Response dynamics: A new window on the decision process

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Abstract

The history of judgment and decision making is defined by a trend toward increasingly nuanced explanations of the decision making process. Recently, process models have become incredibly sophisticated, yet the tools available to directly test these models have not kept pace. These increasingly complex process models require increasingly complex process data by which they can be adequately tested. We propose a new class of data collection that will facilitate evaluation of sophisticated process models. Tracking mouse paths during a continuous response provides an implicit measure of the growth of preference that produces a choice—rather than the current practice of recording just the button press that indicates that choice itself. Recent research in cognitive science (Spivey & Dale, 2006) has shown that cognitive processing can be revealed in these dynamic motor responses. Unlike current process methodologies, these *response dynamics* studies can demonstrate continuous competition between choice options and even online preference reversals. Here, in order to demonstrate the mechanics and utility of the methodology, we present an example *response dynamics* experiment utilizing a common multi-alternative decision task.

Keywords: decision making, methodology, process models, response dynamics, metrics.

1 Introduction

The past few decades have seen a notable change in the level of analysis characterizing theories and models in decision making. Generally, paramorphic models concerned largely with outcome prediction are giving way to computational models that focus on the processes assumed to produce these responses (see Busemeyer & Johnson, 2004, 2008 for overviews). This focus on underlying cognitive processes has enabled explanations of paradoxes (e.g., decoy, compromise effects) within unified frameworks (Johnson & Busemeyer, 2005), rather than increasingly complex algebraic functions divorced from cognitive operations. This theoretical shift demands accompanying empirical methodologies in order to evaluate these more precisely specified process theories. For example, the tracking of information search or acquisition during decision tasks has developed from the use of information boards (e.g., Payne, 1976) to mouse-tracking techniques (e.g., Payne, et al., 1988), to eye-tracking techniques (e.g. Russo & Rosen, 1975; Wedel & Pieters, 2000, Franco-Watkins & Johnson, 2011). Other methods such as think-aloud protocols and response time analyses (e.g. Bergert & Nosofsky, 2007) have been used, as have clever combinations of several methodologies together to provide converging evidence (e.g., Glöckner, 2009; Riedl et al., 2008). Here, we would like to introduce what we consider to be the next important and logi-

cal step in this important methodological evolution of our field—tracking response dynamics in decision making.

The shortcoming inherent in the "process-tracing" techniques identified above (see also Schulte-Mecklenbeck et al., 2010, for a comprehensive review volume) lies in their neglect of the dynamic nature of choice preferences[1]. The process traced by mouse- and eye-tracking is one of information search, not the deliberation process itself that utilizes this information; verbal reports reflect a subject's perception of how they engaged the task, and are subject to demand characteristics; response times (RT) indicate how long a task takes, but not the nature of processing that occurs during that interval. That is not to say that these measures are *always* uninformative; many authors have fruitfully applied RT analyses (for example) to infer characteristics of the decision process (e.g., Glöckner, 2009; Hilbig, 2008). However, traditional metrics generally fail to capture the notion that observed choices are the result of a dynamic process where evidence for various response (choice) alternatives may accumulate over the course of the task. RTs specifically lack sufficient resolution to explore this dynamic evolution of preference in real time. This deficiency is quite serious given that the evidence accumulation assumption has received extensive theo-

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[1]The term "choice preference" here is used broadly to denote an intended response in a decision task, rather than implying a restriction to preferential choice tasks in particular. For example, we include both the option selected as having the higher criterion value in a probabilistic inference task as well as the indication of the "better" option in both risky (e.g., gambles) and multi-attribute preferential choice tasks.

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retical treatment and neurophysiological support (see Busemeyer et al., 2006).

Recently, a growing body of research in cognitive science (e.g., Dale et al., 2007; Spivey et al., 2005; McKinstry et al., 2008; Freeman et al., 2010) has utilized a novel paradigm that compensates for the deficiency in current JDM methods identified above. The research on *response dynamics* captures the continuous, online processing of information as it is revealed in the subject's motor response. Spivey and Dale (2006) describe the theoretical basis and representative mouse-tracking applications of this approach (Song & Nakayama, 2009, survey related work in choice reaching tasks). The basic paradigm involves simply recording the position of the mouse en route to the selection of an option in a decision task. The theoretical assumption is that the competitive "pull" of foregone alternatives exerts an influence on these response trajectories, for which there is now substantial behavioral and neurophysiological evidence (reviewed by Spivey, 2007). Therefore, one can measure properties of the response trajectory and draw inferences about the underlying mental processes. The goal of the current work is to introduce this research stream to the JDM community and illustrate the types of analyses and comparisons it makes possible.

The only other explicitly JDM application (Koop & Johnson, 2011), tracked mouse responses in a risky decision making task with traditional economic gambles involving either gains or losses, and highlighted the ability to describe changes in the direction and strength of preference online (during the task). When choosing the safe gamble in the realm of gains, subjects proceeded very directly to that gamble. Alternatively, when they chose the risky gamble they first proceeded towards the safe gamble before rapidly changing direction towards the risky gamble. The opposite pattern was generally true in the realm of losses. Theoretically, these results support models that allow for momentary preference for one option during the task, but ultimate choice of the other option (e.g., dual-process models or sequential sampling models)—a behavior that would not be captured with existing discrete response methods. In the following demonstration study, we show another application to a traditional JDM task, the Iowa Gambling Task. We chose this task because its ubiquitous use and experience-based design allow us to showcase the utility of response dynamics both within trial types (e.g., following a gain or loss, as classified below) and across the course of the task (as a metric of learning).

The Iowa Gambling Task (IGT; Bechara et al., 1994) has traditionally been used to diagnose decision making deficits in individuals with neurological damage. Subjects are presented with four decks of cards, each of which provides wins on every draw and occasional accompanying losses; but they have slightly different payout characteristics (see Figure 1). Typically, two decks (hereafter A and B) are considered "bad" decks, offering high rewards and high punishments that result in a net loss, whereas two other decks (C and D) are "good" decks with lower rewards but also lower, more infrequent punishments (Chiu et al., 2008), resulting in a net gain. Subjects are not presented with these payment contingencies, but must learn about each deck through self-directed sampling over the course of 100 trials.
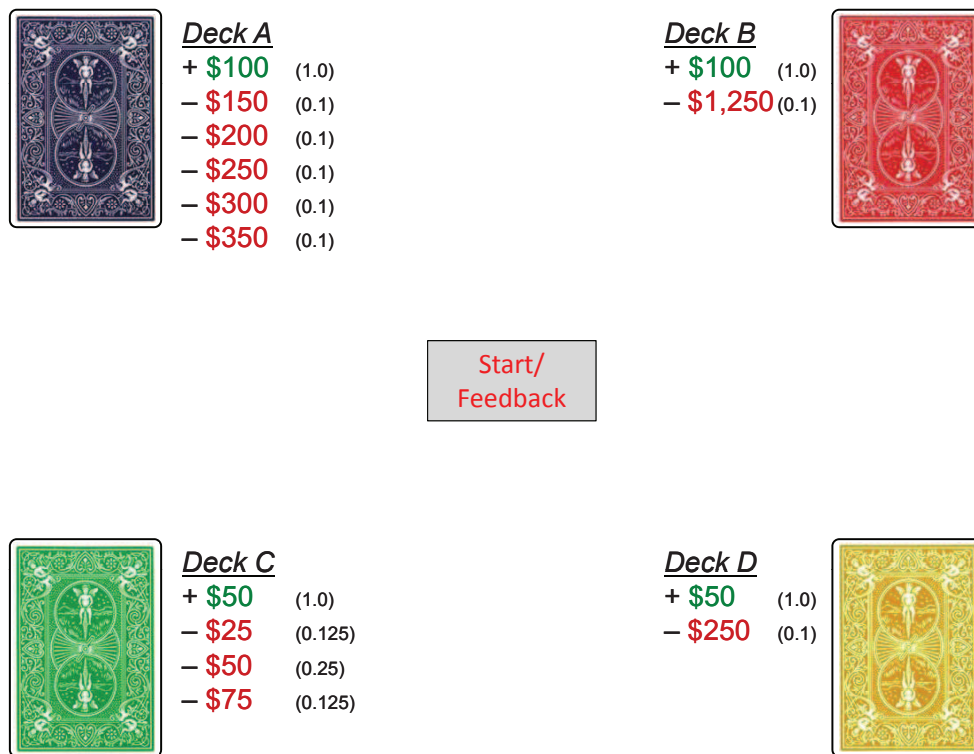
2 Experimental design

General paradigm. The application of the response dynamics methodology simply requires placing choice options in spatially disparate regions and tracking mouse movements while subjects make their selection.[2] In contrast to previous response tracking experiments with binary responses proceeding from the bottom-center of the screen to the upper-left or upper-right corners, we produced a multi-alternative version by requiring movement from screen center to one of the four corners (Figure 1).

To select an option (deck), subjects had to move a cursor from the start position to the deck of their choice and click. In order to exploit greater degrees of freedom in the motor response (and thus allow more opportunity for competitive "pull" to be manifest), we projected the four choice alternatives onto a wall (approximately 3m x 4m) and had subjects use a wireless pointing device (Nintendo's Wiimote; see Dale et al., 2008 for more details) from a distance of approximately 3m. After clicking on the selected deck, a "Feedback" box appeared in the start position. To see the outcome of their selection, subjects had to click on the "Feedback" box, and in doing so return the cursor to the center start position for the next trial. Upon clicking, the chosen deck's outcome was displayed, after which the reappearance of the decks for the next trial occurred automatically after a 1-second delay. This implementation ensured that feedback-related movement was not incorporated into the tracked response movement of the subsequent trial.

Subjects. Undergraduates enrolled in introductory psychology courses were able to sign up for this experiment (among many) online. Forty-nine undergraduates participated in the study with five subjects unable to complete the experiment due to computer failure, producing N = 44 for analyses below. For their participation, individuals received course credit and a performance contingent payment, as described below.

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[2]For this particular study we used custom software, but see Freeman & Ambady (2010) for a freeware program with similar functionality.

Figure 1: Stimulus layout with payment contingencies. Each deck had a guaranteed payment (noted in green) that appeared on every draw; a penalty occurred on only some draws (noted in red, with associated probability). "Start/Feedback" button never actually appeared on screen with the decks—clicking the start button on the first trial caused the decks to appear and the button to disappear. In subsequent trials, clicking on a deck caused the all decks to disappear and the feedback button to appear. After feedback was presented, the button disappeared and the decks reappeared automatically. The deck labels, payoffs, and probability information shown here are illustrative and was not presented to subjects.

Deck A
+ $100   (1.0)
− $150   (0.1)
− $200   (0.1)
− $250   (0.1)
− $300   (0.1)
− $350   (0.1)

Deck B
+ $100   (1.0)
− $1,250 (0.1)

Start/
Feedback

Deck C
+ $50   (1.0)
− $25   (0.125)
− $50   (0.25)
− $75   (0.125)

Deck D
+ $50   (1.0)
− $250   (0.1)

Stimuli. The stimuli in this experiment utilized the payouts and set order from the traditional IGT (Bechara et al., 1994; see Figure 1). Over every 10 draws, Decks A and B had an expected value of -$250 whereas Decks C and D had an expected value of $250. Unlike the original IGT stimuli where decks were exhausted after 40 draws, subjects had unlimited draws from each deck.

Methods. After informed consent and a "participation pledge" to promote investment in the task, subjects received instruction on the task and payment protocol. Subjects were told that they would begin the task with an "endowment" of $2000 ($4 in real money at an exchange rate of $500 to $1) and that their deck selections during the task could either add to or subtract from this amount. Subjects were shown animated example trials and completed one example trial (without feedback) prior to beginning the main task. Each subject made 100 deck selections, after which they were paid their adjusted winnings. Decks were always located in the four corners of the dis-

play, yet the locations of the specific decks were counterbalanced across subjects using four orders (with the original order in Figure 1 either rotated 180°, or flipped, or both). We recorded the (x, y)-position of the cursor at a rate of 100Hz. Importantly, subjects were not told this nor given special instructions regarding movement of the pointing device.

3   Analyses/Results

The richness of the data provided by online response tracking combined with the complexity of the IGT creates an overabundance of possible analyses. For cogency and due to space constraints, we will provide a few analyses that exemplify the benefits of collecting continuous response data, but are by no means exhaustive (see Table 1). For more examples and in depth analyses, we refer the reader to previously published work using this method (e.g., Spivey, et al. 2005; Dale, et al., 2007; Duran, et al., 2010; and Freeman & Ambady, 2010).

Table 1: Metrics of response dynamics

Measure	Explanation	Example article
Area under the curve (AUC)	Geometric area falling between the trajectory and a direct path	Freeman & Ambady (2010)
Average absolute deviation (AAD)	Mean absolute deviation from a direct path	Freeman & Ambady (2010)
Derivative measures	Velocity and acceleration of response trajectory	Wojnowicz et al., (2009)
XY_{dist}	Total x,y distance traveled in response trajectory	Duran et al., (2010)
Maximum absolute deviation (MAD)	Maximum absolute deviation from a direct path	McKinstry et al., (2008)
X_{flips}	Number of directional changes along the x-axis	Duran et al., (2010)

Figure 2: Choice proportion of each deck across all blocks
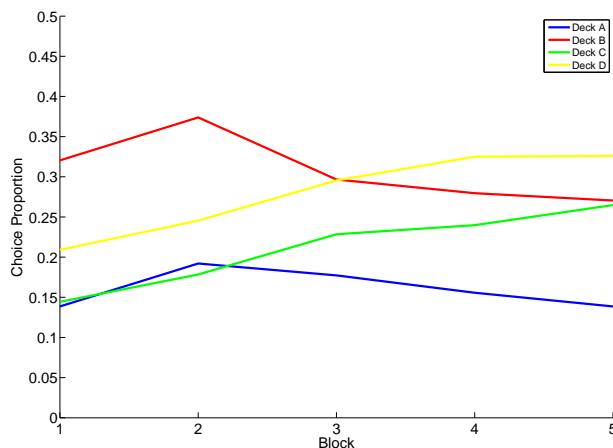
Aggregate measures. In order to lend greater structure to these data, we have divided up subject responses into 5 blocks of 20 trials each. Subjects' choice patterns across these blocks provided an initial check on the validity of our version of the IGT. The general trend (Figure 2) replicates classic findings (e.g., Bechara et al., 1994) on the IGT in that choice of the "good" decks increases throughout the experiment whereas choice of the "bad" decks decreases. It is interesting to note that although choice of Deck B (the high variability "bad" deck) decreases throughout the experiment, it remains relatively high. This paradoxical preference for Deck B has been noted elsewhere (e.g., Rodríguez-Sánchez et al., 2005; Wilder et al., 2008; or see Dunn et al., 2006 for a broad review). Using the metrics facilitated by continuous response tracking, we can explore this tendency in more detail.

The most illustrative descriptive measure of response dynamics is typically the aggregate response trajectory. The inferential logic is that as the competitive "pull" from non-chosen options increases, it is reflected in increased curvature of the response trajectory. Thus, as one learns about the payment contingencies for each deck, the "pull" from the bad decks should decrease, resulting in more direct choices of good decks. Here we present aggregate Deck B trajectories from three blocks in order to illustrate this traditional response dynamics presentation (Figure 3a). The data from early (2), middle (3) and late (5) blocks illustrate changes in this competition (or reluctance) over the course of the task and roughly correspond to changes in choice proportions. We produced these trajectories by time-normalizing each trial with a Deck B selection into 101 time bins (as done by Spivey et al., 2005) and aggregating within and across subjects. These time-normalized response trajectories were reformatted to coincide with Deck B positioned in the upper-left regardless of its actual physical location (to collapse across counterbalance conditions). In all previous applications of this paradigm, which used binary choice, there was only an attraction to one non-chosen option on each trial (i.e., to the upper right of Figure 3a). This single competing attractor enabled aggregation across all trials and subsequent significance testing at each of the 101 time-bins via t-tests (e.g., Spivey et al., 2005), as is typically done on these trajectories. However, in the multi-alternative IGT task here, each of three non-chosen decks could exert an attractive influence in different directions (e.g., to the lower-left).

For clarity, we present in Figure 3a only trials with curvature to the upper right (after "fixing" counterbalanced physical location).[3] The aggregate response trajectories

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[3]To illustrate the need for this filtering, assume that on two trials a

Figure 3: Time-normalized response profiles for Deck B. (a) Aggregate response trajectories across subjects for blocks 2, 3, and 5. Locations of start and response deck are approximate. All responses have been flipped to upper left in order to collapse across counterbalance orders. (b) Aggregate response deviation profiles (in pixels) across subjects for blocks 2, 3, and 5 for each of the 101-time bins (x-axis).
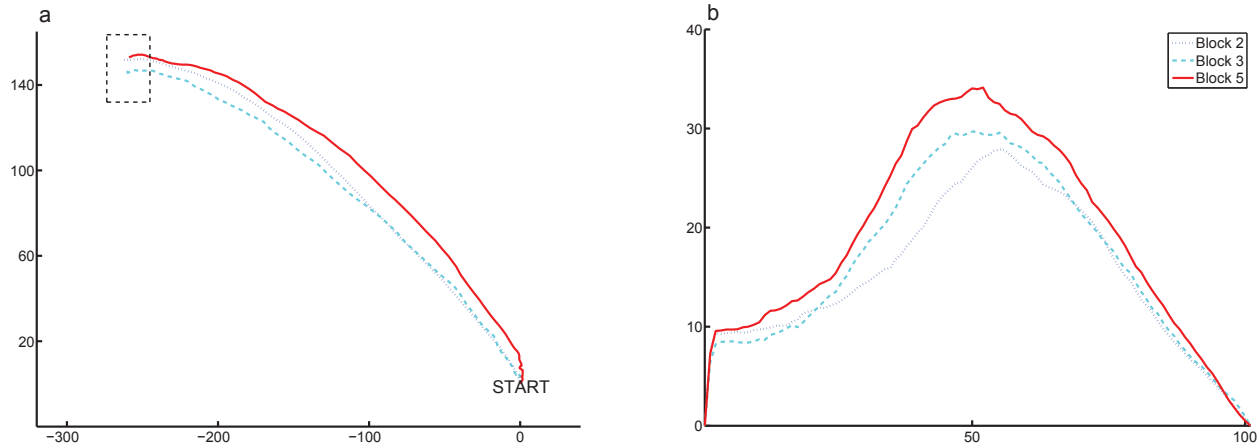
for trials with curvature to the lower left show a similar pattern but are not included. Figure 3b provides similar information in a manner that allows us to retain all directional attractors (i.e., include those trajectories that were not plotted in Figure 3a). Specifically, we computed across time bins the absolute deviations (from a straight line) in *either* direction for each Deck B trajectory for each subject, and then aggregated them. Relative to the curvature in Block 2 (dotted line, N = 330 trials), in Block 3 (dashed line; N = 261 trials) subjects have experienced mainly large gains from the deck and are therefore proceeding more directly to it (lower deviations). By Block 5 (solid line, N = 238), however, subjects have experienced many large punishments, making the decision to select Deck B increasingly difficult as evidenced by the wider path (greater absolute deviations from a direct path) taken during this block.

Individual measures.   The trajectory plots above are aggregated across subjects due to high individual variability, but it is important to analyze individual subject data as well (Estes, 1956; Estes & Maddox, 2005) to ensure the aggregate trajectories do not represent some

"virtual subject" who does not truly exist in the data. In the response dynamics literature, multiple measures have been considered. Here we utilize individual measures of maximum absolute deviation from a straight path (MAD), which most closely correspond to the aggregate data above (Figure 3b). We chose MAD because it highlights differences in the "heart" of each trajectory, and is not diluted by the start and end points held in common by all trajectories. For each individual, we computed the MAD for each deck type: bad (A and B) and good (C and D). A repeated measures ANOVA revealed a main effect of block $F(4,156) = 13.15$, $p < .01$, and a marginally significant interaction effect between block and deck $F(4, 156) = 2.22$, $p = .07$. Figure 4 shows that across blocks, MAD decreases for the good decks but increases for the bad decks. As before, this is interpreted as a decrease across blocks in competition from the bad decks when selecting the good decks (decreased reluctance), but an increase in the competition from the good decks on the bad decks (increased reluctance).

Outcome-based measures.   Finally, we thought that the response dynamics might be especially sensitive to the effects of winning or losing on a deck. For each subject and deck, MAD was calculated separately for two types of trials: (a) trajectories towards a deck when the previous selection from that same deck produced a loss; and (b) trajectories when the previous selection produced a gain.[4] Figure 5 shows the MAD for each deck on trials

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subject chooses Deck A (Figure 2). On trial 1, she makes her choice after also considering Deck C, whereas on trial 2 she makes her choice after considering Deck B. On trial 1, her trajectory will most likely start to the left before proceeding upwards, whereas on trial 2 her path will most likely start upwards before moving to the left. If we were to aggregate across these two responses, we would most likely see a straight path that did not reflect the competition our subject felt in her two choices. Therefore, we calculated deviation from a straight line between the first and last coordinates of each trial and aggregated two separate paths depending on the nature of that deviation. Only the positive deviation is shown in Figure 3a.

[4]For example, if a subject won money drawing from Deck C on trial 1, his next draw from that deck (perhaps trial 7) would be classified as following a win. Continuing the example, let's say on trial 9 our subject selected Deck B and lost money, his subsequent selection from that deck would therefore be classified as a loss.

Figure 4: Mean maximum absolute deviation from direct path. Lines represent bad decks (A and B; red) and good decks (C and D; green). After the globally high deviations associated with the exploratory activity in the first block, maximum absolute deviation (MAD) generally increases over blocks for selections from the bad decks, whereas it decreases for selections from the good decks.

Error Bars: +/- 1 SE
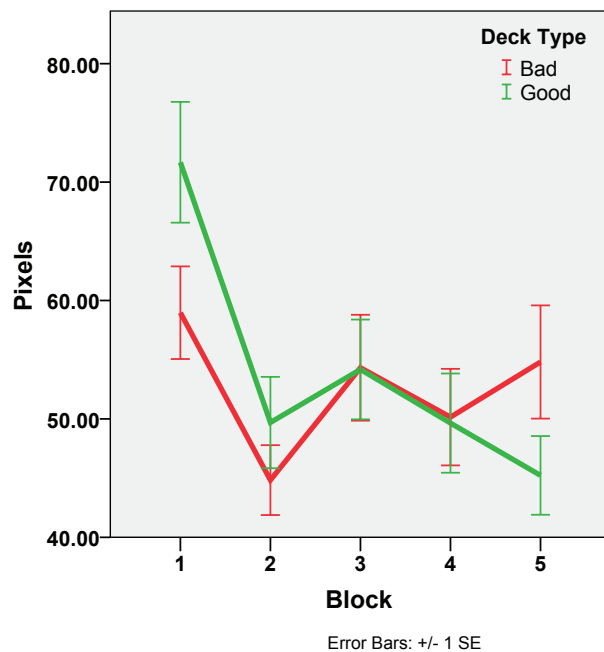
following that deck's wins or losses. As expected, deck selections following a loss have greater deviation (i.e., involve greater hesitation or conflict) than those following gains, although this effect was marginally significant, $F(1,29) = 3.02$, $p = 0.09$. Planned comparisons show a significant effect ($p < .05$) for Deck B and a marginally significant effect ($p < .10$) for the other bad deck, Deck A. A possible critique is that response-tracking metrics merely reframe information from more traditional measures, like response time (RT). To address this, we performed the same analyses on response times for each deck following either losses or wins. Surprisingly, Figure 5b shows the opposite and counterintuitive pattern, with selections following a loss happening *faster* than those following a gain. Again, the main effect of outcome was only marginally significant, $F(1,29) = 3.20$, $p = 0.08$, and only the effect for Deck A was significant ($p < .05$). Performing these analyses on log-transformed RTs produced similar conclusions.

4 Discussion

Our results illustrate the potential of the *response dynamics* methodology in its first application to a multi-alternative choice task, the IGT. Our observed choice proportions are in line with previous IGT results: as the experiment proceeded, subjects increased selections from the good decks and decreased selections from the bad decks. Interestingly, and in line with some previous data, subjects continued to draw from Deck B somewhat frequently, even though this frequency decreased over time. Although there was little change in the choice proportion of Deck B between blocks 3 and 5, time-normalized deviation profiles indicate that selections from Deck B were subject to the most competition from other decks during the final block (Figure 3)—a finding that cannot be inferred from choice proportions alone. Thus, although we demonstrate continued preference towards Deck B, the increased curvature on these trajectories indicates some degree of learning on the task, although determining whether this learning is motivated by "somatic markers" (Bechara, et al., 1997; but see Maia & McClelland, 2004 a,b) is beyond the scope of this experiment. An interesting follow-up question will be whether trajectories between patient and normal populations differ. If patients are truly unable to appreciate the impact of large infrequent penalties, they should not show increases in curvature when drawing from the bad decks.

Aside from simply exploring Deck B responses more fully, we also demonstrated general capabilities of this methodology by expanding on typical IGT analyses. Unique analyses provided by response dynamics suggest greater competition from bad decks when choosing good decks early on (Block 2 in Figure 4), perhaps resulting from a reluctance to leave the large payouts of the bad decks. However, by the end of the task (Block 5 in Figure 4), subjects have generally learned the payoff contingencies and thus show greater reluctance when selecting bad decks rather than good ones. Finally, these inferences can also be related to the experienced payoffs, which differed across subjects, blocks, and trials, and thus may dilute the aggregated effects. In particular, we separately analyzed trajectories following either a loss or a win and found that, especially for bad deck draws, there was greater competition after experiencing their losses relative to their gains (Figure 5a). Importantly, this pattern of results was markedly different than measures of RT, which showed a *decrease* following losses (Figure 5b). Thus, we conclude that metrics afforded by response dynamics provide a window into cognitive processes that is unique from more traditional measures.

While these data provided a brief example of how response dynamics can be fruitfully applied to a common decision task, our excitement about this methodol-

Figure 5: Mean maximum absolute deviation (a) and response time (b) for each deck by outcome. Selections were grouped by deck choice and then by previous outcome experienced on that deck. * p < .05. †*p* < .10.
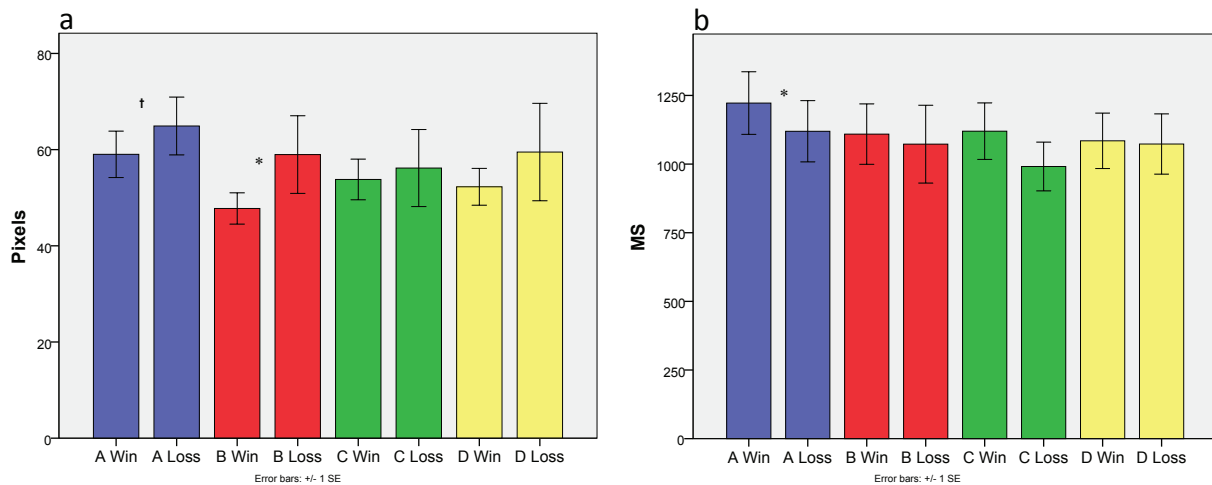
ogy stems largely from its potential to aid in the resolution of theoretical disputes. Below, we provide a brief "roadmap" for how the continuous data provided by response dynamics could distinguish between three different classes of models: one-reason decision making (e.g., Gigerenzer & Goldstein, 1999), so-called default-interventionist (Evans, 2008) dual-systems models (e.g., Kahneman & Frederick, 2002), and sequential sampling models (e.g., Busemeyer & Townsend, 1993; Diederich, 1997). From each of these models, we can derive very specific predictions about the form of response trajectories.

Strong versions of one-reason decision-making models (e.g., Gigerenzer & Goldstein, 1999) would predict non-committal trajectories that suddenly and sharply give way to an expression of preference. This sudden and sharp development of preference would be represented by velocity profiles with late spikes, and would not predict any online preference reversals. Contrarily, dual-systems models would predict these online preference reversals when response options place intuitive (system 1) and deliberative (system 2) systems at odds with one another. Of particular interest would be choices of the option preferred by system 2. Because system 1 is thought to be faster, on these trials trajectories should first proceed towards the system 1 option, before the deliberative system "overrides" this impulse causing an online preference reversal towards the deliberative option. Although these online preference reversals would preclude one-reason decision-making models, they would not necessarily distinguish between dual-systems and sequential sampling models. In order to further break apart these competing models, response dynamics could be paired with eye-tracking to see whether these reversals are the product of changes

in attention. Sequential sampling models would predict that changes in trajectory direction would be directly tied to changes in attention (e.g., Diederich, 1997), whereas dual-systems accounts would not necessarily predict such a systematic relationship between attention and preference.

In summary, we showed that response dynamics provides useful information unique from traditional measures, and provided a broad framework outlining how response dynamics could distinguish between competing models. Because mouse tracking has been shown to provide a real-time measure of cognitive processing (Freeman et al., 2011), we thus conclude that it can be widely applied to directly test process models of decision making and hope the current demonstration can help open the door to future work that will continue to do so.

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