusion theory to offer an alternative account of choice, decision time, and confidence.

Our challenge is to explain with our diffusion model of confidence the massive amount of data that has accumulated about the complex relationships among these three measures. Here are a few. First, there is a speed/accuracy trade-off where faster choices produce higher error rates (Luce, 1986). Second, accuracy generally increases with confidence (Vickers, 1979), but judges are often overconfident (McClelland & Bolger, 1994). Finally, there is a twofold relationship between confidence and decision time. On the one hand, during *optional stopping tasks* (where the respondent determines when to stop and decide), there is an inverse relationship between the time taken and the degree of confidence expressed in the choice (e.g.,Baranski & Petrusic, 1998; Henmon, 1911). On the other hand, during *externally controlled stopping tasks* (where the experimenter determines when to stop and decide) the longer people are given to make a decision the more confident they become (e.g., Irwin, Smith, & Mayfield, 1956).

The purpose of this paper is to present a diffusion model that is capable of explaining all three response variables and their interrelationships using a common underlying processing mechanism. Next we give an intuitive description of how the model works using a prototypical sensory identification task. Then we formalize the model and illustrate how it simultaneously predicts the relationship between decision time and confidence for both the optional stopping and externally controlled stopping tasks. Accounting for both phenomena with a single process is an important hurdle for any model of confidence as most models of confidence can typically only account for one of these effects, but not both (Vickers, 1979). Finally, we will conclude by outlining the theoretical implications of this model. We will also offer some preliminary comparisons between the diffusion model of confidence and the Poisson race model.

A diffusion model of confidence judgments

To begin, consider a standard identification task. On each trial an observer listens through headphones to either white noise or white noise plus a faint tone (signal). The observer has no way of knowing which event has occurred and must decide whether the tone is present (Yes) or if there is only white noise (No). After deciding, the observer rates her confidence in her choice by selecting one of four categories: '1' for doubtful, '2' for little confidence, '3' for fairly confident, and '4' for perfectly confident. With a faint enough signal mistakes are expected and confidence responses should be distributed over the scale.

The diffusion model makes four fundamental assumptions to model observers' Yes/No choices: (a) Evidence favoring each alternative is integrated over time during the trial; (b) The sampled evidence at each time step is subject to random fluctuations; (c) Evidence in support of one alternative

[1] Vickers and colleagues call this the accumulator model.

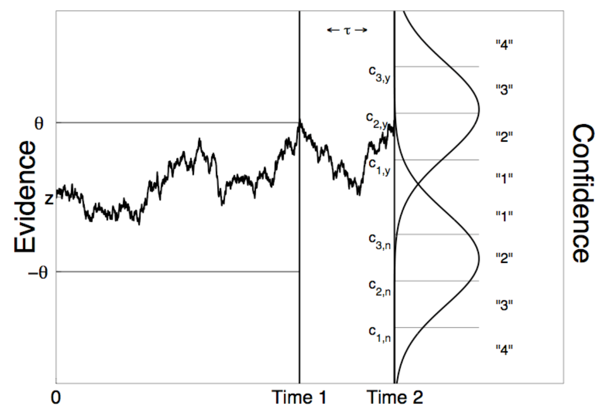

Figure 1. One realization of the diffusion model of confidence for a signal trial where an accurate choice is made. After a fixed time interval passes (τ) more evidence is collected and confidence rating of '2' is selected. The upper distribution is the predicted distribution of the spread of evidence at Time 2. The predicted confidence distribution for errors is also shown had the drift process incorrectly reached -θ.

(signal) is evidence against the other (noise); and (d) When a threshold level of evidence favoring one alternative over the other has accumulated, the observer stops collecting evidence and makes a decision accordingly. A standard diffusion model also allows evidence to be continuous in nature and its accrual is continuous over time. See the left side of Figure 1 for the typical diffusion process during one trial of the identification task. Cognitive models assuming these four assumptions have been shown to account for response time and accuracy data in several different areas (e.g., Busemeyer & Townsend, 1993; Ratcliff, 1978; Ratcliff & Smith, 2004; Roe, Busemeyer, & Townsend, 2001; Usher & McClelland, 2004).

Despite the ability of the diffusion model to so elegantly explain choice and decision time, the model has typically been dismissed as a plausible model of confidence judgments (e.g., Vickers, 1979). Here is why. If the accumulated evidence in the diffusion model is interpreted as the likelihood ratio of the observed data given the two response alternatives then the choice process can be understood as an optimal Bayesian inference model (Edwards, 1965). With this interpretation the choice thresholds are a fixed level of posterior odds that are just small or just large enough for observers to act on. Thus, the model predicts that across all trials – having reached the same level of posterior belief in their choices – judges must have an equal level of confidence in all of their choices. This is clearly false.

To surmount this obstacle we use the actual task the observers are confronted with to relax one assumption of the diffusion model. Recall that during the identification task, judges are first asked to make a choice and then make a confidence judgment. Across 100 years of psychological experiments this procedure is the rule rather than the exception (Baranski & Petrusic, 1998). What are the consequences of this procedure on diffusion models? There are none if observers stop accumulating evidence once a threshold is reached.

Instead, as Figure 1 shows, we remove this feature and instead assume judges, after making a choice, continue to accumulate evidence to estimate their confidence. In our model, judges then interrupt the diffusion process to categorize the accumulated evidence into a confidence response category.

Next we specify in more detail the two stages of our diffusion model beginning with the decision stage.

Decision stage

The decision stage takes the standard form as other diffusion models. At time 0 the state of evidence, $L(0)$, is at its starting point, $L(0) = z$, where $L(t)$ denotes the state of evidence at time t. The parameter z accounts for any response bias observers may have toward one response or the other. If $z = 0$ observers are unbiased, if $z < 0$ then observers are biased to respond No, and if $z > 0$ then they are biased to respond Yes. As Figure 1 shows, at the onset of the trial observers begin accumulating evidence to make a decision. If the accumulated evidence reaches the upper threshold at θ, then judges choose the Yes response. If it reaches $-\theta$ then they would choose the No response. The time it takes for the evidence to reach either threshold is the predicted decision time, t_1.

To formalize the decision stage we will temporarily assume that the accumulation process occurs at discrete and arbitrarily small fixed blocks of time, h. With each passing block of time each sampled piece of evidence, $x(\mathrm{t} + h)$, updates the state of evidence so that at time $t + h$ the state of the evidence would be,

$$L(t+h) = L(t) + x(t + h). \quad (1)$$

The time that has passed after n samples is given by $t = nh$.

As Figure 1 illustrates at each time step the sampled evidence is not constant, but subject to variability. We assume the sampled evidence at each time step is normally distributed with a mean of δh and variance of $\sigma^2 h$ when the signal is present and with a mean of $-\delta h$ and variance of $\sigma^2 h$ when noise is present. Holding everything else constant the larger the magnitude of δ the faster people will reach a response and the fewer errors people will make.

This model is now equipped to account for speed-accuracy tradeoffs. Namely increasing the magnitude of $|\theta|$ will increase the amount evidence needed to reach a choice. This reduces the impact random fluctuations in evidence will have on choice and as a result increase choice accuracy. However, a larger $|\theta|$ means more time will be needed before sufficient evidence is collected. In comparison, decreasing $|\theta|$ leads to faster responses, but also more errors.

A standard Wiener diffusion model – where evidence accrues continuously over time – is derived when the time step h approaches zero so that the above discrete process converges to a continuous time process (Cox & Miller, 1965). Ratcliff (1978) provides the expressions for the predicted choice probabilities of the four different types of responses (hits, false alarms, correct rejections, and misses) and the probability density functions for decision times (see also Cox & Miller, 1965).

Confidence stage

After making a decision we assume judges continue accumulating evidence to make a confidence rating. Our model captures this idea by allowing the diffusion process, after reaching either choice threshold, to continue for a fixed period of time, τ. The parameter τ is empirically observable. Baranski and Petrusic (1998) report over a number of perceptual experiments that with accuracy-stressed conditions and after an initial block of trials the amount of time between making a decision and selecting a confidence level (τ) is between 500 to 650 ms and constant across confidence ratings. For speeded conditions τ was slightly higher (~700 to 900 ms) and tended to vary across confidence ratings.[2] In a memory study where accuracy was emphasized Pleskac, Dougherty, Rivedenera, and Wallsten (2007) found that τ was between 700 to 750 ms and also constant across confidence levels. As a result we fix the interval between the decision time (t_1) and confidence time (t_2) at $\tau = 700$ milliseconds to identify the basic properties of the model. Future work will investigate if τ is sensitive to item difficulty or the speed/accuracy tradeoff.

At the time of the confidence judgment, the accumulated evidence reflects the newly collected evidence plus the evidence collected before making a decision,

$$L(t_2) = L(t_1) + x(t_1 + \tau). \tag{2}$$

[2] The systematic change in τ across confidence ratings may be indicative of τ being a function of other parameters of the diffusion process such as the drift rate or its sensitivity to other experimental factors. However, since all of Baranski and Petrusic's (1998) used the same verbal terms for confidence it is difficult to know if the change in τ is indicative of post-decision computation or the respondent learning how to scale different levels of confidence.

As Figure 1 depicts, analogous to signal detection theory, judges scale the accumulated evidence $L(t_2)$ onto the possible response categories. In the case of our hypothetical identification task there are four response categories conditioned on the Yes/No choice, $R_j|Choice$ where $j = 0, 1, 2, 3$ so each judge needs three response criteria for each option, $c_{k,\ yes}$ where $k = 1, 2, 3$, to select among the responses. The response criteria, just like the choice thresholds, are set relative to values of evidence. The location of the criteria depend, as in signal detection theory, on the biases of judges and may also be sensitive to the same experimental manipulations that change the location of the drift starting point, z. We also assume symmetry in the criteria for a yes or no response (e.g, $c_{1,\ no} = -c_{3,\ yes}$). If judges choose the Yes option and the cumulated evidence is less then $c_{1,\ yes}$ ($L(t_2) < c_{1,\ yes}$) then judges select confidence level 1, if it rests between the first and second criteria, $c_{1,\ yes} < L(t_2) < c_{2,\ yes}$, then they chooses confidence level 2, and so on.

The distributions over the confidence ratings are a function of the distribution of evidence in the diffusion process. However, the properties of the distributions reflect the fact that we know what state the evidence was in at the time of decision, either θ or $-\theta$. So our uncertainty about its location at t_2 is only a function of τ. Consequently, during a signal trial for a given δ the distribution of evidence at time t_2, $f[x(t_2)]$, is normally distributed with a mean of $\tau\delta + \theta$ if Yes was chosen and $\tau\delta - \theta$ if No was chosen. The means for noise trials can be found by replacing the δ's with $-\delta$. The variance in all cases is $\sigma^2\tau$. The distribution over the different confidence ratings for hits trials is then

$$Pr(R_j \mid \text{Hit}) = P(c_{j,Yes} < L(t_2) < c_{j+1,Yes} | \delta, \sigma^2, \tau) \tag{3}$$

where $c_{0,\ yes}$ is equal to $-\infty$ and $c_{j+1,\ yes}$ is equal to ∞. Similar expressions can be formulated for the other choices. The precise values can be found using the standard normal cumulative distribution function.

We leave the model as specified and now turn to some basic properties of the model and how it accounts for the known relationships between confidence, choice accuracy, and decision time.

Qualitative Predictions

Notice that our diffusion model has the same strengths as signal detection theory in accounting for confidence ratings. Namely it can capture the basic relationship between confidence and accuracy where larger δ's lead to greater discrimination and also, ceteris peribus, higher levels of confidence. Like signal detection theory it can also account for situations when the observer is overconfident. For example, Erev, Wallsetn, and Budescu (1994) provide a detailed account of how signal detection can account for overconfidence assuming improper criteria placement and random error (see also Ferrell & McGoey, 1980).

The model goes beyond signal detection theory though in that it predicts that confidence is sensitive to the speed-accuracy tradeoff. Larger magnitudes of $|\theta|$ will not only

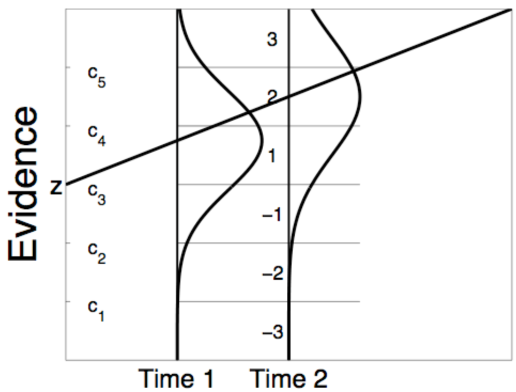

Figure 2. The predicted direct relationship between decision time and confidence.

lead to slower decision times and more accurate choices, but also higher levels of confidence. This is because the mean of the confidence distributions are a function of the choice thresholds, θ and $-\theta$. The opposite is true for speeded trials where the model predicts lower levels of confidence. Vickers and Packer (1982) report experimental results that support this prediction.

Next we show how the diffusion model can account for the twofold relationship between confidence and decision time. Though historically the inverse relationship between the two variables was shown to exist first, for simplicity's sake, we begin with the later finding that there is a direct relationship between confidence and decision time.

Confidence and decision time directly related

The result that in some cases there is a direct relationship between confidence and decision time has been investigated primarily with what Irwin, Smith, and Mayfield (1956) call the *expanded judgment task*. The task essentially externalizes the sequential sampling process asking people to physically sample observations from a distribution and then make a choice. For example Vickers et al. (1985) allowed observers to sample horizontal lines on a computer monitor. Their location on the horizontal axis of the screen was determined by a normal distribution with either a positive or a negative mean. The participant had to determine the sign of the mean based on the location of the sampled lines. Generalizing results from expanded judgment tasks to situations when sampling is internal, like our hypothetical identification task, is justified as results from both tasks mimic each other (Vickers et al., 1985a; Vickers et al., 1985b).

The direct relationship between decision time and confidence was uncovered when an external stopping rule was used during the expanded judgment task. With this stopping rule, the experimenter interrupts observers at different sample sizes and asks them for a confidence judgment. For example, whether the mean is above or below 0. In this case, confidence increases with larger samples (Irwin et al., 1956; Vickers et al., 1985b). As Figure 2 shows the diffusion model naturally predicts this relationship. It shows the average path of the drift process with $\delta > 0$ and the predicted distributions over the confidence scale at different points in time. Because the expected state of evidence at any point in time is δt, observers' confidence will naturally increase holding the response criteria constant.

The direct relationship between confidence and decision time, has posed a problem for early models of confidence. That is because they assumed that confidence was an inverse function of response time (Audley, 1960; Ratcliff, 1978). But, can our model predict the inverse relationship between confidence and decision time? As we show next, for a complete account we need to incorporate trial-by-trial variability in δ.

Confidence and decision time inversely related

A common result is that confidence and decision time are inversely related (e.g., Baranski & Petrusic, 1998; Henmon, 1911). These studies employ a discrimination task with an optional stopping procedure where observers control their own sampling by choosing when they are ready to make a choice. The results in these tasks show that across stimuli the average decision time monotonically decreases as the confidence level increases.

The model naturally accounts for the inverse relationship between confidence and decision time when the objective difference between stimuli varies from trial to trial. The diffusion model handles this by assigning more difficult stimuli lower levels of δ. For these stimuli, low δ's result in slower predicted decision times, and lower confidence levels - the inverse relationship.

The difficulty for the diffusion model comes in that Henmon (1911) and Baranski and Petrusic (1998) (see Experiment 1) showed that this inverse relationship holds even when the objective difference between stimuli is held constant in the same block of trials. The model in its present form does not predict this relationship. In fact it predicts that during an optional stopping task for a given δ any observed decision time will have an identical distribution over confidence. This is because the distribution over decision time $g(t_1 \mid \delta, z, \theta)$ is conditionally independent from the distribution of evidence at the confidence time point, $f_\delta[x(t_2) \mid \delta, \theta, \tau, Choice]$. In other words, the time in which the diffusion process reaches θ does not directly depend on the accumulated evidence at time t_2, and visa versa. Instead the relationship, as we have previously shown, is mediated by the values of δ and θ.

To account for this inverse relationship for a fixed level of difficulty we introduce a slight modification to the model. Due to factors like fluctuations in attention or motivation, we allow δ for a given stimulus to vary randomly between trials. The modification is not new. Ratcliff and colleagues (Ratcliff, 1978; Ratcliff & Smith, 2004) used the same modification to account for the often-observed phenomenon

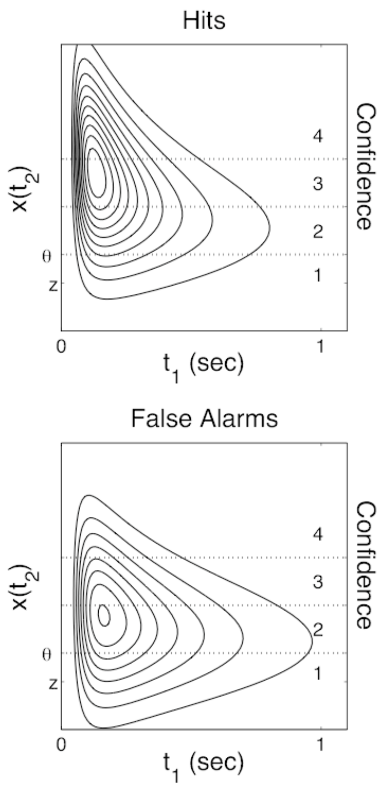

Figure 3. Contour plots of the marginal density of decision time and evidence at the time of confidence for hits and false alarms. Parameters from Ratcliff (1978) were used.

that decision times for errors are slower than times for correct choices (for another modeling strategy see Lee, Fuss, & Navarro, 2006).

To model trial-by-trial variability in the drift rate we – like Ratcliff – will assume that δ is normally distributed with a mean v and variance η^2. Now with trial-by-trial variability the model does predict the inverse relationship for the same reason as when objective difficulty varied between stimuli. To see the predicted inverse relationship, Figure 3 shows a contour plot of the marginal joint density function of t_1 and $x(t_2)$ for both hits and false alarms. The distributions were found by calculating the joint distribution of δ, t_1, and $x(t_2)$, and integrating over δ,

$$u\left[x(t_2),t_1\right] = \int g\left(t_1|\delta\right) f_\delta\left(\delta|hit\right) f_{x(t_2)}\left[x(t_2)|\delta\right] d\delta . \quad (4)$$

Notice that the distribution over δ reflects our knowledge of the type of choice at t_1 (hit, miss, false alarm, or correct rejection),

$$f_\delta\left(\delta|choice\right) = \frac{\Pr\left(choice|\delta\right) f_\delta\left(\delta\right)}{\int \Pr\left(choice|\delta\right) f_\delta\left(\delta\right) d\delta}. \quad (5)$$

The parameters of the model were approximated from Ratcliff's (1978) diffusion model parameters.

The top panel plots the joint distribution for hits and the bottom for false alarms. Comparing the two density functions reveals, consistent with past work (e.g., Ratcliff & Smith, 2004), that decision times for errors will on average be slower than decision times for correct choices. This is because the tail for the errors extends beyond the tail for correct choices. The top panel of Figure 3 also shows the predicted inverse relationship for hits. Taking slices of the joint density function at different values of $x(t_2)$ along the y-axis we see that the peak of the density function travels south, southeasterly across plot. That together with the increasing tail of the decision times as we move down $x(t_2)$ will draw the average decision time out for lower levels of evidence. Because confidence is directly scaled from the accumulated evidence this in turn implies an inverse relationship. The plot shows a hypothetical set of criteria and confidence scales for such a mapping. The bottom panel shows the same inverse relationship for incorrect choices.

Conclusion

Vickers (2001) commented that "despite its practical importance and pervasiveness, the variable of confidence seems to have played a Cinderella role in cognitive psychology - relied on for its usefulness, but overlooked as an interesting variable in its own right." (p. 148). Our diffusion model helps confidence relinquish this role and reveals that a single stochastic cognitive process can give rise to the three most important response variables in cognitive psychology: choice, decision time, and confidence.

The model uses a standard drift diffusion process to account for choice and decision time. To make a confidence rating, we assume that evidence continues to accumulate after a choice. Judges then interrupt the process to categorize the accumulated evidence into a confidence rating. The formally specified model qualitatively accounts for the known interrelationships between choice, decision time, and confidence.

An advantage of this model is that it is a generalization of signal detection theory. Therefore, it is immediately applicable to the same basic and applied tasks that signal detection has been used for such as lie detection (see Ben-Shakhar, Lieblich, & Bar-Hillel, 1982); jury decision making (Mowen & Darwyn, 1986); and HIV screening (Meyer & Pauker, 1987).

The model can also be adapted to account for other confidence procedures. For example, often judges are asked to directly evaluate their confidence that the current stimulus is a signal without explicitly making a choice. An intriguing possibility that deserves investigation is that even in these situations respondents implicitly make a choice (signal or noise) then scale their confidence. Indeed, applications of the Poisson race model often make this assumption when modeling these types of confidence ratings (e.g., Van Zandt, 2000).

The Poisson race model is a viable competitor for the diffusion model in that it also accounts for choice, response time, and confidence. Our diffusion model holds two advantages over the Poisson race model. First, the diffusion model accurately predicts skewed response time distributions where the Poisson model tends to predict more symmetrical distributions (Ratcliff & Smith, 2004). A second advantage is that the diffusion model explicitly models the response mapping function, whereas the Poisson model typically contains no such component. Future tests of these two models can only improve our understanding of the cognitive underpinnings of choice, decision time, and confidence.

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