



Comparing fixed and collapsing boundary versions of the diffusion model



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HIGHLIGHTS

- We compare fixed bound and collapsing bound versions of the diffusion model.
- An appropriate model selection method prefers the fixed bound model for our data.
- The two models produce response time distributions with similar shape.
- The estimated collapsing bounds were similar to estimated fixed bounds because the amount of collapse was small.
- Bounds that collapse over time do not provide an improvement over fixed bounds.

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ABSTRACT

Optimality studies and studies of decision-making in monkeys have been used to support a model in which the decision boundaries used to evaluate evidence collapse over time. This article investigates whether a diffusion model with collapsing boundaries provides a better account of human data than a model with fixed boundaries. We compared the models using data from four new numerosity discrimination experiments and two previously published motion discrimination experiments. When model selection was based on BIC values, the fixed boundary model was preferred over the collapsing boundary model for all of the experiments. When model selection was carried out using a parametric bootstrap cross-fitting method (PBCM), which takes into account the flexibility of the alternative models and the ability of one model to account for data from another model, data from 5 of 6 experiments favored either fixed boundaries or boundaries with only negligible collapse. We found that the collapsing boundary model produces response times distributions with the same shape as those produced by the fixed boundary model and that its parameters were not well-identified and were difficult to recover from data. Furthermore, the estimated boundaries of the best-fitting collapsing boundary model were relatively flat and very similar to those of the fixed-boundary model. Overall, a diffusion model with decision boundaries that converge over time does not provide an improvement over the standard diffusion model for our tasks with human data.

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1. Introduction

Over the last 50 years, sequential sampling models such as the diffusion model have been applied extensively to a wide variety of tasks and participant populations. The tasks include recognition memory (Ratcliff, 1978; Ratcliff, Thapar, & McKoon, 2011; Starns, Ratcliff, & McKoon, 2012), lexical decisions (Ratcliff,

Gomez, & McKoon, 2004; Ratcliff, Thapar, Gomez, & McKoon, 2004; Wagenmakers, Ratcliff, Gomez, & McKoon, 2008), perceptual discrimination (Ratcliff, 2014; Ratcliff & Rouder, 1998; Ratcliff, Van Zandt, & McKoon, 1999; Smith, Ratcliff, & Sewell, 2014), value-based decision making (Krajbich, Armel, & Rangel, 2010; Krajbich & Rangel, 2011; Milosavljevic, Malmaud, Huth, Koch, & Rangel, 2010) go/no-go tasks (Gomez, Ratcliff, & Perea, 2007); simple reaction time (Ratcliff & Strayer, 2014; Ratcliff & Van Dongen, 2011; Smith, 1995), the response signal task (Ratcliff, 2006, 2008), and visual signal detection (Smith & Ratcliff, 2009; Smith, Ratcliff, & Wolfgang, 2004). The participant populations include older adults (Ratcliff, Thapar, & McKoon, 2001, 2003, 2004,

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2010; Ratcliff et al., 2011; Spaniol, Madden, & Voss, 2006), children and adolescents (Ratcliff, Love, Thompson, & Opfer, 2012), children with ADHD (Mulder et al., 2010), children with dyslexia (Zeguers et al., 2011), people undergoing sleep deprivation (Ratcliff & Van Dongen, 2009), people with induced hypoglycemia (Geddes et al., 2010), and people with anxiety or depression (White, Ratcliff, Vasey, & McKoon, 2010a,b). In sequential sampling models with fixed boundaries, noisy evidence about a stimulus is accumulated over time toward one of two decision boundaries, each of which represents a decision alternative. The distance between the boundaries may vary from trial to trial but they remain constant within trials, that is, from the time of stimulus presentation until the time of the response. Such models aim to account for all aspects of the experimental data, namely, the distributions of correct and error response times and the proportions of correct and error responses.

These fixed or constant boundary models have been able to successfully fit a wide variety of data (see previous paragraph). However, some researchers have instead proposed models with decision boundaries that converge over time during a trial, such that progressively less evidence is required to trigger a response as the trial progresses (Bowman, Kording, & Gottfried, 2012; Churchland, Kiani, & Shadlen, 2008; Cisek, Puskas, & El-Murr, 2009; Ditterich, 2006a,b; Hanks, Mazurek, Kiani, Hopp, & Shadlen, 2011; Rao, 2010; Sanders & Ter Linden, 1967; Thura, Beauregard-Racine, Fradet, & Cisek, 2012; Thura & Cisek, 2014; Viviani, 1979a,b; Viviani & Terzuolo, 1972).

Support for these collapsing or converging boundary models has come from several sources. In the neurophysiological literature, firing rates in the lateral intraparietal area of macaques appear to reflect the accumulation of evidence for a particular choice in a dot-motion task (Churchland et al., 2008). Because the increase in firing rate is also found on trials on which there is no coherent motion, the authors proposed that the time-dependent increase in firing rates represents an urgency-signal, which they argued is equivalent to a collapsing boundary (but this is not true for other urgency-signal implementations, e.g. Thura et al., 2012; Thura & Cisek, 2014). Models with collapsing boundaries may also be able to represent certain physiological properties such as the refractory period after a neuron has fired (Kryukov, 1976) or certain dynamics of the basal ganglia (Ratcliff & Frank, 2012).

In the behavioral literature, numerous researchers have demonstrated that subjects are willing to make decisions based on less evidence as a trial progresses in expanded judgment or deferred decision-making tasks (Busemeyer & Rapoport, 1988; Drugowitsch, Moreno-Bote, Churchland, Shadlen, & Pouget, 2012; Rapoport & Burkheimer, 1971; Sanders & Ter Linden, 1967). However, these kinds of tasks are quite different from the standard two-choice tasks used in most speeded decision-making studies. In most expanded judgment tasks, evidence is presented at a slower rate (e.g., a new piece of information every 2 s) and subjects' response times can be much longer (e.g., 20–40 s). Some of these tasks also include an explicit cost associated with acquiring new information. Given the differences between these tasks and the standard two-choice tasks, evidence for collapsing boundary models in expanded judgment tasks cannot be taken as evidence of their appropriateness for standard rapid two-choice tasks.

Some researchers have also argued in favor of models with collapsing boundaries on the grounds of optimality (Busemeyer & Rapoport, 1988; Deneve, 2012; Ditterich, 2006a; Drugowitsch et al., 2012; Rapoport & Burkheimer, 1971; Thura et al., 2012). If subjects are trying to achieve a short mean response time for a given level of accuracy and a single fixed stimulus strength, then a model with fixed boundaries is statistically optimal, assuming that there is no variability in drift rate across trials (Moran, 2015; Wald & Wolfowitz, 1948). However, if there is variability in drift

rate across trials, then a model with boundaries that change over time is statistically optimal if subjects are trying to maximize their reward rate (i.e., make the most correct responses per unit of time; Ditterich, 2006a; Thura et al., 2012) or minimize mean response time for a given level of accuracy (Moran, 2015). A model with boundaries that collapse over time has also been argued to be optimal if there is a cost associated with time spent on a decision (Busemeyer & Rapoport, 1988; Drugowitsch et al., 2012; Rapoport & Burkheimer, 1971). It has also been argued that collapsing boundary models are optimal in response-deadline tasks in which subjects are trying to find a balance between being accurate and still making a response before a deadline (Frazier & Yu, 2008), although in practice, subjects do not appear to behave optimally in these kinds of tasks (Balci et al., 2011; Karsilar, Simen, Papadakis, & Balci, 2014), and this type of data can be accounted for with a forced decision at the deadline (Ratcliff, 1988, 2006). Karsilar et al. (2014) examined accuracy as a function of response time in a response deadline task and found that subjects do show a decrease in accuracy before a response deadline, but the size of the decrease is more consistent with the predictions of a fixed boundary diffusion model than with the predictions of a collapsing boundary model with boundaries selected to optimize reward rate.

Although collapsing boundary models have become increasingly popular in both the behavioral and neurophysiological literature, many researchers using sequential-sampling models in these domains have successfully used fixed boundary versions of these models (Bode et al., 2012; Brown, Hanes, Schall, & Stuphorn, 2008; Ding & Gold, 2010, 2012; Forstmann et al., 2010, 2008; O'Connell, Dockree, & Kelly, 2012; Ramakrishnan & Murthy, 2013; Ramakrishnan, Sureshbabu, & Murthy, 2012; Ratcliff, Philastides, & Sajda, 2009; Salinas & Stanford, 2013; Schall, 2003; Schurger, Sitt, & Dehaene, 2012; Smith & McKenzie, 2011; Usher & McClelland, 2001; Wang, 2002; Wong & Wang, 2006). Hawkins, Forstmann, Wagenmakers, Ratcliff, and Brown (2015) recently conducted a large-scale analysis of data from both humans and non-human primates from several different tasks and found that support for fixed or collapsing boundary versions of the model appears to depend on the specific tasks and procedures used. Overall, Hawkins et al. found that a fixed-boundary model was preferred for most of the human subjects, but a collapsing boundary model was preferred for most of the non-human primates. This may be a result of practice effects, given that the non-human primates in these studies received much more extensive training on these tasks (e.g., months) than the human subjects.

The results we present in this article complement and extend those of Hawkins et al. (2015) in several ways. First, unlike Hawkins et al., who used Monte Carlo simulation to obtain predictions for the collapsing boundary model, we used exact predictions based on the integral equation methods described in Smith (2000). These methods make it possible to derive exact response time distribution and accuracy predictions for diffusion models with time-varying drift rates or boundaries or both. This ensures that our model predictions are reliable and were not dependent on our simulation method or sample size. Second, the collapsing boundary model we examined had a different functional form for the boundary collapse than the one used by Hawkins et al. We used a hyperbolic ratio function, which Shadlen and colleagues (Churchland et al., 2008; Hanks et al., 2011) previously used to quantify the hypothetical urgency signal in physiological data, whereas Hawkins et al. used a Weibull function (which was chosen for its ability to mimic a wide range of possible boundary collapse functions). The hyperbolic ratio function we used can be well-approximated by a Weibull function, but has fewer parameters than the Weibull function and is more constrained in terms of the variety of shapes it can take. Third, we applied our methods to a different set of tasks and manipulations than the ones considered by Hawkins et al., so our

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