Advanced mouse-tracking analytic techniques for enhancing psychological science

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Abstract
Computer mouse-tracking is a relatively recently developed behavioral methodology that can contribute unique insight into a wide variety of psychological phenomena. By recording mouse movements en route to specific responses on a screen, researchers glean continuous information about tentative commitments to multiple response alternatives over time. This approach yields a richness of data that can be fully explored with a variety of sophisticated analytic techniques, but these approaches are relatively underutilized and can be difficult to adopt. Here we describe several techniques for researchers to examine the onset and timing of evolving decision processes; test the degree of response competition at different time points; assess trajectory complexity with spatial disorder analyses; identify qualitatively distinct psychological processes during response generation; and finally to distill unique and meaningful components from mouse-tracking data for subsequent analysis. With this guide, we hope researchers can address novel hypotheses otherwise inaccessible with more traditional methods.

> "The best laid plans of mice and
> men often go awry."
>
> (Burns, 1785)

And often, going awry is psychologically meaningful. Recent advances in psychological science have shown that motion trajectories reflect underlying cognitive processes. In the current article, we discuss how analysis of computer mouse-trajectories and their temporal dynamics can provide powerful insight into these processes. Our goal is to describe how researchers might

incorporate mouse-tracking into their psychological toolbox such that they can address novel hypotheses within their areas of research. We primarily focus on recently developed advanced

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analytic techniques that capitalize on the richness of data provided by a mouse-tracking approach. First, to provide a larger framework conducive for understanding, we discuss the basic paradigm, the theoretical principles underlying the method, and provide examples of what novel hypotheses this technique has already been used to test. **[AQ: 1][AQ: 2][AQ: 3]**

We then provide step-by-step instructions for researchers to analyze the high-resolution temporal data provided by mouse-tracking with several techniques, and how these data might be analyzed to address unique questions that would otherwise be unanswerable with more traditional measures. Namely, we focus on (a) time course analyses of mouse-trajectory coordinates, useful in examining how various factors exert influence on or are integrated into the evolving decision process over time; (b) examination of velocity and acceleration, which can index the degree of response competition at different time points; (c) assessment of spatial disorder in trajectories, indicative of complexity and unpredictability associated with response dynamics; (d) the identification of smooth versus abrupt response competition, which can yield important insights into the presence of more dynamic versus more discrete-like cognitive processes; and finally, (e) principle components analysis (PCA), which can distill unique and meaningful components from the mouse-tracking data for subsequent analysis. Because of our own work with mouse-tracking, many of the examples will be drawn from the person perception and social categorization literature, but we stress that the methodology is readily applicable to diverse domains (see also Freeman, Dale, & Farmer, 2011; Song & Nakayama, 2008).

Basic Paradigm

Because of the ubiquity of a computer and mouse environment, setting up a mouse-tracking task is fairly simple, and requires no more hardware than that accompanying a common computer. While proprietary software could be used, a software package called MouseTracker has been developed, is frequently updated and maintained,

and is freely available for download online at http://www.freemanlab.net/mousetracker or by searching for "MouseTracker." This package has been rigorously tested and validated (Freeman & Ambady, 2010), and because it is the most easily accessible and widely available package, the rest of this manuscript will use the framework of this software for example purposes.

In a standard two-choice MouseTracker task,[1] participants are presented with an image, letter string, sound, video (or a combination of these) and then make a response using options that appear in the top left or right corners (see Figure 1). As participants move a mouse cursor to select the appropriate response across numerous trials, the x-, y-coordinates of the mouse pointer en route to response selection are recorded. These mouse trajectories are then aggregated and analyzed, providing a highly sensitive measure of both the extent to which and when during real-time processing a response was activated and partially committed to, even if not ultimately selected (Freeman & Ambady, 2010; Freeman, Dale, et al., 2011). Following the detailed help manual available on the MouseTracker website or by downloading the software locally, researchers can easily program an input file for various tasks.

Examples

Some of the earliest research studies implementing mouse-tracking as an index of response competition examined how atypical exemplars activated an opposing category to a greater extent than typical exemplars. Participants categorized animal pictures into "Mammal" and "Fish" categories. Critical trials featured atypical animals, such as whales, that resemble members of the fish category but truly belong to the mammal category. While participants correctly selected the accurate category, computer mouse-trajectories during these critical trials deviated more towards the unselected category than control trials, reflecting the partial activation of the "Fish" category, in turn activating initial motor movements toward that response that were suppressed over time (Dale, Kehoe, & Spivey, 2007).
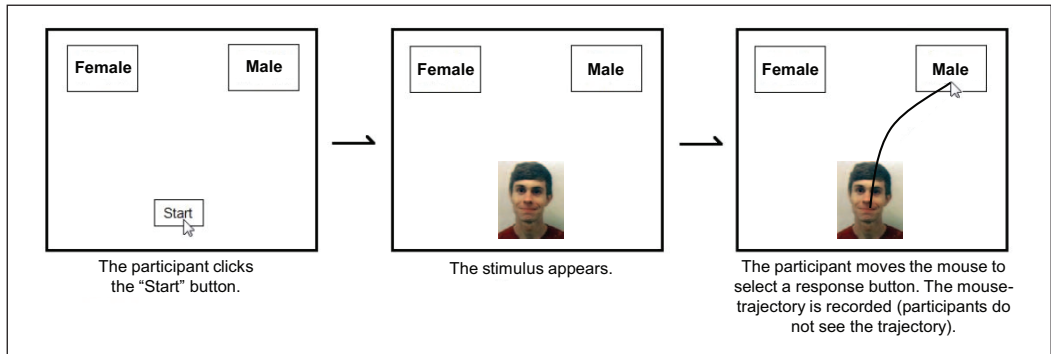
Figure 1. Example of mouse-tracking trial.

This result demonstrates how category activation can reflect "bottom-up" competition, or competition as a result of the visual characteristics shared by whales and fish. In addition, category activation can be influenced by "top-down" cognitive factors such as attention, motivation, or knowledge/expectations (e.g., stereotypes). One series of studies demonstrating this possibility drew from stereotypes of White individuals having high status and of Black individuals having low status in the US. Participants categorized faces surrounded by different status attire as "White" or "Black." When participants categorized a target as "White," if the target was wearing low-status attire (e.g., janitor clothing) their mouse-trajectories deviated toward the "Black" response. Conversely, when participants categorized a target as "Black," if the target was wearing high-status attire (e.g., business clothing) their mouse-trajectories deviated toward the "White" response (Freeman, Penner, Saperstein, Scheutz, & Ambady, 2011). These results suggest that, even when stereotypic expectations do not completely bias a perceptual outcome, they can nevertheless lead to a partial, tentative bias in perception. Thus, both bottom-up visual features and top-down social cognitive factors can influence mouse-trajectories individually or in conjunction, making mouse-tracking uniquely suited to examine both influences.

Researchers from diverse domains have since adopted mouse-tracking to answer their unique research questions. For instance, mouse-tracking has provided insight into the cognitive mechanisms underlying: the implicit association test (Yu, Wang, Wang, & Bastin, 2012), social evaluation and attitudes (Wojnowicz, Ferguson, Dale, & Spivey, 2009), target selection in visual search (Song & Nakayama, 2008), syntactic transfer in English-speaking Spanish learners (Morett & Macwhinney, 2012), how individuals with Williams syndrome perceive others (Martens, Hasinski, Andridge, & Cunningham, 2012), a wide range of category competition in person perception (e.g., Freeman & Ambady, 2009; Johnson, Freeman, & Pauker, 2012), and the downstream consequences of category competition in domains such as politics (Hehman, Carpinella, Johnson, Leitner, & Freeman, in press), among many other examples.

Theoretical Foundation

Understanding the theoretical principles driving mouse-tracking is critical to understanding how it is useful and distinct from other measures. Initially, mouse-tracking was used to distinguish traditional, discrete stage-based accounts of cognitive processing from continuous, dynamic accounts. Discrete stage-based accounts generally argue one cognitive process must be completed before the next can begin, whereas dynamic accounts argue that partial products of multiple parallel cognitive processes converge onto a stable and integrated response over time (Spivey & Dale, 2004).

One of the most prominent variants of discrete stage-based approaches are dual-process models, prevalent in the social cognitive literature. For example, dual-process models of social evaluation argue that people initially evaluate others in an automatic fashion, but that this initial evaluation can be further modified by a second discrete stage involving explicit, deliberative assessment. For instance, an individual's prejudice may lead to an implicit negative evaluation of another person, but this may be controlled by a deliberate motivation to be nonprejudiced (Devine, 1989). In contrast, research adopting a dynamic, rather than discrete, perspective of the social evaluation process has proposed that explicit evaluations emerge out of the continuous interaction between two attitudes, one that rapidly gains activation early in processing (i.e., implicit) and one whose activation slowly increases in magnitude but ultimately dominates (i.e., explicit) (Wojnowicz et al., 2009). Together, these parallel processes cohere into an integrated and stable evaluation over time. Thus, a traditional dual-process account would predict that an initial, implicit evaluation is discretely activated (e.g., "I don't like African Americans"), which is then countermanded by a more deliberate, explicit evaluation (e.g., "I like African Americans"). In contrast, a dynamic account would predict that both evaluations are simultaneously active and integrated in parallel into a stable response over time (Wojnowicz et al., 2009).

Another example comes from the domain of person construal. It has long been known that cues specifying gender, race, age, emotion, and other social categories are processed in the first hundreds of milliseconds in the perceptual stream (Hehman, Stanley, Gaertner, & Simons, 2011; Ito & Urland, 2003; Macrae & Bodenhausen, 2000). A recent theoretical framework and dynamic-interactive model of person construal argues that the early processing of such category-specifying cues triggers tentative hypotheses as to another's social category memberships. These initial hypotheses are refined as more information accumulates, until a final categorization that optimally integrates all available information stabilizes over time. Thus, cues extracted early (e.g., long hair) might initially elicit partial commitments to one gender category (e.g., female), but as additional facial information is processed and incorporated (e.g., masculine facial features), another category representation may increasingly become activated (e.g., male). Beyond bottom-up sensory cues, the constraints of top-down social factors (e.g., stereotypes, context, goals) also influence this process, placing excitatory and inhibitory pressures on consistent or inconsistent social category representations. Any conflicting representations (e.g., male vs. female) then resolve through dynamic competition, in which the two categories compete until stabilizing onto one over time. In this framework, person construal is thus argued to be an interactive, rather than compartmentalized, process in which multiple social category alternatives are simultaneously and partially active, competing for activation while evidence is dynamically integrated into a stable "compromise" over time (Freeman & Ambady, 2011a).

How can computer mouse movements distinguish between such discrete stage-based versus dynamic accounts? Because discrete stage-based models of cognition posit two independent and subsequent processes, mouse-trajectories would be expected to display an identical pattern of two independent and subsequent movements. More specifically, mouse movements would display an initial movement toward one response option that is abruptly and sharply redirected toward the other response option. A dynamic account, in contrast, would predict an attraction toward one response option that is then adjusted toward the other response option in a smooth and graded manner. Accordingly, previous research has used the characteristics of mouse-trajectories to address whether cognitive processes are better described by discrete stage-based or dynamic accounts. When responding whether they liked or disliked Black and White individuals, participants demonstrated a greater partial attraction toward "Dislike" when responding to Black individuals, and this trajectory was smoothly adjusted toward "Like" over time (Wojnowicz et al., 2009).

Similarly, when categorizing long- and short-haired males and females as "Male" and "Female," participants demonstrated a partial attraction toward the opposite gender when categorizing long-haired males and short-haired females, and these trajectories dynamically stabilized on the correct response over time (Freeman, Ambady, Rule, & Johnson, 2008). Because mouse-trajectories in both these examples exhibited partial attraction toward parallel competing responses that smoothly and continuously resolved over time (rather than an initial discrete activation of one response that was abruptly corrected by a later discrete activation of another response), such results support dynamic rather than discrete-like cognitive processes. At present, most research domains likely have far greater theoretical specification than the mere distinction between dynamic versus discrete-like processes, but this is one general manner through which mouse-tracking can distinguish between competing theoretical accounts in psychological science.

Why is measuring participants' hand movements a valid index of real-time cognitive dynamics? This approach is valid because response competition readily manifests in goal-directed motor movements. Specifically, research has shown that dynamic activity in neuronal populations of the premotor cortex is strongly tied to continuous motor movements, and these neuronal populations are stimulated by the decision process. For instance, single-cell recordings of neuronal activity in nonhuman primates revealed that during two-choice tasks in which primates have to reach out to select a response option, directionally tuned cells in the premotor cortex initially fire for both choices simultaneously. Over time, however, activity for the unselected choice decreases while activity for the selected choice increases (Cisek & Kalaska, 2005). These neuronal patterns of activity are consistent with predictions by dynamic models of response competition, in which multiple potential responses compete and resolve over time into a single stable representation. Moreover, behavioral work has long established that motor movement is continuously updated by cognitive processing over time (Goodale, Pélisson, & Prablanc, 1986), and electrophysiological work suggests that the process of categorizing a visual stimulus may immediately share its ongoing results with the motor cortex to continuously guide a hand-movement response over time (Freeman, Ambady, Midgley, & Holcomb, 2011). Thus, during a continuous movement in selecting one of two choices, the diverse elements of movement during response selection (e.g., acceleration of the hand, deviations toward one or another category, how frequently direction is changed) can be recorded and analyzed for insight into the psychological processes underlying the movement.

Recommendations for Basic Set-Up

Prior to discussing data-analytic approaches for analyzing these psychological processes, there are first several methods employed in our experiments we recommend as best practice for mouse-tracking data collection, to obtain the "cleanest" data possible for analysis. We note, however, that these approaches have not been empirically validated, and instead are derived from our previous experience.

First, prior to beginning experimental trials, participants are given several practice trials to familiarize themselves with the paradigm. Participants are encouraged to start moving as quickly as possible following stimulus onset, even if not yet fully certain of a response, and to feel comfortable "going with their gut." We intentionally avoid, however, specifying mouse-movement as the index of interest. Prior to starting an experiment, the experimenter ensures that participants understand the importance of initiating movement early. Indeed, we typically set the *initcut* feature to 400 ms, which causes trials in which movement initiation exceeds 400 ms following stimulus onset to display a warning message after participants have made their responses, encouraging faster initiation time on future trials. However, whether or not initiation time monitoring is implemented and, if so, what the *initcut* threshold is set at depends on the timing of experiments

and the particular interests of researchers. In a psycholinguistics or moral decision-making experiment, for example, the need for initiation time monitoring could be quite different. Without having an initiation time, participants may be tempted to begin moving only once a decision has been completely finalized, thus rendering the measure off-line. On the other hand, encouraging extremely fast initiation times by setting *initcut* to extreme thresholds such as 100 ms poststimulus onset may be so difficult that it may lead participants to strategize (e.g., making early, random movements to pass the threshold), which can bias results and/or dampen sensitivity to effects. For each particular task and psychological process being investigated, we recommend researchers conduct some pilot work to determine if initiation time monitoring would be helpful and what an appropriate threshold would be.

Other considerations include counterbalancing whether response alternatives appear in the top left versus right of the screen across participants (at least for the standard two-choice design with static response alternatives; in other experiments, response alternatives may change trial by trial). We also recommend using right-handed individuals, given the primacy of right-handed motor movement in these experiments. In the standard two-choice design, leftward and rightward kinematics can differ slightly likely due to right-handedness (e.g., Spivey, Grosjean, & Knoblich, 2005). A great deal of future methodological work is needed to investigate the role of handedness and numerous other factors that may influence mouse-tracking data. For hardware recommendations and other considerations, see Freeman and Ambady (2010).

Data Analysis

Mouse-Trajectory Deviations

The most commonly used method of mouse-tracking analysis thus far has focused on averaged deviations in trajectories toward one response or another. The measures specifically rely on area under the curve—the geometric area between the observed mouse-trajectory and an idealized straight-line trajectory drawn from the start and end points—and maximum deviation, the length of a perpendicular line between the idealized straight-line trajectory and farthest point from that straight line in the observed trajectory. Both measures assess the degree of attraction toward an unselected response, indexing the magnitude of activation for each response option as the decision process unfolds over time. Analysis of these measures has been more fully covered elsewhere (Freeman & Ambady, 2010). Instead, this paper will focus on more sophisticated data analytic techniques that allow researchers to fully capitalize on the richness of data resultant from recording dynamic mouse-trajectories over time.

Temporal Analyses

With MouseTracker, the position of the mouse cursor is recorded between 60–75 times per second (Freeman & Ambady, 2010). The onset and timing of mouse-trajectory deviations can therefore be used as a milliseconds resolution measure of the time course response activation (Dale & Duran, 2011; Farmer, Cargill, Hindy, Dale, & Spivey, 2007; Freeman & Ambady, 2010), and how behavioral responses evolve differently over time.

For specific examples as to how this temporal information might be used, one series of studies had participants categorize female political candidates as male or female, and examined how the activation of the male category (from masculine facial features) was associated with electoral outcomes. Attraction to the male category was negatively associated with electoral victory for female candidates. The researchers then examined when in the perceptual stream mouse-trajectories might differentiate female winners from losers, finding that a partial activation of the male category (i.e., partial attraction toward the "male" response) as early as 380 ms following face presentation was significantly predictive of electoral failure (Hehman et al., in press). In addition, other work has compared mouse-trajectories of Chinese and American participants during race categorization,

finding that a race-relevant visual context influenced the mouse-trajectories of Chinese participants earlier in the processing stream than for American participants, thus indicating that the context exerted an earlier influence on the categorization process in Chinese participants (Freeman, Ma, Han, & Ambady, 2013). Finally, other work examining gender categorization has shown that the atypicality of facial pigmentation cues led to trajectory deviations starting 100 ms earlier than that of facial shape cues, providing fine-grained time course information that pigmentation cues were processed earlier than shape cues (Freeman & Ambady, 2011b).

How to. To begin these analyses, researchers would import their data into MouseTracker Analyzer normally as described elsewhere (Freeman & Ambady, 2010). However, on the "Time" tab, researchers would instead select "Raw time analysis." Doing so will refrain from standardizing the length of trajectories, the default option, and thus allow for increased precision when examining movement within trajectories (however, if trajectories should substantially differ in length as a function of experimental condition, we recommend either normalized time analysis or performing raw time analysis only within each respective condition). "Max time" specifies at which point raw time trajectories would no longer be recorded, and "Time bins" specifies the amount of data points reported across a single trajectory (e.g., for a 1,000 ms trajectory, 20 time bins would equal 20 data points of *x-* and *y-*coordinate information averaged across 50 ms). With raw time analysis selected, when exporting the data from MouseTracker Analyzer to a comma-separated-value (CSV) file, raw *x-* and *y-*coordinates over time will be appended to each row of data (i.e., each trial). Cursor movement over time can then be analyzed as a function of other variables.

For instance, returning to the previous political example (Hehman et al., in press), we compared mouse-trajectories for targets receiving more votes (+1 *SD*) with targets receiving fewer votes (−1 *SD*). To do so, we averaged all mouse-trajectories for each political candidate to estimate the average *x-* and *y-*coordinate of the mouse cursor at each time bin. Using a series of correlations, we then tested whether the *x-*coordinate was significantly correlated with the electoral success of each candidate at each time bin (see Figure 2). *X-*coordinates were significantly associated with electoral outcomes starting at 380 ms and throughout the rest of the trajectory, supporting the possibility that the activation of the male category early in the perceptual stream might be influencing electoral outcomes.

Instead of *x-*coordinates alone, proximity to response options might instead be of interest to some researchers. Proximity is the Euclidean (i.e., straight line) distance between the cursor and response option, incorporating both *x-* and *y-*coordinates, and thus would be particularly useful when examining the potential for both horizontal and vertical deviations in trajectories over time. The formula for calculating Euclidean distance at any single time point is:

$$\text{distance}((x, y), (a, b)) = \sqrt{(x - a)^2 + (y - b)^2}$$

when (x, y) would represent the *x-* and *y-*coordinates of the cursor at any time point and (a, b) would represent the coordinate location of either response option. Although distance itself can be helpful, prior mouse-tracking studies have typically calculated proportional proximity:

$$1 - \text{distance} / \max(\text{distance})$$

After calculating proximity at each time point, researchers could examine the mouse's proximity to the unselected response option over time (e.g., Freeman & Ambady, 2009; Freeman, Pauker, Apfelbaum, & Ambady, 2010), its proximity to the selected response option over time, or both (e.g., Spivey et al., 2005). For example, Spivey et al. (2005) examined what point in time the mouse's proximity to the selected response significantly differed from its proximity to the unselected response. Such an analysis is akin to
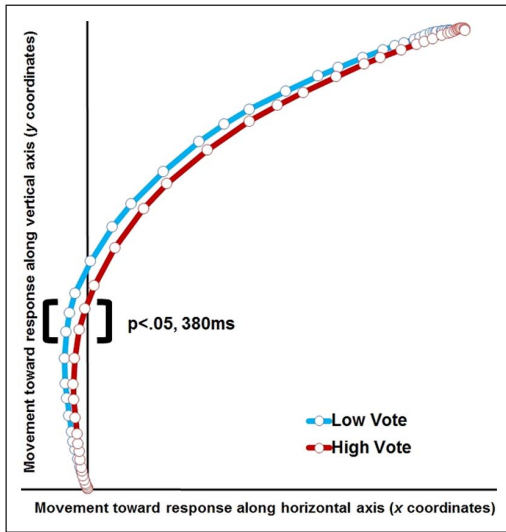
Figure 2. Example plotted *x-, y* coordinate data. We tested at which time bin mouse cursor *x*- coordinates were significantly correlated with electoral outcomes. Here, *x*-coordinates were significantly correlated at 380 ms (indicated by the brackets) and remained significant until the end of the trajectory. White dots represent the location of each time bin.

examining *x*-coordinate divergence over time, except that divergence using proximity scores incorporates both horizontal and vertical (i.e., *x*- and *y*-coordinate) divergence over time.

These are but two examples of how the time course of trajectory data might be used, and researchers might of course compare *x*- or *y*-coordinates across experimental conditions, across participant personality variables, across different populations, among many other possibilities.

Velocity and Acceleration

Examining time bins can additionally provide useful information about both the acceleration and peak velocities of the mouse cursor during response selection, and the psychological processes that might be driving such movement dynamics. Analysis of these components can shed insight into the temporal dynamics of response activation and competition. For instance, some quantitative theoretical models of

response competition posit that, when competing response alternatives inhibit one another early in processing, as the competition is resolved this inhibition is alleviated and rapid gains in activation of the previously inhibited response alternative should be observed (Usher & McClelland, 2004). This leads to the prediction that stronger competition between response options should be characterized by an initial decreased velocity as competing choices inhibit each other, followed by an increase in velocity once the system converges upon a decision and the inhibition is alleviated (see Figure 3).

Recent work has tested these models by analyzing the velocity profile of mouse movements during response selection. Investigating explicit racial attitudes, the researchers demonstrated that when participants made positive evaluative judgments of Black individuals, the velocity profile of mouse movements during the evaluative judgment process fits this predicted pattern of an initial decreased velocity and subsequent increased acceleration. Mouse movements when making positive evaluations of White individuals, on the other hand, were smoother and more continuous (Wojnowicz et al., 2009). This change in velocity might reflect the competition between positive and negative attitudes when evaluating Black individuals. Thus, velocity and acceleration provide unique information that can subtly but powerfully index the degree of competition, as well as its resolution over time. Importantly, such continuous behavioral data can additionally be compared with the real-time predictions of quantitative theoretical models.

Velocity and acceleration may also reflect the degree of response activation and thus allow for inferences about when commitments to a particular response are made. For example, in one series of studies participants affirmed or denied autobiographical information, after being instructed to respond honestly or deceptively (Duran, Dale, & McNamara, 2010). False affirmative responses showed smaller peak velocities than true affirmative responses, and velocity peaks were significantly delayed for false relative to true responses. Thus, peaks in velocity may
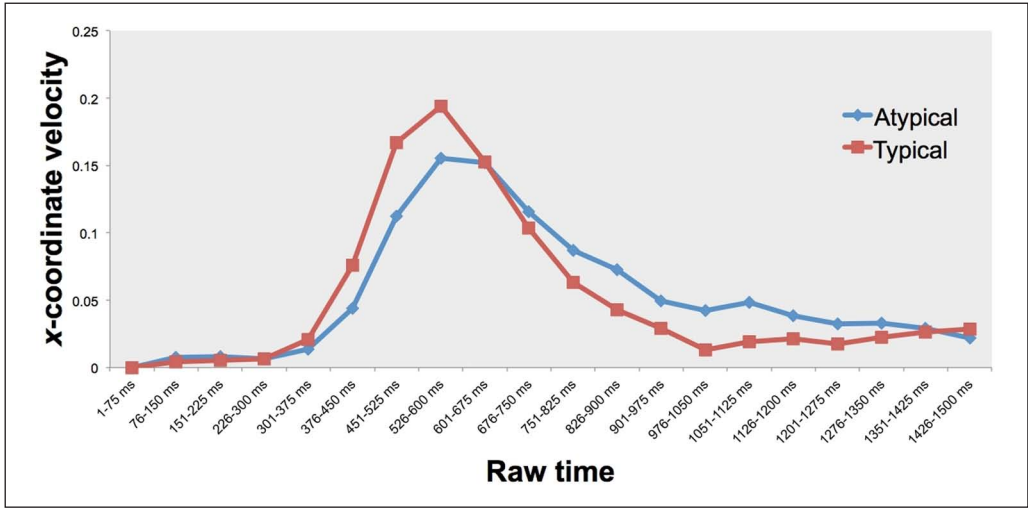
Figure 3. *X*-coordinate velocity plotted over time of mouse-movements when categorizing typical and atypical exemplars. Note that for atypical targets, velocity is initially slower than for typical targets (e.g., at 600 ms), but over time becomes increases to "catch up." These velocity profiles thus indicate different initial response commitments and how response options compete over time.

reveal the degree and onset of response commitment, potentially unveiling cases in which multiple response commitments occur.

How to. In the standard two-choice mouse-tracking paradigm, velocity is calculated as the distance between subsequent coordinates at different raw time points, and acceleration may be computed from changes in velocity across time points. MouseTracker Analyzer can compute these values on the basis of *x*-coordinates only (horizontal velocity/acceleration), *y*-coordinates only (vertical velocity/acceleration), or both (Euclidean-based velocity/acceleration), and include them in output upon specification. To do so, researchers would again select "Raw time analysis" in the "Time" tab of MouseTracker Analyzer. Proceeding normally, upon clicking "Compute," researchers will be asked to indicate from which coordinates to compute velocity and acceleration. After exporting the data to the CSV file, velocity and acceleration values will be appended to the end of each trial per the number of time bins specified in the "Time" tab. From these data, researchers may explore how velocity

and acceleration relate to their psychological phenomena of interest.

Spatial Disorder Analysis

Complexity arises in the behaviors of many dynamic biological systems, including the human brain. In some cases, it may be helpful to measure the complexity of mouse trajectories. Should multiple response alternatives act as simultaneous attractors exerting an influence on participants' mouse trajectories (relative to only one), this additional stress might manifest as less smooth, more complex, and unpredictably fluctuating trajectories (see Figure 4). For instance, research has found that atypical (e.g., whale) relative to typical (e.g., cat) exemplars of a category (e.g., mammal) elicit more complex trajectories (Dale et al., 2007). For researchers subscribing to dynamical systems perspectives, complexity in response trajectories may be taken as evidence for a formal dynamical process at work (e.g., Dale et al., 2007; Spivey, Anderson, & Dale, 2009). Spatial disorder analyses are optimal for those interested in estimating the complexity of trajectories. Spatial disorder may be
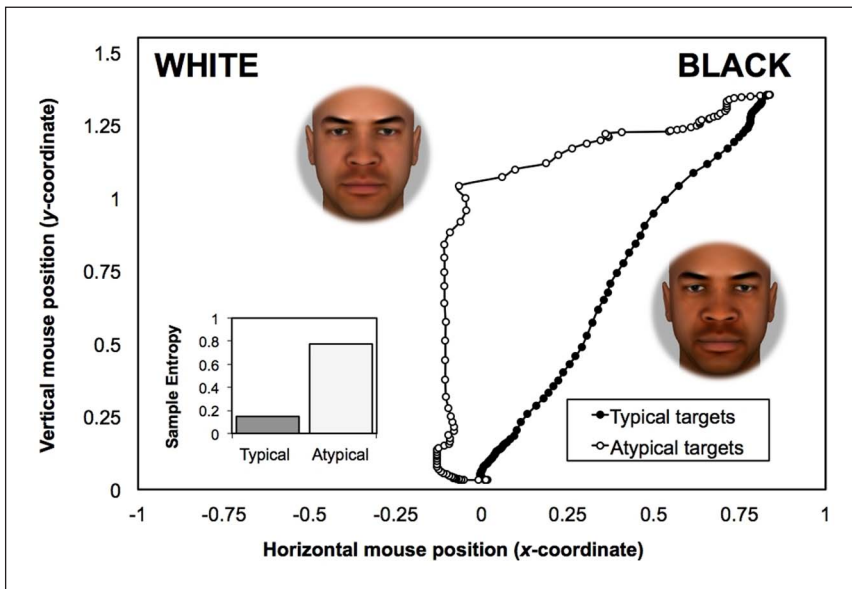
Figure 4. The sample entropy of two different mouse-trajectories. Here, the more jagged and complex trajectory during categorization of the atypical than typical target results in greater sample entropy.

analyzed through various trajectory parameters. Sample entropy (Richman & Moorman, 2000) is likely the most comprehensive measure, measuring the degree of irregularity and unpredictability in movement across the *x*-axis. Although far more crude, the simplest measure is *x*-flips, the total number of directional shifts made in a trajectory and supplying information about directional consistency. However, if disorder in *x*-axis movement does not involve directional changes, *x*-flips often will not pick up on these changes (Dale, Roche, Snyder, & McCall, 2008).

How to. Spatial disorder analyses may be performed several ways. In mouse-tracking sample entropy analyses, we are interested in spatial disorder along the decision axis as complexity upon this axis should relate to competition. For discussion, we assume the *x*-axis is the decision axis in a task. The sample entropy of a time series is the "negative natural logarithm of the conditional probability that … sequences similar for *m* points remain similar at the next point" (Richman & Moorman, 2000, p. 2039). Thus, sample entropy increases as areas in a trajectory similar at one

length are no longer similar at a greater length, meaning there is greater complexity and fluctuation in the trajectory.[2] To compute sample entropy, researchers would first convert the data to normalized time so that trajectory length does not confound entropy between trials (the default option in MouseTracker). Next, researchers would determine various parameters, including (a) the number of time steps to normalize time to (*N*), (b) the "window" size (*m*; length of sequences to be compared for similarity), and (c) the tolerance (*r*; threshold for determining similarity between windows). There are no universal standards for these parameters, but we make several recommendations. By default, MouseTracker normalizes trajectories to 101 time steps, and we use that here. Evidence indicates windows between *m* of 3 and 6 most sensitive (Dale et al., 2007), though researchers may want to test different window sizes. Finally, to determine similarity between windows, researchers can count the number of window pairs that are similar within a tolerance based upon a distance measure. For example, recent work (Dale et al., 2007) computed the maximal difference between pairs of

x-shifts within a window, and determined the window pair to be similar if the difference was within a tolerance of .2 multiplied by the standard deviation of the *x*-shifts (the method employed in our Python script in the Supplementary Material).

After data is exported with *x*-axis points in normalized time per trajectory (101 time steps on the *x*-axis per trajectory), researchers would compute the *x*-shifts between each step in normalized time ($\Delta x = x_{timestep+1} - x_{timestep}$, which should result in $N - 1$ *x*-shifts). Next, researchers would count the number of similar m and $m + 1$ sized *x*-shift windows (M_m and M_{m+1}). Finally, researchers would calculate the average count of similar windows for all m and $m + 1$ sized windows, whereafter sample entropy can be computed as $-\ln(M_{m+1}/M_m)$ (i.e., $\ln[M_m] - \ln[M_{m+1}]$). See the Supplementary Material for a Python script to calculate sample entropy and further detail. This measure may then be submitted to statistical tests to investigate its relation to other variables.

In normalized time, MouseTracker automatically provides *x*-flips (and *y*-flips) per trajectory in its output. The user may set parameters regarding what constitutes a change in direction. To do so, after the data has been imported and visualized but prior to selecting "Compute," researchers would select "Settings" to indicate the minimum and maximum distances to be considered a change in direction. To detect very subtle changes in direction, a minimum change of .01 may be appropriate; to detect larger scale changes, however, a minimum of .25 may be more appropriate. Following exporting the data to a statistical analysis software package, *x*-flips can then be analyzed an as outcome measure of interest.

Smooth Versus Abrupt Response Competition

Trajectories. A visual inspection of individual mouse-trajectories from any mouse-tracking experiment will quickly reveal that they may take several general shapes. In this section, we examine how these different shapes may themselves be analyzed to test whether different experimental conditions might result in different types of competition or response-activation patterns. One distinction that has been theoretically valuable is between mouse-trajectories exhibiting smooth, graded competition (Figure 5, Panel A), and those in which competition results in initial movement towards one response that is abruptly redirected midflight toward the other response (Figure 5, Panel B). Researchers may find that these two response trajectories are an index of unique cognitive processes, which, when analyzed, help to answer their theoretically important psychological questions.

For instance, consider a situation in the domain of person perception. When perceiving a face, some features are highly salient but not very diagnostic of the social categories in question, and some features are not very salient but highly diagnostic. Consider hair length, a highly salient but not very diagnostic feature (as both males and females can vary in hair length), and gendered facial features, less salient but highly diagnostic in accurately categorizing another's gender. When categorizing targets with gender-typical hair but a mixture of masculine and feminine facial features, the activation of the male and female category representations could be smooth and gradual, as additional cues are integrated until ultimately one category is selected and the activation of the competing category is inhibited. Mouse-trajectories capturing this process would similarly be smooth and graded, as in Panel A. On the other hand, targets with gender-atypical hair might elicit a qualitatively different kind of trajectory. For example, when categorizing a male with long hair, because hair is highly salient, the "female" category might initially receive a great deal of activation. Only upon further processing of the target and incorporating the masculine facial cues would activation of the female category be suppressed, and the male category come to be fully activated. Mouse-trajectories capturing this process would reveal an initial direct path toward the female category that is then abruptly shifted toward the male response midflight (Figure 5, Panel B). Recent work has provided evidence for both these smooth and abrupt
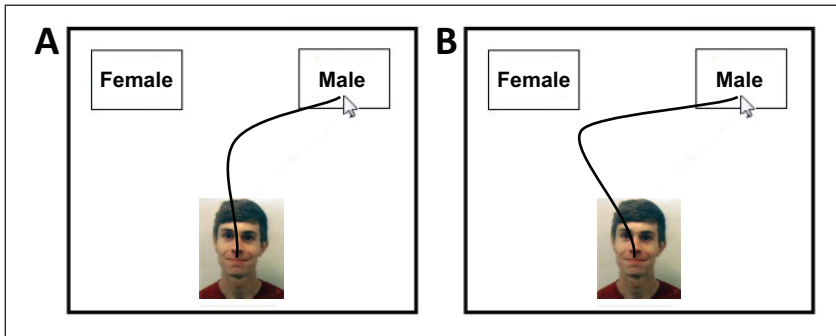
Figure 5. Examples of mouse-trajectories indicative of (A) smooth, continuous competition between responses and (B) a discrete, abrupt shift in categorization. Whether trajectories more resemble one or the other of these alternatives can provide insight into the underlying cognitive processes determining response options.

competitive dynamics during gender categorization (Freeman, 2014).

How to. Several approaches can be taken to determine if mouse-trajectories are better defined as smooth versus abrupt response competition. The first is a qualitative approach. Researchers can examine each trial for each participant in Mouse-Tracker Analyzer, and manually code each trial as smooth or abrupt (accordingly, coders should be blind to hypotheses). To mark a trial with an abrupt direction change, select a particular trajectory and right-click on it in the "Selected Trajectories" box in the bottom right of the window. Select the "Assign single trajectory to condition" option, and input whatever code is being used to demarcate trajectories with abrupt shifts. Upon exporting the data into the CSV file, this code will accompany the trajectory for use in subsequent analysis.

While rigorous, examining all trajectories for all participants can be quite time-consuming and subject to human error, and faster quantitative approaches might be adopted utilizing default output from MouseTracker Analyzer. Previous research has defined trajectories with abrupt shifts as those with a maximum deviation exceeding .9, indicative of a significant deviation toward an unselected category (Freeman, 2014). In this particular study, the qualitative method described in the previous lines and the quantitative approach described here were highly correlated, but

researchers should use their own judgment in deciding which is best for addressing their hypotheses. A final option is to use the measures of velocity and acceleration, covered earlier in the current work, to index smooth versus abrupt response competition. Previous research has found that abrupt shifts in trajectory were marked by an initial spike in velocity towards one response, followed by a second spike in velocity after the reversal in direction (Freeman, 2014).

Following identification, trajectories with abrupt directional changes may then be statistically compared to those with smoothed movement, or whether a smooth versus abrupt change trajectory was evidenced may be used as a dependent variable for various analyses. For instance, previous research has found that when categorizing targets by gender, more ambiguous targets elicited a greater likelihood of abruptly shifting mouse-trajectories, as compared to smooth trajectories (Freeman, 2014).

Distribution. While the above section lays out how individual trajectories might be defined as smooth versus abrupt shifts to answer particular research questions, often a given experimental condition can contain a mixture of subpopulations varying in form. For example, and as discussed earlier, researchers have argued that a given experimental condition involves dynamic competition of multiple responses continuously competing over time (Dale et al., 2007; Freeman & Ambady, 2009;
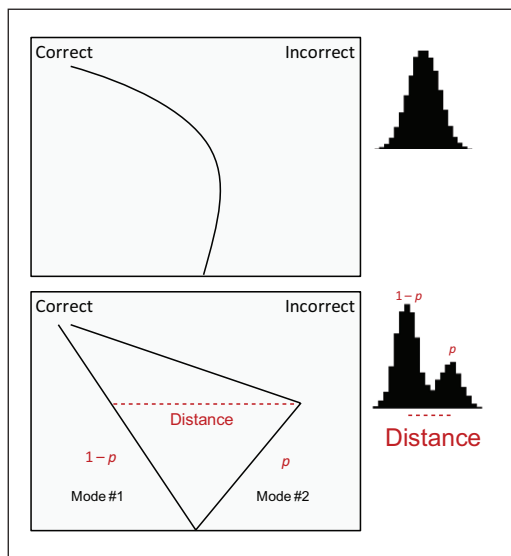
Figure 6. A schematic illustration of how a single mode of dynamic competition (top panel) and dual modes of discrete response patterns (bottom panel) manifest in the distributional characteristics of mouse-trajectory deviations. Adapted from Freeman and Dale (2013).

Spivey et al., 2005). The mean trajectory of this condition should therefore appear similar to that in the top panel of Figure 6, exhibiting graded, dynamic attraction toward the opposite response. However, it is also a strong possibility that such a mean trajectory could be spuriously produced by one subpopulation of trajectories exhibiting abrupt shifts in direction (Mode #2 in the bottom panel, Figure 6) and another subpopulation exhibiting a completely direct movement with virtually no attraction (Mode #1 in the bottom panel, Figure 6)—the exact prediction made by discrete rather than dynamic models. Previous research has empirically demonstrated that averaging across these two modes of discrete-like trajectories (some "incorrect" trials exhibiting abrupt shifts and other "correct" trials exhibiting direct movements) produces a mean trajectory that feigns graded, dynamic attraction as in the top panel of Figure 6 (Freeman et al., 2008).

Because it is highly unlikely that every single trajectory within a given condition would exhibit such extreme abrupt shifts (rather than only a certain proportion doing so), the critical analysis needed to understand the underlying nature of responding in this condition and to distinguish between dynamic versus discrete models is whether the trajectory curvatures are unimodally or bimodally distributed. A unimodal distribution would indicate one population of trajectories exhibiting smooth, graded competition with a distributed range of low, medium, and high strength (consistent with dynamic models), whereas a bimodal distribution would indicate two subpopulations of trajectories exhibiting two different modes of discrete-like responding (consistent with discrete models). As such, distributional characteristics are treated as empirical patterns to be predicted and tested directly, as they reveal temporal dynamics across an entire condition (e.g., Dale & Duran, 2011). Given the importance of these analyses for understanding the nature of a condition's temporal dynamics, Freeman and Dale (2013) recently conducted simulations to examine how various bimodality measures are influenced, and in some cases biased, by how divergent the two response modes are (i.e., "distance" in Figure 6), the proportion of trials in the two response modes (i.e., "proportion" in Figure 6), the total number of trials used, and the amount of skew present (often observed in response data).

How to. To examine the distributions, researchers would export normalized area under the curve or maximum deviation data within the population of responses they wish to analyze from Mouse-Tracker. Recent simulations of bimodality measures found Hartigan's dip statistic, a measure of multimodality, to be most sensitive and accurate in most contexts (Freeman & Dale, 2013). This test can be performed using the dip test package in MATLAB (http://www.nicprice.net/diptest) or R (http://cran.r-project.org/web/packages/diptest/index.html).

Distributions with dip statistics under .05 are considered significantly bimodal, those under .1 marginally bimodal, and those greater than .1 unimodal (Hartigan & Hartigan, 1985). However,

the measure historically used in mouse-tracking research since Spivey et al. (2005) has been the bimodality coefficient (*b*). To manually calculate the bimodality coefficient (*b*), a researcher computes:

$$b = \frac{g_1^2 + 1}{g_2 + \dfrac{3(n-1)^2}{(n-2)(n-3)}}$$

in which g_1 is skewness of the distribution, g_2 is kurtosis, and *n* is the number of observations. The distribution is bimodal if $b > .555$ (Freeman & Dale, 2013). To date, the *b* coefficient has been used in many published mouse-tracking papers, and it was empirically demonstrated to have sufficient sensitivity to distinguish between dynamic versus discrete models using mouse-tracking data (Freeman et al., 2008). However, recent work found that it can suffer from strong biases due to positive skew in addition to more anomalous biases, and that the dip statistic may instead be the optimal bimodality measure for future work (Freeman & Dale, 2013). Nevertheless, the *b* coefficient is available through MouseTracker. Once researchers have run "Compute" on their time-normalized data, they may then right-click the condition panes in order to see the distributional analysis for that condition. The distributional analysis window provides various statistics including the *b* coefficient, choice of attraction measure ("Area Under the Curve" or "Maximum Deviation"), and visualization options.

Principle Components Analysis

In this final section we will discuss using principle components analysis (PCA) to identify distinct components within averaged mouse-trajectories that can be extracted for subsequent analysis. PCA is a data-driven dimensionality reduction technique that can be used to identify core components underlying vast amounts of data. By assessing the variance shared between numerous data points, this technique forms linear combinations of the original measures that capture most (e.g., 99%) of the original variance while reducing

the dimensionality of the data to its "core" components (Dunteman, 1989). An advantage of this technique is that it can create components that are 100% orthogonal by definition, allowing for statistical tests of single dimensions without concern for overlap or interactions with other dimensions.

In social psychology, PCA frameworks are perhaps best known for use in both exploratory and confirmatory factor analyses examining how many dimensions a self-report scale might have. But PCA can be used in a wide variety of situations in which data reduction is of interest to researchers, such as identifying latent components on both spatial and temporal dimensions in electrophysiological data (Hehman et al., 2011; Hehman, Volpert, & Simons, 2014; Spencer, Dien, & Donchin, 2001). Similarly, it is ideal for identifying unique components within a mouse-trajectory, in which the data points within each component may be more correlated than with data points in other components. These separate components may index unique psychological constructs. PCA thus provides a method to identify and extract multiple components from averaged mouse-trajectories for purposes of submitting them to further analysis. For instance, researchers might wish to examine whether cues processed early in the perceptual stream (e.g., race, gender) influence early components of the trajectory whereas cues processed later in the stream (e.g., context, facial configuration) influence later components of the trajectory.

How to. To conduct PCA on mouse-trajectory data, researchers would first feed the *x*-and *y*-coordinate information (found appended to each trial in the exported CSV file) into a data analysis software package (e.g., R, SPSS). What specific data is submitted to the PCA is at the researcher's discretion and depends upon the research question; here we use normalized *x*-coordinates (though other measures covered in previous sections such as velocity and acceleration might be revealing). Once the data is loaded, researchers would perform a principle components analysis on the data. In SPSS, this would be
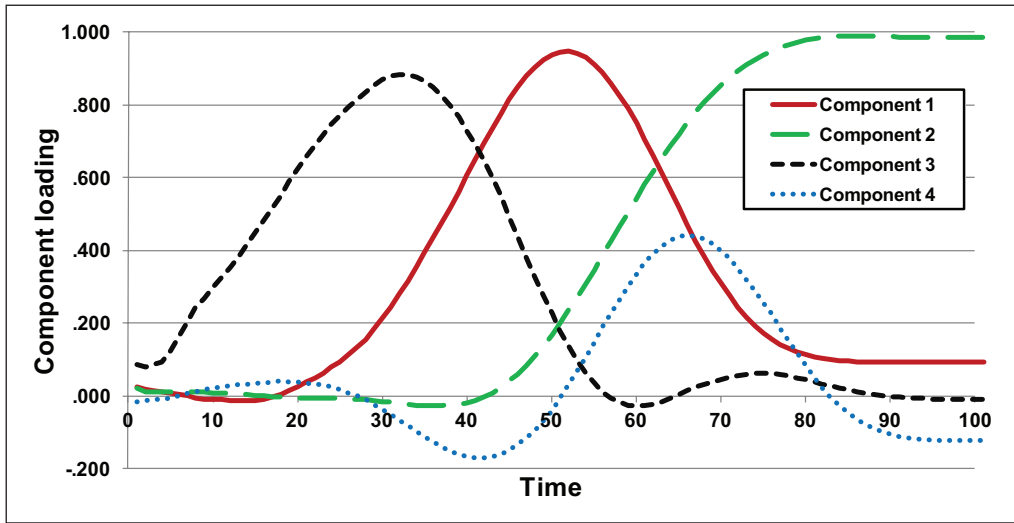
Figure 7. Principal components analysis decomposing distinct components of *x*-coordinates within hundreds of averaged mouse-trajectories.

done by selecting Analyze-> Dimension Reduction->Factor. Variables representing all time bins would then be entered into the "Variables" box. To derive orthogonal components, varimax rotation would be specified on the "Rotation" tab.[3] See Supplementary Material for SPSS syntax and further detail.

Upon running the analysis, researchers would examine the "Rotated Component Matrix" in the output. These are the unique components identified in the mouse-trajectory data. Loadings on each of these components can then be plotted over time for interpretation (see Figure 7). In mouse-tracking tasks typically conducted in our research, we generally find three to five distinct components driving mouse-trajectories. For example, Figure 7 demonstrates four distinct components within the *x*-coordinates of mouse-trajectories averaged around 50 participants with several hundred trials each. Simply, the *x*-coordinates within each of these components are more correlated than between these components. From these results, researchers might surmise that what appears as continuous *x*-coordinate movement throughout a mouse-trajectory is driven by four unique components, which may index unique cognitive processes. Plotted across percentage of

time of the full trial on the *x*-axis, individual components might reflect, for example, an initial impulse upon seeing the stimulus peaking around 30% of the way through the trial (Component 3), a midflight correction of this impulse occurring about 50–60% of the way through the trial (Component 1), and finally movement towards the final selection decision (Component 2) (components are labeled according those accounting for the greater percentage of variance in the total trajectory, so Component 1 accounts for the greatest percentage of variance, Component 2 the second most, etc).

Component matrices can then be used to guide the creation of new variables, using the time bins that load highest on each component. For instance, referring to the example in Figure 7 and using time bins that load .6 or higher, a "Component 3" variable might be created by averaging time bins 20 through 40, a "Component 1" variable by averaging time bins 45 through 65, and a "Component 2" variable from averaging time bins 66 through 100. Statistical tests can then compare individual variation on these components to address particular research questions. For instance, earlier we referenced theoretical perspectives on social evaluation that describe how less

explicit attitudes guide evaluations of others ear- lier in processing but then how the dynamic evalu- ative process is overcome by a slower, more explicit attitude later in processing (Devine, 1989; Wojnowicz et al., 2009). Researchers with similar interests in examining early and automatic versus slower and more deliberative processing might implement PCA to identify components uniquely associated with each of these processes. These extracted components could then be submitted for a targeted and more sensitive analysis.

General Discussion

Computer mouse-tracking is an easily implementa- ble method that produces data with great richness and depth. While most published research using mouse-tracking has focused on analyzing devia- tions in trajectories, here we present five additional and more sophisticated techniques that allow researchers to answer theoretically significant questions across many domains in psychological science. These techniques are (a) statistical com- parison of mouse-coordinates over time, useful in examining the onset and timing of evolving deci- sion processes; (b) examination of velocity and acceleration, which can index the degree of com- petition at different time points during the decision process; (c) assessment of trajectory complexity with spatial disorder analyses, revealing unpredict- able movements due to additional stress from mul- tiple response alternatives attracting response trajectories; (d) the identification of smooth versus abrupt response competition, which can shed insight into potentially qualitatively distinct psy- chological processes during response generation; and finally (e) PCA, which can distill unique and meaningful components from mouse-tracking data for subsequent analysis.

Given the multiple potential analyses dis- cussed before and the richness of mouse-tracking data, there are several final points important for researchers employing these methods to consider. "Researcher degrees of freedom" is an issue receiving a considerable amount of attention in the sciences recently (Francis, 2013; Simmons, Nelson, & Simonsohn, 2011), and reanalyzing a

dataset with multiple approaches increases the likelihood of finding spurious significance. The techniques presented before, however, are based on the same underlying data, and can be used as complementary analyses supporting the conclu- sions of the primary approach. That said, many of these different analytic approaches carry their own implications and theoretical significance, as they all answer unique questions about underly- ing patterns in the data. The value of any single approach will depend on the goals of a given study. As with any methodology, we recommend researchers use the analytic approaches that best address their specific hypotheses, but in addition consider complementary approaches to provide converging evidence for their conclusions or more deeply examine the nuances of their data.

In conclusion, we hope this guide will facilitate the incorporation of more advanced mouse- tracking techniques into researchers' psychologi- cal toolboxes, so that they may address novel hypotheses that are more difficult to assess using more traditional measures.

Notes

1. While the two-choice design has been stand- ard, recent research has adopted four-choice or other multiple-response options as well (Cloutier, Freeman, & Ambady, 2014; Freeman, Nakayama, & Ambady, 2013).
2. Specific software packages exist for sample entropy analyses, but for greatest accessibility we here report how to run such analyses without them (see the PhysioNet MATLAB package; Dale et al., 2007).
3. For an introductory but in-depth discussion of the advantages and disadvantages of various rota- tion techniques, we recommend Field (2009).

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