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Note

Neglect as a disorder of prior probability

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Abstract

Subjects with spatial neglect are slower and more variable in detecting visual targets, especially on the side opposite their brain injuries. These deficits can be seen by plotting cumulative distribution functions (CDF) of response times (RT). I demonstrate that dividing RT's by their means normalizes the RT CDF's of neglect subjects. The motivation for this transformation comes from Carpenter's LATER model [Carpenter, R. H. S., & Williams, M. L. L. (1995). Neural computation of log likelihood in control of saccadic eye movements. *Nature*, *377*, 59–62]. The most direct interpretation of this result is that some symptoms of neglect reflect abnormal estimates of stimulus prior probability.
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1. Introduction

While the behavior of subjects with spatial neglect is frequently puzzling, e.g. the crossover effect (Bisiach, Rusconi, Peretti, & Vallar, 1994; Savazzi, Posteraro, Veronesi, & Mancini, 2007) it is not simply noise. Neglect subjects show consistent mathematical relationships between stimulus characteristics and their responses (e.g. Chatterjee, Mennemeier, & Heilman, 1994; Mennemeier et al., 2005). In this note, I will demonstrate that a simple mathematical transformation, dividing reaction times (RT) by the mean RT, normalizes the response distributions of neglect subjects. Next, I will introduce Carpenter's LATER model (Carpenter & Williams, 1995), as it provided the motivation for this transformation. Lastly, in the discussion, I will argue that the most direct interpretation of the result is the Bayesian one, and that this leads to the suggestion that some neglect signs reflect abnormal estimates of stimulus prior probability.

2. Material and methods

The note reports a mathematical reanalysis of two different RT datasets (Anderson, Mennemeier, & Chatterjee, 2000; Anderson, unpublished). Since the emphasis is on the mathematical transformation and its implication for theories of neglect, the details of the methods and patients are presented only briefly. It is important to note that the two datasets differed in several ways. The first dataset used a computer, responses were keyboard presses, times were measured in milliseconds and the task was detection. The second dataset used stimuli printed on paper, responses were pointing with the index finger, times were measured in fractions of a second with a stopwatch, and the task was target discrimination from distractors. These differences in the two datasets are highlighted to emphasize that the RT effect to be demonstrated is not tied to a particular task, timescale, or measurement method. Data collection preceded this reanalysis by years.

2.1. Dataset A

These data were the basis for a previous publication (Anderson et al., 2000) where additional details can be found. This reanalysis includes 15 people: 4 normal controls, 4 right brain damaged (RBD) subjects with neglect, 5 RBD subjects without neglect, and 2 left brain damaged subjects (LBD) without neglect. Definition of neglect used the Behavioural Inattention Test (Halligan, Cockburn, & Wilson, 1991) and conventional bedside clinical assessment. RT measurement used a locally written program and a laptop computer. Each trial required the subject to look at the center of the laptop screen and press a key to initialize a trial. The subject then pressed the key again as soon as they detected a small white rectangle that appeared after a random delay in any 1 of 80 positions from the far left of the screen to the far right. RT responses were processed to eliminate all anticipatory errors, which were defined as all responses of less than 200 ms. The mean RT value for each subject at each position was calculated from the linear regression equation that was fit for each subject individually (MATLAB, Natick, MA).

2.2. Dataset B

These data came from 15 subjects (1 subject with LBD and neglect, 5 subjects with RBD and neglect, 4 subjects with LBD and no neglect, and 5 subjects

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with RBD and no neglect). Neglect was defined as in Dataset A. The overall aim of this investigation was to evaluate lateralized systems for preattentive and attentive visual processing. Subjects had to search for the letter "O" within a line of "Q"s or vice versa. A preliminary measure of pointing speed was used to exclude individuals with lateralized effects on motor response time. The stimuli for the task were presented centered in front of seated subjects on landscape oriented sheets of white letter paper with six large letters printed on them. Subjects started with their hands in a standard position in front of them while looking at the test administrator. Subjects would be told which letter they were looking for (either the "O" or the "Q") and then given a go command which started the timing and permitted the subjects to look at the sheet of paper to locate their target. When the subject made physical contact with the letter on the page the administrator stopped the timer (a stop watch) and recorded the time. Then the next trial began. There were five trials for each position and each letter administered in a single test session. For the reanalysis the data from "O" and "Q" trials are pooled. The mean RT value for each subject at each position was directly calculated using the 10 trials at that position.

2.3. Cumulative distribution plots

To generate the cumulative distribution functions (CDF), the raw (or transformed) RT's for each subject were sorted from quickest to slowest. Each was then replaced by its order and divided by the total number of trials. This value was plotted on the y-axis and the RT on the x-axis to generate the curves. The y-axis of the CDF shows the cumulative probability that a new random value from the same distribution would be less than or equal to a particular value (specified on the x-axis). For example, the median time of the responses could be found by locating the 0.5 value on the y-axis, tracking over to a specific subject's CDF, and then tracing down to the x-axis.

3. Results

The principal results are shown in Fig. 1. The two graphs on the left show the empirical CDF's for all subjects in each of the two datasets. For dataset A the CDF's of the brain damaged subjects are slanted towards the right, indicating a slower mean RT and a greater response variance. Generally, subjects with neglect (dashed lines) are worse than brain damaged subjects without neglect, but not always. The same pattern is observed for dataset B, except that no normal controls were tested on this protocol. The right side of Fig. 1 replots the data after each RT has been transformed by dividing it by the mean RT for that subject at that location. Note that now all CDF's from all subjects lie largely on top of each other and that the separation of normal controls from brain damaged subjects (dataset A) and between brain damaged subjects with and without neglect (datasets A and B) is markedly reduced.

4. Discussion

4.1. Why divide by the mean RT?

The motivation for this transformation comes from Carpenter's LATER model (Carpenter & Williams, 1995). LATER stands for Linear Approach to Threshold with Ergodic Rate

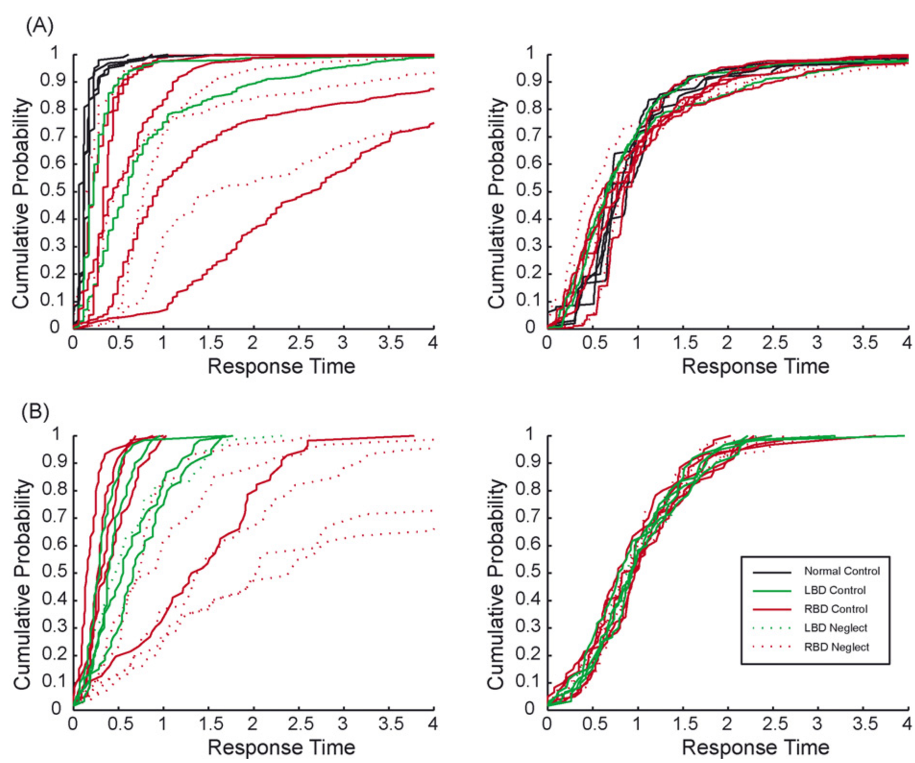

Fig. 1. Panel A shows the data from dataset A and panel B shows the data from dataset B. Plots in the left column are of the untransformed data and show the empirical CDF of RT. In the right column the same data are replotted after the RT for each spatial position has been divided by the mean RT for that spatial position for that subject. Note that this mathematical transformation results in all data from all subjects becoming much more similar. This transformation is different from that used to transform a variable into a standard normal variate. In that case the mean is *subtracted* from each value (not divided) and the result is then divided by the *standard deviation* (not the mean).

and this model has been extensively developed and tested by Carpenter and colleagues (e.g. Carpenter, 2004; Oswal, Ogden, & Carpenter, 2007; Reddi, Asrress, & Carpenter, 2003). The model was developed to account for the length and variability of saccade times to simple targets. The LATER model posits that when a target is present the accumulation of sensory evidence in favor of that target is at a constant, but random, rate (denoted AR for accumulation rate). That is, within a particular trial the rate is constant, but across trials the rate is random. The rate of accumulation is assumed to be distributed with mean = μ and variance = σ^2.

Evidence for a target accumulates from some initial level to a threshold, at which point a behavioral response is triggered. Lowering or raising the initial level of evidence is the same as raising or lowering the threshold for a response. The critical value therefore is the difference between them. AR is the slope of the line for the constant, linear accumulation of evidence within a trial. As such, RT is equal to the difference between the initial level of evidence and the threshold (the difference is denoted Θ) divided by the AR.

These simple assumptions, and the recognition that Θ is assumed a constant, allow us to write the expected value of RT as,

$$E[\mathrm{RT}] = E\left[\frac{\Theta}{\mathrm{AR}}\right] = \Theta E\left[\frac{1}{\mathrm{AR}}\right] = \frac{\Theta}{\mu}. \tag{1}$$

With this result we can see what happens to the variance of a new random variable, RT divided by the mean; this is the transformation used in the figure above.

$$V\left[\frac{\mathrm{RT}}{E[\mathrm{RT}]}\right] = V\left[\frac{\Theta/\mathrm{AR}}{\Theta/\mu}\right] = V\left[\frac{1/\mathrm{AR}}{1/\mu}\right] = \mu^2 V\left[\frac{1}{\mathrm{AR}}\right] = \frac{\mu^2}{\sigma^2}. \tag{2}$$

The first equality uses our result above for the expected value of RT, the second uses the fact that the Θ's cancel, and then we recognize that we can factor μ. The last equality is true by definition.

What is important to note here, and what justifies our transformation, is that neither the mean nor the variance of our new random variable, the one we created when we divided the RT's by their means, retains the Θ value. This transformation has removed one of the model's unknowns. Since this transformation greatly normalizes the data from the spatial neglect and brain damaged subjects, we can deduce that, if this model is accurate, the injury in neglect must affect the Θ term.

4.2. What does Θ mean?

The less likely something is, the more evidence required to persuade us. A quick glance might be enough to confirm that the white fluffy stuff we see outside the window on a winter's morning is snow. A longer look and additional inspection would be required before reaching the same conclusion in summer. Θ, the term in the LATER model that reflects the amount of evidence that must be accumulated before a response is made, can be informally argued to equate with our initial belief in a position. Stated differently, if we fix a threshold, the initial level of evidence can vary depending on our prior expectation that a proposition is true. From this perspective, Θ is a proxy for prior probability.

We can deduce from these ideas that humans possess an implicit internal estimate of the likelihood of where important targets will appear. In neglect there is a disorder of prior probability estimation. The "improbability" of anything appearing on the left results in a need to wait longer, on average, for sufficient evidence to accumulate and result in a behavioral report. However, since the accumulation rate is a random variable, an occasionally fortuitous roll of the "rate" die results in a fast rate, and a fast report, even in neglected hemispace. The LATER formulation provides an account for the variability seen in neglect as well as the average trends. To explain extinction in this system one only needs to imagine the two stimuli as competing in a race to threshold. On average the pathological estimate of left sided prior probability results in the right sided target winning.

While important progress has been made in understanding the behavioral, rehabilitation, and anatomical correlates of neglect (Corbetta, Kincade, Lewis, Snyder, & Sapir, 2005; Karnath, Fruhmann Berger, Kuker, & Rorden, 2004), less progress has been made in providing a unifying theoretical framework. Bayesian approaches have recently received extensive application in neuroscience (for some examples see Brainard et al., 2006; Donovan & Manning, 2007; Knill & Pouget, 2004; Körding & Wolpert, 2004; Lalanne & Lorenceau, 2004; Roach, Heron, & McGraw,2006). Being able to employ such a framework for neglect should provide a useful context for the design and interpretation of research on neglect and for designing future rehabilitative strategies. Equally important, if this Bayesian approach to spatial neglect is confirmed, then research on neglect would more directly inform work in normal human attention and consciousness.

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