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Failure of self-consistency in the discrete resource model of visual working memory

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ABSTRACT

The discrete resource model of working memory proposes that each individual has a fixed upper limit on the number of items they can store at one time,due to division of memory into a few independent "slots". According to this model, responses on short-term memory tasks consist of a mixture of noisy recall (when the tested item is in memory) and random guessing (when the item is not in memory). This provides two opportunities to estimate capacity for each observer: first, based on their frequency of random guesses, and second, based on the set size at which the variability of stored items reaches a plateau. The discrete resource model makes the simple prediction that these two estimates will coincide. Data from eight published visual working memory experiments provide strong evidence against such a correspondence. These results present a challenge for discrete models of working memory that impose a fixed capacity limit.

1. Introduction

Working memory, the ability to maintain information from the external world in an active internal state, is highly limited. Correctly characterizing this limitation is essential for understanding changes over the lifespan, exploring individual differences and for clinical assessment. Most early models assumed the limit could be adequately described by a fixed maximum number of objects retained at one time (Cowan, 2001; Luck & Vogel, 1997; Miller, 1956). However, it is now well established that the precision (resolution) with which information is stored declines monotonically with the number of items in memory (Bays & Husain, 2008; Palmer, 1990; Wilken & Ma, 2004). This finding is most straightforwardly accounted for by continuous resource models, which propose that a fixed quantity of a representational medium is shared out between items: precision of an item's recollection is determined by the amount of resource allocated to it (Bays, Catalao, & Husain, 2009; Gorgoraptis, Catalao, Bays, & Husain, 2011; Ma, Husain, & Bays, 2014; van den Berg, Shin, Chou, George, & Ma, 2012). According to continuous resource models there is no fixed upper limit: instead, as the number of objects in memory increases, representational fidelity degrades until recall is indistinguishable from noise. A strong advantage of continuous resource models is their biological plausibility, and they have found support in neurophysiological data (Emrich, Riggall, LaRocque, & Postle, 2013; Sprague, Ester, & Serences, 2014) and neurally-inspired models (Bays, 2014; Schneegans & Bays, 2017).

An alternative viewpoint retains the concept of a fixed maximum number of items, but combines it with a resource or resource-like behavior below this capacity. Most prominently, Zhang and Luck (2008) proposed a "discrete resource" model, in which a fixed number of memory slots can be flexibly allocated to items, such that a single object can be stored multiple times, enhancing the precision of its recall. This conclusion was based on fitting a model in which responses were drawn from a mixture of two distributions: a normal (von Mises) distribution corresponding to noisy recall of an item in memory, and a uniform distribution

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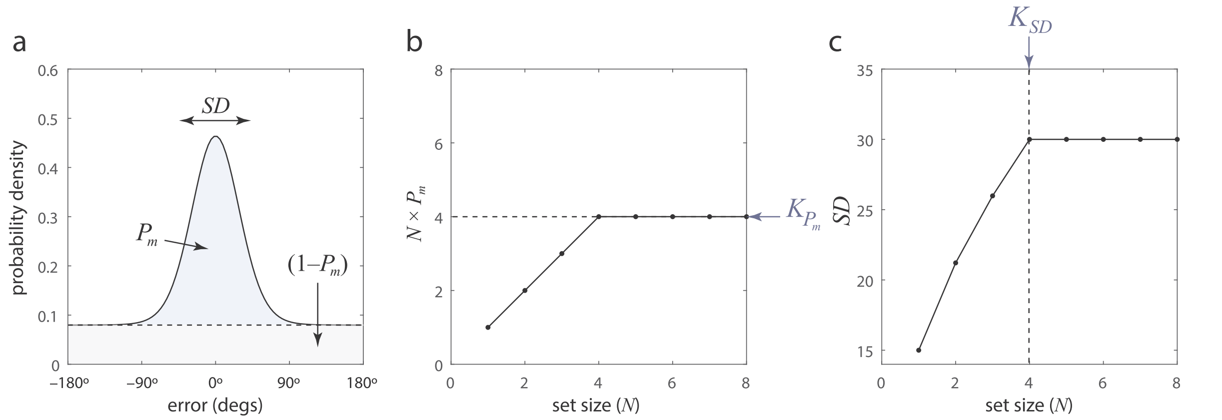

Fig. 1. Two methods of estimating capacity, according to the discrete resource model. (a) Response errors arise from one of two distributions. When the item is in memory, with probability P_m, a response is drawn from a von Mises distribution (blue) with width *SD*. When the item is out of memory, with probability $1-P_m$, a response is drawn from a uniform (guessing) distribution (gray). (b) The number of items in memory, estimated by $N \times P_m$, reaches a maximum at the capacity limit, providing a capacity estimate K_{P_m}. (c) The width of the von Mises distribution, *SD* reaches a maximum and plateaus when the capacity limit is reached, providing a second capacity estimate K_{SD}. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

corresponding to random guessing when the item tested is out of memory (Fig. 1a). The discrete resource model predicts that the capacity limit will affect the parameters of this fit in two ways: first, the mixture proportion of the normal component (P_m) should reflect the probability that an item is in memory, so the product of the set size with P_m reaches a maximum at capacity (Fig. 1b); second, the standard deviation (*SD*) of the normal component should increase with set size until capacity is reached and then plateau (Fig. 1c).

This allows for a simple test of the self-consistency of the discrete resource model: capacity estimates calculated from P_m and *SD* should be equal[1]. Here we tested this prediction and found it to be false, providing evidence against the concept of discrete representations in working memory.

2. Methods

2.1. Studies

We analysed data from eight studies that used the continuous reproduction method to test visual working memory recall (Bays, 2014; Bays et al., 2009; Gorgoraptis et al., 2011; Pratte, Park, Rademaker, & Tong, 2017; van den Berg et al., 2012; Wilken & Ma, 2004; Zhang & Luck, 2008). Four studies tested memory for color and four tested memory for orientation. Data from six of the eight studies were previously made public as part of the Ma lab benchmark data set (http://www.cns.nyu.edu/malab/resources.html); we included all (unretracted) studies from that data set in which at least four different set sizes were tested, including set size one. One additional study (Bays, 2014) was from the author's own laboratory, and the final study (Pratte et al., 2017) was data originally made available to the author as part of another project.

2.2. Analysis

Following Zhang and Luck (2008) we obtained fits to response data, from each participant at each set size, of a model that assumed responses were generated from a mixture of two distributions, one von Mises (a circular analogue of the Gaussian) and one uniform:

$$p(\hat{\theta}) = P_m \phi_{SD}(\hat{\theta}-\theta) + (1-P_m)\frac{1}{2\pi}, \tag{1}$$

where θ is the target feature value, $\hat{\theta}$ is the reported feature value, and P_m is the probability that the target item is in memory. $\phi_{SD}(\cdot)$ denotes the probability density function of a von Mises with mean of zero and circular standard deviation *SD*. Maximum likelihood fits were obtained using an Expectation Maximization algorithm and a range of initial parameter values (code available at http://www.bayslab.com/code/JV10/).

To estimate capacity based on the frequency of guessing, for each subject we calculated an estimate of the number of items in memory at each set size, equal to the product of the set size, N, with $P_m(N)$, the estimated probability of remembering an item at that set size. We then took the maximum of these values as our estimate of capacity:

[1] Note that the correlation between these variables was previously examined in several papers by Anderson, Vogel & Awh that have subsequently been retracted.