Running head: MENTAL REPRESENTATIONS

The Nature of Information Loss Across a Range of Tasks

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Abstract

Theories of cognition specify that stimulus information is either gracefully degraded or lost completely on a trial. Testing these competitors remains controversial. We leverage an improved technique from Province and Rouder (2012) that uses confidence ratings. Mixtures in ratings from detect and guess states are evidence of complete loss; shifts in ratings are evidence of graceful degradation. Analyses of recognition memory of words and the identification of briefly presented words reveal both tasks are mediated by complete loss. Here, we apply the technique to the discrimination of orientation differences. We find the opposite result—loss is graceful rather than complete. The contrasting results provide confidence that the technique does not have excessive method bias and may be used to assess information loss across many tasks. The contrast also raises the question of why the identification of words is mediated by complete loss while the judgment of orientation is mediated by graceful degradation.

The Nature of Information Loss Across a Range of Tasks

Theories of cognition center on how information is encoded, represented, and processed in the chain from stimulus to response. A critical element of this chain is information loss, and indeed, most theories of cognition specify how information degrades across processing steps. The most common specification is what we term *graceful loss*: stimulus information is represented more or less faithfully, but is disturbed by internal noise to some degree. Examples of this theme of graceful loss are the theory of signal detection (Egan, 1975), the diffusion model of perception (Ratcliff, 1978), and ideal observer models (Attneave, 1959; Ma, Beck, Latham, & Pouget, 2006). An alternative viewpoint is that on some proportion of trials, information loss is complete and that behavior on these complete loss trials reflects a guessing process devoid of any stimulus information. Examples of this theme of complete information loss are limited capacity models of working memory (Cowan, 2001; Rouder et al., 2008; Zhang & Luck, 2008) and threshold models of perception (Blackwell, 1953; Egan, 1975; Fechner, 1966; Luce, 1963; Townsend, 1971). Unfortunately, methods for discriminating these themes with behavioral data have been controversial, especially in working memory (e.g., Anderson, Vogel, & Awh, 2011; P. M. Bays & Husain, 2009; P. Bays, Wu, & Husain, 2011; Cowan & Rouder, 2009; Thiele, Pratte, & Rouder, 2011) and recognition memory (e.g., Dube & Rotello, 2012; Broder & Schutz, 2009; Klauer & Kellen, 2011).

Recently, Province & Rouder (2012) introduced a novel and straightforward approach to test whether information loss is graceful or complete. We outline this approach in the next section and then apply it to tasks in three domains: recognition memory, perceptual identification of words, and the discrimination of orientation disparity. We find clear results in all three domains: the recognition and perceptual identification of words are clearly mediated by complete loss in a discrete-state architecture. In contrast, the discrimination of orientation disparity is mediated by graceful loss as described by the theory of signal detection. The presence of these opposing results has three ramifications: First, they show it is possible to discriminate between these theories of loss. Second, they demonstrate that the type of loss is task and stimulus dependent. Third, they motivate the question of what overarching principles may determine which domains are characterized by complete loss and graceful loss. We speculate here that words are subject to complete loss because they are inherently categorical in nature while orientation disparities are not.

Complete Information Loss Predictions

Province & Rouder (2012) introduced a test of discrete-state models of complete information loss. The test is most easily explained in the context of an example, and we discuss it here in the context of a recognition memory task. In our task, participants first study a list of words. Then, at test, they are presented both a studied word and a novel word, one on the left and the other on the right. Participants place a slider somewhere between the two words to indicate simultaneously which is old and how confident they are in the judgment. Stimulus strength is also manipulated, and in the recognition memory task, some words are repeated once at study, and others are repeated four times at study. Additionally, on a small minority of trials participants are presented two new words at test so that the behavior under guessing may be localized should participants guess. We refer to these perhaps euphemistically as *zero-repetition* trials as the target word was studied no times.

Figure 1A-F shows predictions for a discrete-state model in this paradigm. Let's suppose a participant has previously studied the word *STATUE* and at test is presented *STATUE*, the target, and *MIRROR*, the lure. The top row, Panels A & B, show respectively hypothetical confidence-rating distributions when the participant is guessing and when the participant has correctly detected that *STATUE* rather than *MIRROR* was studied. The hypothetical confidence ratings under guessing are centered to show a lack of overall bias toward the target or lure (Figure 1A). This pattern differs from the hypothetical confidence ratings under detection (Figure 1B), which are shifted toward the target item. In the discrete-state model, observed responses are trial-by-trial mixtures of detect and guessing states. For the zero-repetition trials, where two new items are shown, participants must guess, and the observed responses reflect solely the guessing state (Figure 1C). For one repetition of the studied item, there is a more balanced mixture, and Figure 1D shows the case where half the responses are from guessing and the other half are from detection. For four repetitions of the studied items, more responses are from detection than guessing (Figure 1E).

The key characteristic of these predictions is that while repetition at study certainly affects the probability of entering either a guess or detect state, the guess and detect components of the observed mixture distributions remain stable across repetition conditions. This key characteristic is termed *conditional independence*: conditional on a mental state, the probability distribution over responses is independent of the number of repetitions, or more generally, of the stimulus strength manipulation. Conditional independence imposes clear and testable constraints on the distributions of confidence ratings. Figure 1F shows these constraints—all three distributions from the previous mixtures are represented here in a single plot to aid comparison. The confidence ratings for the zero-repetition and the four-repetition conditions are presented in the usual orientation; the confidence rating distribution for the one-repetition condition is projected downward to reduce clutter. The conditional independence property guarantees that the global gestalt will be a lining up of components, much like looking at two mountain peaks reflected in a lake. The predictions of the discrete-state model of complete loss may be contrasted to a signal-detection model of graceful loss. Figure 1G shows the predictions of this competitor. The distributions shift toward the target response with increasing repetitions, or more generally, with increasing strength. The global gestalt violates this vertical symmetry. Because the contrast between these two predictions is visually salient, we present confidence ratings across strength conditions in the format of Figures 1F and 1G, with distributions from extreme conditions projected upward and those from intermediate conditions projected downward.

Figure 1 show the case where the target is on the right. If the target is on the left, the predictions follow a mirror symmetry where the detection component is on the left under complete loss (cf., Figure 1F) and shifts leftward with increasing strength under graceful loss (cf., Figure 1G). We will present all data as if the target is on the right, and when the target is on the left, we will reverse the confidence ratings such that Figures 1F and 1G describe the differential predictions.

Results from Word Recognition and Word Identification

Province and Rouder (2012) collected confidence ratings across repetition conditions in the recognition memory task just described and found that participants by-and-large obeyed the complete information loss predictions. Figure 2A shows patterns from two selected participants. The patterns here are most like those in Figure 1F in that the components line up and the mixture is obvious. To quantify the evidence across all participants, Province and Rouder (2012) fit typical discrete-state and signal-detection models to individuals' uncollapsed data. Each model had the same number of parameters, and consequently difference in fit is an appropriate model comparison statistic. This statistic is shown in Figure 3. Here, 75 of 89 participants (84%) were better fit by the discrete-state model than by the signal detection alternative. Hence, Province and Rouder (2012) provide strong support for the complete information loss account in recognition memory.

Swagman et al. (submitted) employed the above methodology to assess whether perceptual identification of briefly-presented-and-subsequently-masked words, a perceptual task, was better accounted for by complete or graceful loss. In their experiment, words were presented at three brief durations or not at all, analogous to the repetition conditions of Province & Rouder (2012). In one of Swagman et al.'s tasks, participants responded in the two-alternative paradigm with confidence ratings analogous to those in Province and Rouder, and the data from this condition are germane here. Figure 2B shows the confidence-rating histograms for two representative participants, and these patterns support the discrete-state model of complete loss much like those from Province and Rouder. The results of these two participants are typical, and Figure 3 shows model-comparison results across two experiments that encompass 50 participants. As can be seen, the discrete-state model fit better for 45 of the 50 participants (90%).

Orientation Discrimination

In this paper, we employ the same methodology to the identification of low-level perceptual information, namely orientation disparity. Orientation disparity is a critical domain because the physiological underpinnings are relatively well understood. Orientation is mediated by cells in the primary visual cortex that are differentially tuned to varying degrees of orientations for salient segments in the visual field. The perception of the orientation of these segments reflects the summed activation of these tuned cells (Hubel & Wiesel, 1962; Ringach, Hawken, & Shapley, 1997; Ben-Yishai, Bar-Or, & Sompolinsky, 1995), and overall performance is modeled as reflecting small errors in firing rates, which is an instantiation of graceful loss. Hence, if responses reflect these neural dynamics, confidence ratings should be better described by graceful loss as exemplified by Figure 1G than by complete loss as exemplified by Figure 1F.

To test these competing accounts, participants in Experiments 1 and 2 were presented with Gabor patches that had slight tilts from vertical. Participants indicated their relative confidence by moving a slider anchored by "Sure Left," indicating they believe surely the tilt at the top of the Gabor was leftward, and "Sure Right," indicating they believe surely the tilt at the top was rightward. The magnitude of the tilt angle is analogous to repetition in Province and Rouder (2012). The analog of the zero-repetition condition was the presentation of a Gabor at the exact vertical orientation, and for this stimulus we assume participants always enter a guessing state. With these analogs to the previous experiments, the data may be analyzed as before.

Experiment 1

Method

Participants. Thirty students in an introductory psychology course at the University of Missouri served as participants in exchange for course credit.

Stimuli. Stimuli were the supposition of Gabor patches and pixelated noise (see Figure 4). The Gabor patches were 400×400 pixel arrays comprised of 2-D sinusoidal gratings with a wavelength of 50 pixels oriented at $\pm0.23°$, $\pm0.46°$, and $\pm1.37°$ from vertical. These gratings were attenuated by a 2-D Gaussian envelope which had full width at half maximum dispersion of 100 pixels in each direction from center. The pixelated noise was generated on each trial by sampling a 400×400 array of independent, zero-centered normal random variables with standard deviation equal to 1/4 the peak-to-peak amplitude of the gratings. These stimuli were displayed at center on a 1440×900 resolution monitor which had a height and width of 23 and 37 centimeters, respectively, and was placed approximately 50 centimeters away from participants.

Design. The experiment was a 2×4 within-subject factorial design with magnitude (4 levels) and direction of tilt (left/right) serving as factors. There were 55 trials for each non-vertical tilt magnitude-by-direction combination and 30 trials for the exact vertical orientation. The order of these trials was randomized across the session. Each participant performed a total of 360 trials which were evenly divided into 6 blocks of 60 trials.

Procedure. The experiment was run on Mac OS-X computers with the display controlled by the Psychophysical Toolbox (Kleiner, Brainard, & Pelli, 2007) running under Octave. Each trial began with the presentation of a 1-second centered fixation cross. This cross was followed by a display of pixelated noise for an additional second. The Gabor patch was then superimposed onto this noise and remained visible until a confidence-ratings judgment was made, which ended the trial. The time between subsequent trials was 500 milliseconds. Responses were made by sliding a mouse cursor across a horizontal rating scale with anchors labeled by "sure left" and "sure right" designations. Participants rated their confidence by wagering points in the following manner: For each position x on the rating scale ($-1 \leq x \leq +1$), subjects would gain $100|x|$ for correct responses and lose $100|x| + 400|x|^5$ for incorrect responses. This point structure was first used in Province & Rouder (2012). At the end of each trial, the gained or lost points were displayed, and this display served as feedback.

Results

Confidence-ratings histograms for two representative participants are shown in Figure 2C. As before, we display the histograms as if the correct answer is on the right side, and for leftward tilted gratings we reversed the confidence ratings around zero before collapsing. The blue histograms are data from the vertical Gabor display trials, the red histograms are data from the easiest 1.37 degree trials, and the purple histograms, projected downward, are combined data from the harder 0.46 and 0.23 degree trials. The data patterns are in stark contrast to those from select participants in word recognition and identification shown in Figure 2A and B. For this experiment, the components of the histograms from the intermediate condition do not line up with those from the other conditions. Instead, we see a gradual shift in confidence ratings from one condition to the next. This gradual shift is not only disconfirmatory of complete loss, it is supportive of graceful loss.

To quantify the evidence across all participants, we fit the ten-parameter discrete-state and signal-detection models presented in Province and Rouder (2012) and in the supplement of Swagman et al. (submitted). These models were fit to all 30 participants by maximizing likelihood, and maximum values were confirmed by use of multiple random starting points. Deviance comparisons for each participant in Experiment 1 is plotted in Figure 3. The signal-detection model was preferred for 25 of 30 participants (83%). Such a result is a dramatic reversal of those from our prior work in the recognition and identification of words.

Experiment 2

Experiment 1 provides a rich contrast to our previous work. One of the potential issues in Experiment 1, however, is that participants may not have been using the confidence-ratings scale as intended. It is plausible that instead of reporting confidence, they were reporting the perceived orientation of the grating. Clearly, if they were using the confidence scale in this manner, then the graded results are easily explained as noise-prone orientation disparity estimates. We think that misuse of the scale is plausible in this task because both the ratings scale and the stimuli use the same salient horizontal dimension. In fact, in our experience it is easy and natural to see this correspondence when performing the task as a participant.

To help mitigate the possibility that the confidence scale was used as a disparity scale, we placed the confidence-ratings scale in a vertical rather than horizontal configuration, and the anchor “Sure Left” was placed below the anchor “Sure Right.”

Figure 4B shows the display. In our experience as participants, it is far less natural to use this scale for disparity and doing so requires attention and effort. Therefore, we expect that if there is a misuse of the scale for disparity, this misuse will be less probable. If the graceful loss result in Experiment 1 reflects a misuse of the confidence-rating scale, then the support for graceful loss will be less in Experiment 2. In fact, as is discussed below, we find strong support for the signal-detection model of graceful loss even with the vertical confidence-ratings scale, indicating to us that the graceful-loss finding is robust and not likely due to a misuse of the scale.

The method for Experiment 2 was identical to Experiment 1 in all regards except that the vertical confidence-ratings scale was used instead of the horizontal confidence-ratings scale, and that a new set of twenty-four University of Missouri students served as participants.

Figure 2D shows confidence-ratings histograms for two select participants, and these patterns are largely the same as those from Experiment 1. They contradict the discrete-state model of complete loss and support the signal-detection model of graceful loss. Model fittings across all 24 participants (see Figure 3) are also largely the same as before, again supporting graceful loss. The concordance of these results with those in Experiment 1 indicate that the graceful loss result is likely not due to a misuse of the confidence-ratings scale. Taken together, the results from the two experiments provide clear and convincing evidence that these orientation disparity judgments are not mediated by complete loss but by graceful loss.

General Discussion

The current results obtained here, that the discrimination of near-vertical orientation disparities are mediated by graceful loss, while anticipated by most perceptual decision-making approaches, stands in sharp contrast with our prior results on the perceptual identification and mnemonic recognition of words. This contrast affords a few noteworthy conclusions: First, the method we promote based on the comparison of confidence ratings distributions across strength conditions does not appear to have excessive bias. The contrast shows that both signal-detection and discrete-state conclusions may be reached depending on the data. Second, the lack of obvious method bias strengthens our previous claims that word identification and word recognition are mediated by discrete states with complete loss. The current data, especially the patterns exhibited by the four selected participants in Figure 2, provide a salient graphical view of graceful loss. None of our participants in our word identification and in our word recognition tasks have data patterns that resemble graceful loss. Hence, the contrast strengthens our prior claims about discrete states in these domains.

The current results in conjunction with the prior results motivate a new question: Why is it that word recognition and identification are mediated by complete loss while orientation disparity discrimination is mediated by graceful loss? There are a number of procedural differences between the orientation experiments reported here and the prior experiments. We speculate, however, that the main difference is the nature of the stimuli themselves. Words are inherently categorical and likely have fairly discrete representation while the orientation of lines is inherently continuous and likely corresponds to a continuously varying representation. We suspect this difference rather than any particular procedural difference is most salient in accounting for the disparate loss results.

References

Anderson, D., Vogel, E., & Awh, E. (2011). Precision in visual working memory reaches a stable plateau when individual item limits are exceeded. *Journal of Neuroscience*, *31*, 1128-1138.

Attneave, F. (1959). *Applications of information theory to psychology A summary of basic concepts, methods, and results.* New York: Holt, Rinehart and Winston.

Bays, P., Wu, E., & Husain, M. (2011). Storage and binding of object features in visual working memory. *Neuropsychologia*, *49*, 1622-1631.

Bays, P. M., & Husain, M. (2009). Response to Comment on "Dynamic shifts of limited working memory resources in human vision". *Science*, *323*(5916), 877.

Ben-Yishai, R., Bar-Or, R. L., & Sompolinsky, H. (1995). Theory of orientation tuning in visual cortex. *Proceedings of the National Academy of Sciences*, *92*(9), 3844-3848.

Blackwell, H. R. (1953). Psychological thresholds: Experimental studies of methods of measurement. *Bulletin of the Engineering Research Institute of the University of Michigan*, *No. 36*.

Broder, A., & Schutz, J. (2009). Recognition ROCs are curvilinear - or are they? On premature arguments against the two-high-threshold model of recognition. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *35*(3), 587-606.

Cowan, N. (2001). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral and Brain Sciences*, *24*, 87-114.

Cowan, N., & Rouder, J. N. (2009). Comment on "Dynamic shifts of limited working memory resources in human vision". *Science*, *323*(5916), 877.

Dube, C., & Rotello, C. M. (2012). Binary ROCs in perception and recognition memory are curved. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *38*, 130-151.

Egan, J. P. (1975). *Signal detection theory and ROC analysis.* New York: Academic Press.

Fechner, G. T. (1966). *Elements of psychophysics.* New York: Holt, Rinehart and Winston.

Hubel, D. H., & Wiesel, T. N. (1962). Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. *Journal of Physiology*, *160* (1), 106-154.

Klauer, K., & Kellen, D. (2011). The flexibility of models of recognition memory: An analysis by the minimum-description length principle. *Journal of Mathematical Psychology*, *55* (6), 430-450.

Kleiner, M., Brainard, D., & Pelli, D. (2007). What's new in Psychtoolbox-3? *Perception*, *36*. (ECVP Abstract Supplement)

Luce, R. D. (1963). A threshold theory for simple detection experiments. *Psychological Review*, *70*, 61-79.

Ma, W., Beck, J., Latham, P., & Pouget, A. (2006). Bayesian inference with probabilistic population codes. *Nature Neuroscience*, *9* (11), 1432-1438.

Province, J. M., & Rouder, J. N. (2012). Evidence for discrete-state processing in recognition memory. *Proceedings of the National Academy of Sciences.*

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*, 59-108.

Ringach, D., Hawken, M., & Shapley, R. (1997). Dynamics of orientation tuning in macaque primary visual cortex. *Nature*, *387*, 281-284.

Rouder, J. N., Morey, R. D., Cowan, N., Zwilling, C. E., Morey, C. C., & Pratte, M. S. (2008). An assessment of fixed-capacity models of visual working memory. *Proceedings of the National Academy of Sciences*, *105*, 5976-5979.

Swagman, A., Province, J., & Rouder, J. (n.d.). *Evidence for discrete-state processing in perceptual word identification.*

Thiele, J., Pratte, M., & Rouder, J. (2011). On perfect working-memory performance with large numbers of items. *Psychonomic Bulletin & Review*, *18*(5), 958-963.

Townsend, J. T. (1971). Alphabetic confusion: A test for models of individuals. *Perception & Psychophysics*, *9*, 449-454.

Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*, *453*, 233-235.

Figure Captions

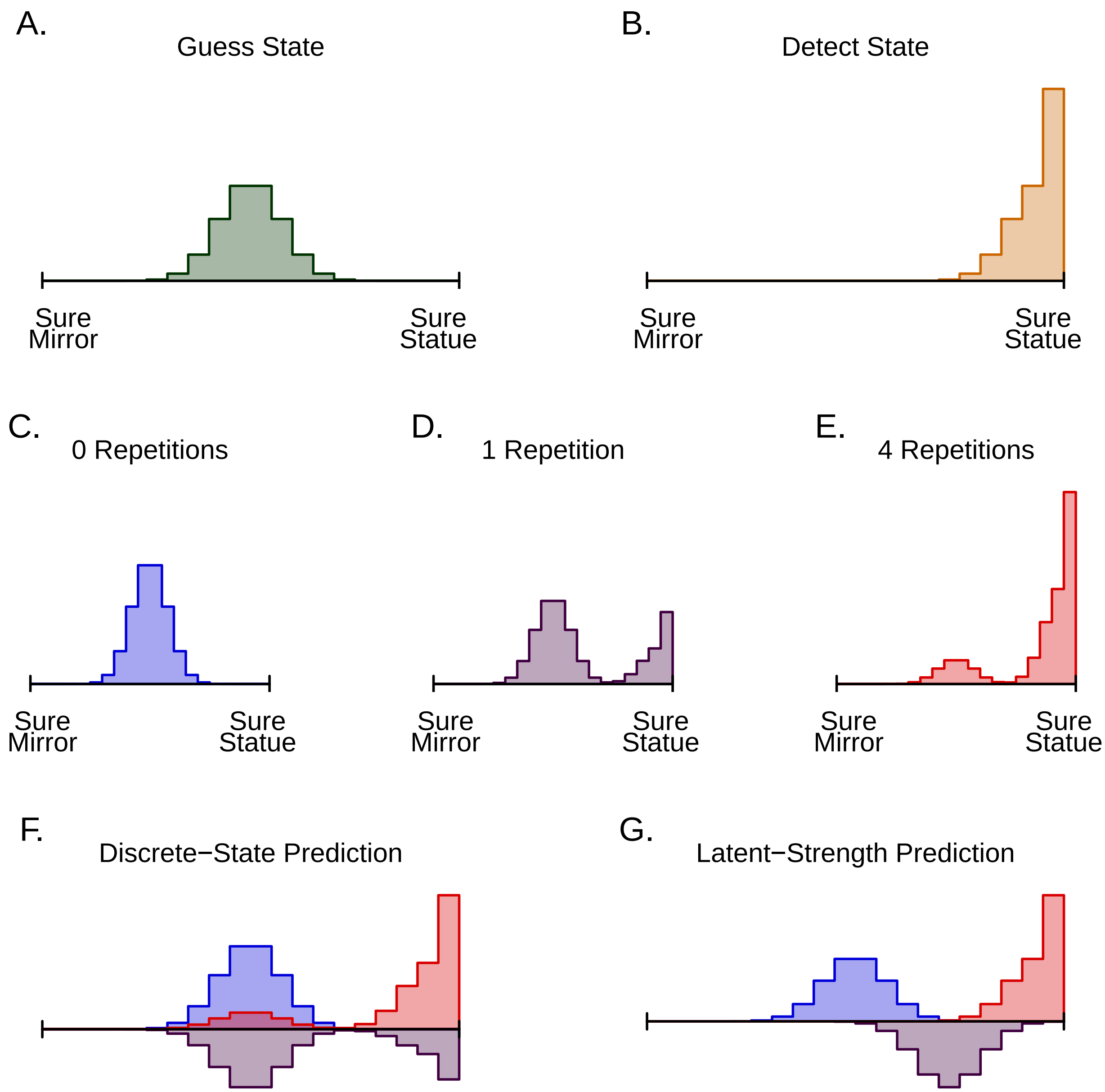
Figure 1. Predictions for a discrete-state model of complete information loss in a two-alternative recognition memory paradigm. The top row shows hypothetical distributions conditional on mental states. The middle row shows mixtures of these states for the strength conditions. The bottom row shows the differential predictions of the discrete-state model and a signal-detection alternative. **A.** Hypothetical distributions of confidence ratings conditional on guessing. **B.** Hypothetical distributions of confidence ratings conditional on detection. **C.-E.** Discrete-state predictions for the distribution of confidence ratings for the zero, one, and four repetition conditions, respectively. **F.** A discrete-state model predicts that confidence ratings are a mixture of ratings from detect and guess states. Increases in study repetition increases the probability that a judgment is from the detect state distribution. **G.** A latent-strength model predicts that as the stimulus is repeated more often, the distribution of confidence ratings shifts towards high confidence correct responses. Ratings for the zero-repetition and four-repetition condition are shown upright; ratings for the one-repetition condition are projected downward to reduce clutter.

Figure 2. Individual histograms of confidence ratings for selected participants across all three tasks. **A.** Confidence ratings for two participants from Province and Rouder's (2012) recognition memory task. Blue, purple, and red histograms denote distributions from zero-repetition, 1-repetition, and 4-repetition conditions, respectively. **B.** Confidence ratings for two participants from Swagman et al.'s word identification task. Blue, purple, and red histograms denote distributions from a no-time presentation, a quick-duration presentation, and a slow-duration presentation, respectively. **C-D.** Confidence ratings for two participants each in Experiments 1 and 2, respectively. Blue and red histograms denote distributions for disparity magnitudes, measured from vertical, of 0° and 1.37°,

respectively. The purple histograms denote the combined distributions for disparity magnitudes of 0.23° and 0.46°. As can be seen, the patterns for word recognition and word identification conform to the discrete-state predictions of Figure 1F while the patterns for orientation disparity conform to the signal-detection predictions of Figure 1G.

Figure 3. Model comparison results across three recognition memory experiments from Province & Rouder (2012); two word-identification experiments from Swagman, Province, & Rouder (submitted); and the two orientation disparity tasks reported here. Each observation is the result of a participant with 89, 50, and 54 participants contributing to the recognition memory, word identification, and orientation disparity discrimination tasks, respectively. Scores are differences in deviance values (badness of fit as indicated by -2 times the log of likelihood evaluated at the maximum likelihood estimates); positive scores indicate better fit for the discrete-state model of complete loss while negative values indicate better fit for a signal-detection model of graceful loss.

Figure 4. Displays for Experiments 1 and 2. On each trial, the participant moves the slider toward either the "Sure Left" or "Sure Right" anchor to make a response for the displayed stimulus and the distance from the center of the scale indicates their confidence. As the slider moves across the scale, the positive and negative numbers represent the amount of points gained and lost for correct and incorrect responses, respectively. The number at the top of the display indicates the current number of points up to the present trial. In both Experiments 1 and 2, each participant started with 100 points on the first trial. **A.** Display for Experiment 1 in which the confidence scale was displayed horizontally. **B.** Display for Experiment 2 in which the confidence rating scale was displayed vertically.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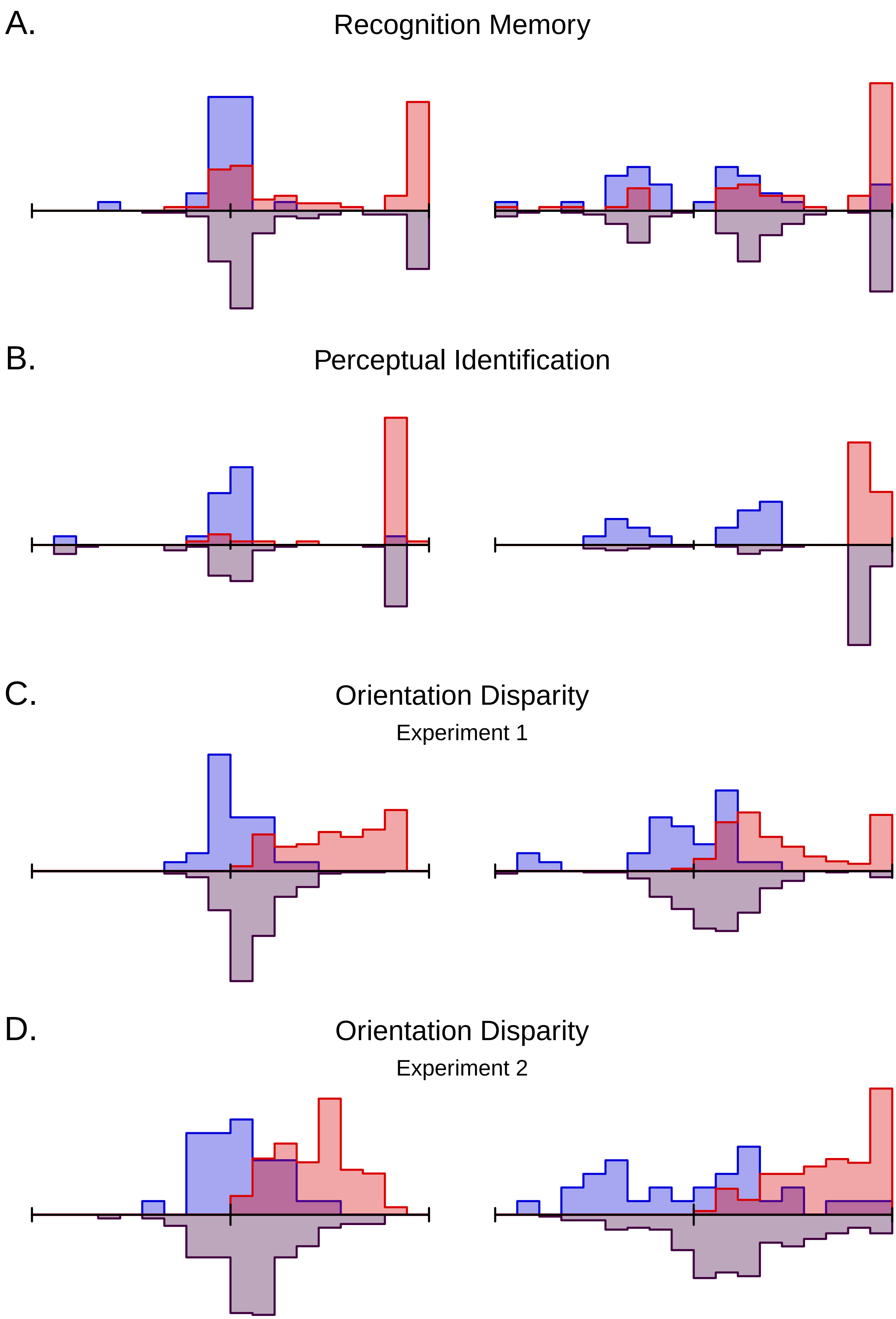
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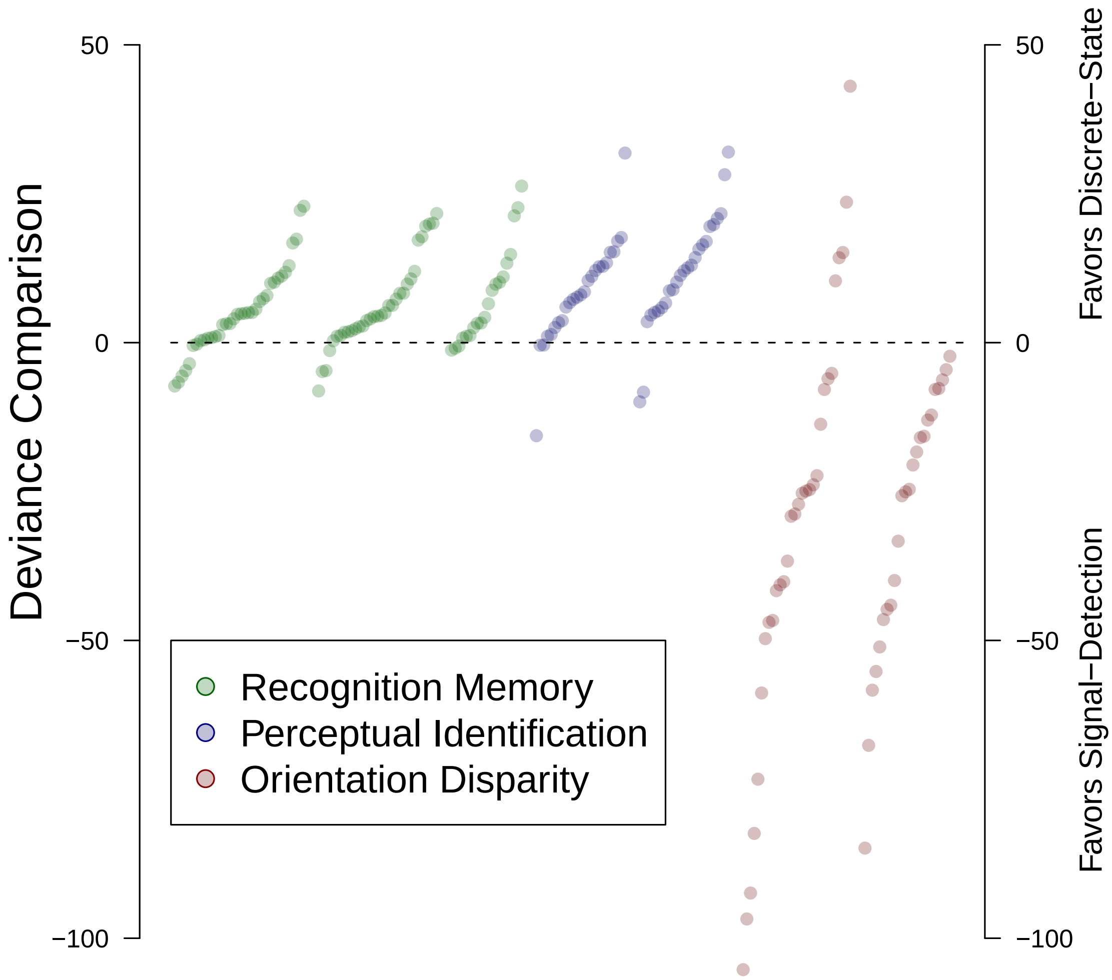
Deviance Comparison
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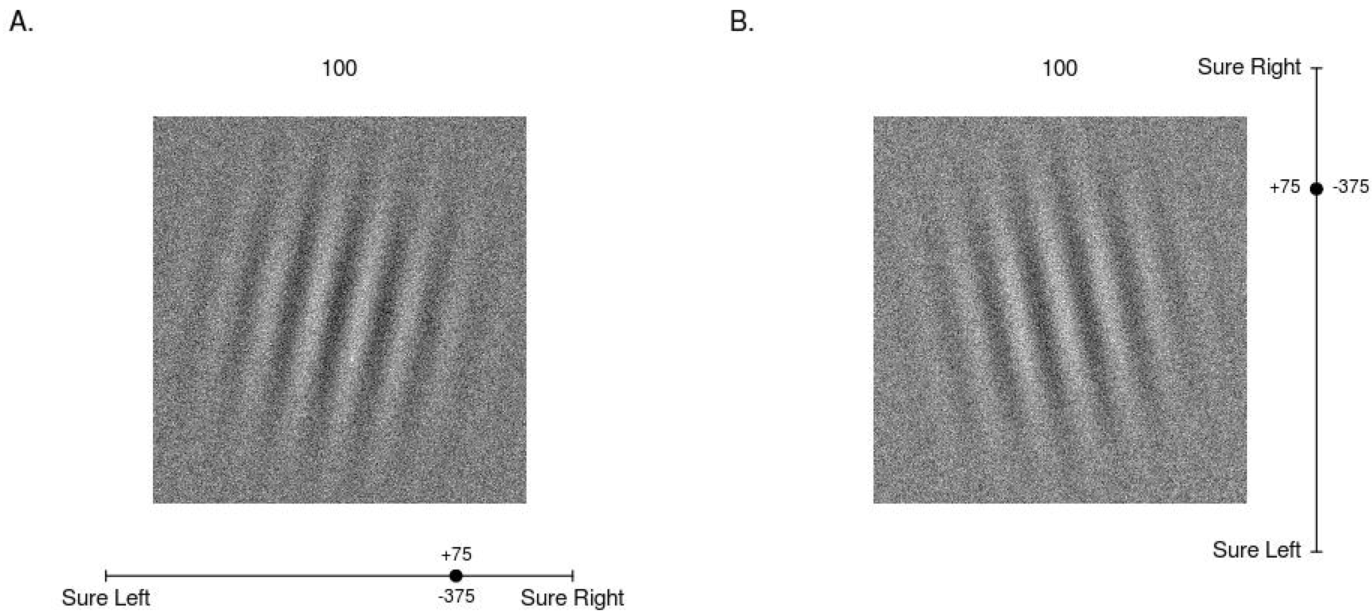
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