RESOLVING THE CONFLICT BETWEEN THE DISCRETE-SLOTS AND DISTRIBUTED-RESOURCES MODELS OF WORKING-MEMORY CAPACITY

A Thesis presented to the Faculty of the Graduate School at the University of Missouri – Columbia

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In Partial Fullfilment of the Requirements for the Degree

Master of Arts

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by

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December 2011

The undersigned, appointed by the dean of the Graduate School, have examined the thesis entitled

RESOLVING THE CONFLICT BETWEEN THE DISCRETE-SLOTS AND DISTRIBUTED-RESOURCES MODELS OF WORKING MEMORY CAPACITY

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ACKNOWLEDGEMENTS

I would like to thank Jeff Rouder, Mike Pratte, and Jory Province for their advice in conducting the experiments and analyses and in writing this thesis. I would like to thank Jeff Rouder, Nelson Cowan, and Michael Cusumano for allowing me to use the data from their experiment for the purposes of this thesis.

I would also like to thank Jessica Hargrove, Elliot Cade, Michael Cusumano, Greg Moss, Chris Selle, Corey Beczkala, and Sarah Hargrave for helping me with running the experiments.

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ABSTRACT

It is generally accepted that Working Memory is limited in capacity. However, there has been substantial debate over whether this limit in capacity is best described as a finite limit on the number of items that can be stored or a decline in the precision of memory as the number of memoranda increases. In an attempt to resolve this debate, ten mathematical models that incorporate the above assumptions were fit to the data from six experiments, encompassing 155 participants, using Maximum Likelihood Estimation. Measures of fit derived from the maximized likelihoods were used to compare the two descriptions of capacity. Overall, Working-Memory Capacity seems to be more accurately described as a limit on the number of items that can be held in memory.

Chapter 1

Introduction

Working Memory refers to the collection of information that is consciously available at a given point in time. This collection is limited in both duration of availability and size, but the exact nature of these limits and the theoretical explanaitons of them remain controversial (see Cowan, 2001, and following discussion). One common model, termed here the *discrete-slots model*, states that working memory is composed of a fixed number of slots in which items or groups of items are temporarily held (Cowan, 1995; Miller, 1956). An alternative model, termed here the *distributed-resources model*, states that Working Memory consists of a general attentional resource that can be flexibly allocated across several items (Bays and Husain, 2008; Sperling and Melchner, 1978; Wilken and Ma, 2004). In the next section, I describe the types of results used to support both models. In fact, there are quite strong results supporting each, which creates a problem—how can both be approximately correct? This question motivates my Master's Thesis, which consists of a critical reassessment of the most important findings for each model.

1.1 Evidence for the Discrete-Slots Model

The discrete-slots model describes Working Memory as a set number of slots, each of which can hold information about an item. This description produces the following consequences: First, items are stored, as integrated wholes, in slots. Second, the number of slots does not vary with the number of items. Third, when items are not represented in a slot, participants must guess with no information. Evidence for the plausibility of these consequences is provided below.

1.1.1 Invariance of Capacity to Object Complexity

The first consequence, that items are stored as unitized wholes, yields a startling prediction: items should always occupy a single slot in Working Memory regardless of the number of features they possess. Hence, item complexity manipulations should not affect the number of slots in Working Memory, termed here the *capacity of Working Memory*.

A common way to assess the capacity of visual Working Memory is the *change-detection task*, first introduced by Postman and Phillips (1974), and subsequently popularized by Luck and Vogel (1997). This task requires participants to study an array of items and, after a brief interval, study another array in order to determine if an item in the array has changed. A version of the task is shown in Figure 1.1A.

Figure 1.1A shows the case for items composed of a single feature. Luck and Vogel compared performance on these items with those composed of two or four different features. An example of a two-featured item consisted of small squares embedded in larger ones, each with a unique color (see top of bottom right insert of Figure 1.1A). The two features were the colors of the inside and outside squares. An example of a four-featured item consisted of bars that were either long or short, red or green, horizontally or vertically oriented, and unbroken or broken by a black gap (see bottom of bottom right insert of Figure 1.1A). Luck and Vogel report that performance is invariant across the number of

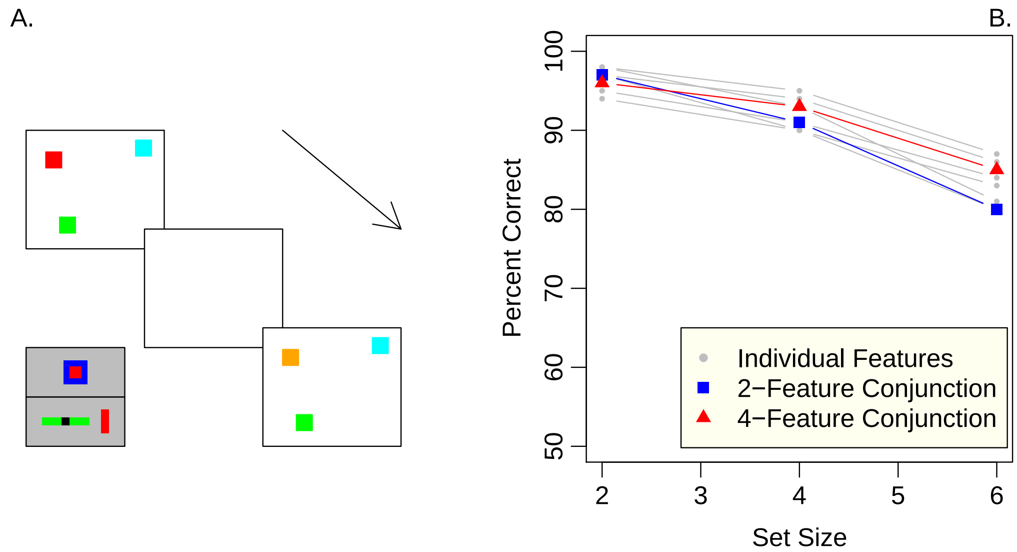

Figure 1.1: **A.** Example of a change detection task stimuli from Luck and Vogel (1997) with insert displaying examples of 2- and 4-feature stimuli. Participants are briefly shown an array of items. The screen is blanked, and then the participants are either shown the whole array (as shown here) or a single item and are asked if the item(s) shown did or did not change. **B.** Results of 2- and 4-feature item task adapted, without permission, from Luck and Vogel (1997). Results illustrate that performance for complex items is approximately the same as performance for simple items.

features (see Figure 1.1B).

Further evidence for this position comes from Awh, Barton, and Vogel (2007), where participants performed a change detection task using cubes and Chinese characters as array items. Although participants performed poorly for changes within a class (cube-to-cube or character-to-character), they were nearly perfect at detecting changes across classes (cube-to-character or vice versa). This near-perfect performance with cross-class changes suggests that items are stored as integrated wholes, with error resulting from confusion between similar items.

1.1.2 Invariance of Capacity to Array Size

The second consequence of the discrete-slots model is that capacity does not change with the number of items in the study array. The number of items in the study array is termed the *array size* throughout. Performance will surely change with array size. As set size increases, and as more items are not represented in Working Memory, performance necessarily declines. This decline, however, should be orderly and follow a specific form.

Cowan (2001) proposed a Working Memory paradigm that attempts to describe this decline. In this paradigm, Working Memory is described as the portion of all memory at which attention is currently directed. Attention is posited to be limited in capacity, unlike any other cognitive faculty, and it is this capacity that limits Working Memory. This capacity is constant and can be estimated from proportions of correct and incorrect responses on a change detection task. Two such rates that readily lend themselves to such estimation are the *hit* and *false-alarm* rates, defined as the percentage of times when a participant responds that an item changed when it did change and the percentage of times when a participant responds that an item changed when it did not change, respectively. For the discrete-slots model, the hit and false-alarm rates are defined as

$$h = d + (1-d)\,g, \tag{1.1}$$

$$f = (1-d)\,g, \tag{1.2}$$

$$d = \min\left(1, \frac{K}{N}\right), \tag{1.3}$$

where h is the hit rate, f is the false-alarm rate, d is the probability that an item is in memory, g is the probability of responding that an item changed when the item is not in memory, K is capacity, and N is the array size. In this paradigm, capacity is estimated by *Cowan's K*:

$$K = N(h-f), \quad K \leq N.$$

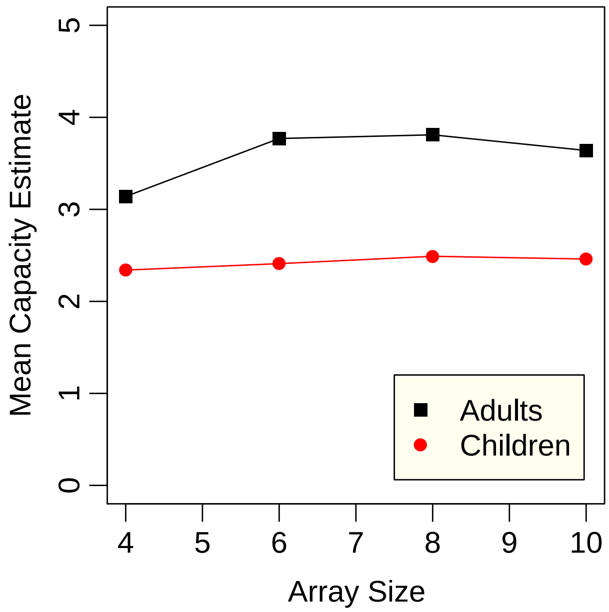

Figure 1.2: Results, adapted without permission, from Cowan et al. (2005). Capacity of visual Working Memory for adults and elementary school children was estimated, using *Cowan's K* formula, from a visual Working Memory task similar to that used in Luck and Vogel (1997). The mean capacity estimates are invariant across set size.

The critical question is whether this capacity estimate remains invariant as array size is increased past the theorized capacity limit. Figure 1.2 is taken from Cowan et al. (2005) in which elementary school students and adults performed a change detection task similar to the original Luck and Vogel experiment. As can be seen, capacity does obey this invariance. As N necessarily increases, then $h - f$ must decrease, supporting an orderly decline in performance.

1.1.3 Differential Performance to Items in and out of Working Memory

The third consequence of the model is that judgments of items in Working Memory are accurate while those of items not in Working Memory are uninformed guesses. Thus, performance on Working Memory tasks can be assumed to depend on two states, defined

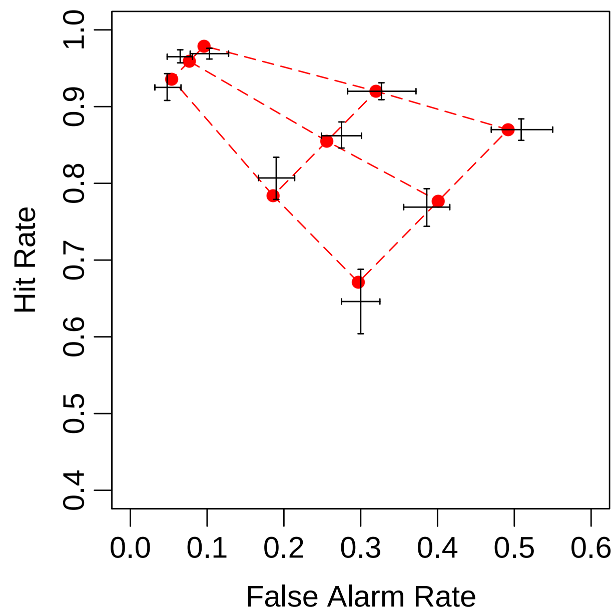

Figure 1.3: ROC plot adapted, without permission, from Rouder et al. (2008). Participant performance is indicated by the double error-bars with the straight-line ROCs in red. Straight-line ROCs are produced by double high-threshold models, which are common formulations of the discrete-slots model of Working Memory.

by when an item is in Working Memory or is not in Working Memory, the latter termed here the *guess* state. Rouder et al. (2008) noted that this assumption yielded a double high-threshold model (Egan, 1975). Double high-threhsold models make exacting predictions for hit and false-alarm rates.

These exacting predictions are best illustrated with receiver operating characteristic (ROC) plots. Rouder et al. (2008) conducted a simple change-detection task. In their experiment, two factors were manipulated: array size and the proportion of change and same trials in each block. This second factor is intended to change the tendency for participants to guess change or same when an item is not in memory. Illustrated in red in Figure 1.3, the double high-threshold assumption produces straight-line ROCs. The data show this prediction holds.

In addition to ROCs, strong evidence for items being out of memory leading participants to guess comes from a modified version of the change detection task, termed here the *item-memory task*. In this task, instead of detecting if an item has changed, participants are asked to recall a feature of an item.

In the Zhang and Luck (2008) task, participants studied an array of colored squares and then judged the original color of one square, with their judgments being drawn from a continuous range of color. Differences between participant responses and respective original colors appeared to follow a mixture of a normal and a uniform distribution, as shown in Figure 1.4, with the normal component centered near the original color of the item. The proportion of the distribution derived from the normal component equals the probability that the tested item is in memory. As such, the normal component makes up a smaller proportion of the distribution at larger array sizes, as can be seen in the fatter tails of the distribution for array size 6. This change in response distribution supports difference in performance for items in or out of memory. However, the evidence only indirectly suggests a difference, as it does not directly measure differential responses between items that are in or out of memory. Their analysis produces a symmetric result, which is of little use in indicating if an item is or is not in memory.

Asymmetric results provide the strongest evidence for differential performance, such as the results of the item-memory task from Rouder, Cowan, and Cusumano (in preparation). Participants were shown arrays of large circles, each with a smaller circle located on their perimeter (see Figure 1.5A for an example of the stimuli and Figure 1.5B for a frame-by-frame view of the experiment), then were asked to rotate a test item to where the item was oriented at study. The results, shown in Figure 1.5C, show that participants' judgments were best described as a mixture of recalling items and pure guessing of items. When participants recalled an item, their judgments were generally close to the original orientation. This formed a cluster around the main diagonal of the plot of judgments against actual orientations. When they guessed, their judgments were generally grouped around one of

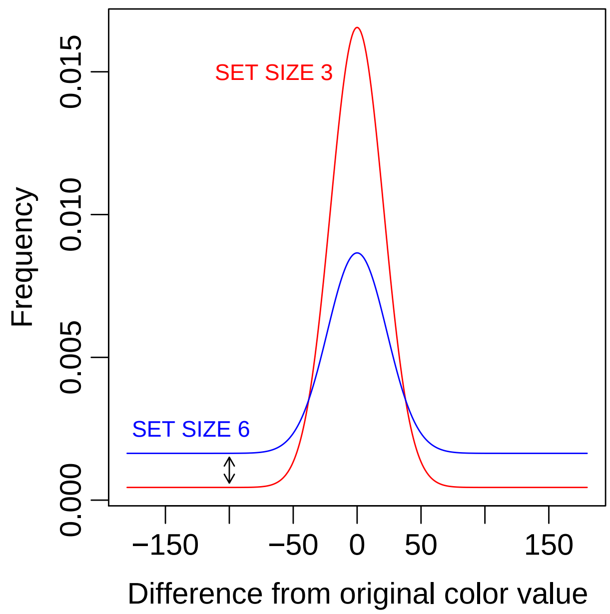

Figure 1.4: Results, adapted without permission, from Zhang and Luck (2008). The distributions depicted above are mixtures of a normal and a uniform, with the normal distribution representing responses when an item was in memory and the uniform distribution representing responses when an item was not in memory. The change in distributions from set sizes of 3 to array sizes of 6 is due to an increased proportion of the mixture being composed of the uniform distribution (from .16 with a array size of 3 to .59 with a array size of 6).

two orientations. This formed two horizontal bands on the plot. As can be seen, participants' judgments tended to be close to the original orientation, especially with arrays of 1 item. But, as the array size increased, participants guessed more frequently, producing more noticeable bands on the plot. These bands are especially noticeable for the judgments made on arrays of 6 items. These patterns in judgments cannot be accounted for by the distributed-resources model.

1.2 Evidence for the Distributed-Resources Model

In contrast to the discrete-slots model, the distributed-resources model posits that Working Memory is composed of a general resource that is flexibly allocated across several items. The distributed-resources model produces the following consequences: First, binding features into integrated objects requires cognitive resources, reducing the resources available for holding other items in memory. Second, the ROCs for change-detection tasks are not restricted to forming straight lines. Third, as items are added to memory, the precision at which each item is stored declines. Fourth, participants can reach perfect performance in a change-detection task with extreme changes in items. Evidence for the plausibility of these consequences is provided below.

1.2.1 Object Complexity and Organization

The first consequence of the distributed-resources model is that the binding of features into integrated wholes also requires the use of cognitive resources. This suggests that complex items require more space in memory than simple items. Because of this additional memory requirement, performance on a memory task should be worse for complex items than for simple items.

To test this prediction, Wheeler and Treisman (2002) replicated the original Luck and

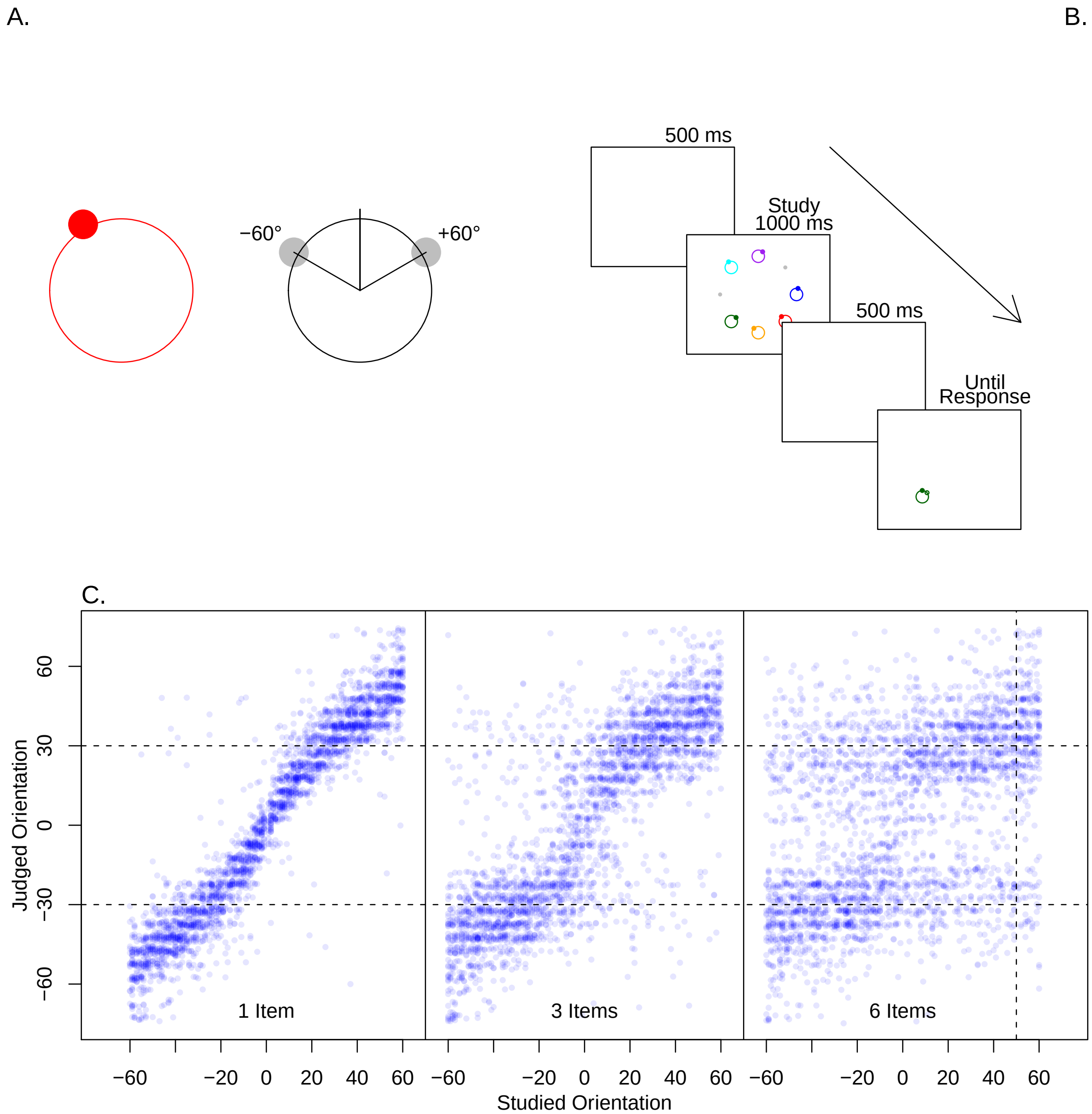

Figure 1.5: **A.** Example Stimuli from Rouder, Cowan, and Cusumano (in preparation) **B.** Trial layout of Rouder, Cowan, and Cusumano (in preparation) **C.** Scatterplot from Rouder, Cowan, and Cusumano (in preparation). Participant responses are plotted against actual displacements on the corresponding trials, grouped by array size. As array size increases, responses shift towards two bands centered around plus or minus 30 degrees from vertical, suggesting that participants are guessing more frequently as array size increases.

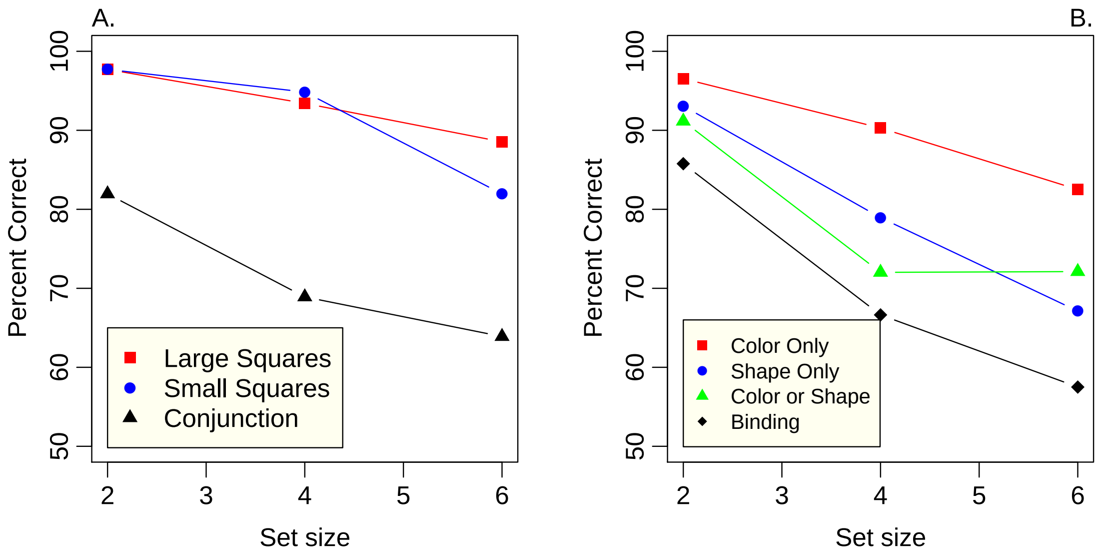

Figure 1.6: Results, adapted without permission, from Wheeler and Treisman (2002). **A.** Results from Experiment 2; a strict replication of the Luck and Vogel (1997) two-color item test. **B.** Results from Experiment 4A; similar to Experiment 2, except that the items tested were colored shapes. Changes were for color, shape, either color or shape, or switching a feature of two items.

Vogel (1997) experiment with two-colored squares (see blue-and-red square in Insert of Figure 1.1A). Their result, in Figure 1.6A, shows that performance with complex items is significantly worse than performance with simple items. In addition, they tested for performance with colored items. Participants were tested in four change conditions: *color only*, *shape only*, *color or shape*, or *binding*, in which two items switched in either color or shape. The results of these tests are shown in Figure 1.6. The difference between these results and the original Luck and Vogel results (see Figure 1.1B) show that minor variation in the task can produce vastly different results.

Alvarez and Cavanagh (2004) also provide support for the use of resources in binding features together. They conducted a visual search task with five classes of objects, with each class differing in complexity. Participants were asked to determine if an item had changed in arrays of between 1 and 15 objects for each object class. Visual search time was measured. Their results show that participants spent more time searching complex items than simple items.

1.2.2 Curved ROCs

The second consequence of the model is that ROCs for change detection tasks are not restricted to straight lines. Evidence for this consequence comes from Wilken and Ma (2004). Wilken and Ma performed a series of change detection tasks with confidence ratings accompanying the change/same answer. These confidence ratings yielded ROCs that did not lie on straight lines, contrary to the results found by Rouder et al. (2008).

1.2.3 Decline in Precision for Items in Memory as Array Size Increases

The third consequence of the model is that the precision with which an item is held in memory decreases monotonically as array size increases. This monotonic decrease suggests that there is no set limit on the number of items that can be held in memory.

The most important change occurs between array sizes 1 and 2, both below the common estimates of capacity in the discrete-slots model. Changes in precision with array sizes below capacity cannot be accounted for by the discrete-slots model. The first example of this decrease actually comes from Zhang and Luck (2008). The estimates for the standard deviation calculated from the tested model increased with array size, especially between array sizes of 1 and 2. Zhang and Luck attempted to explain this result with a post hoc change to their model. This change to the model proposed the possibility that multiple copies of the same item could be stored in several slots. Having multiple copies of the same item would increase precision and allow the discrete-slots model to explain changes in accuracy not caused by exceeding the capacity limit of Working Memory. However, there is no significant evidence that multiple copies of items are stored in several slots.

Evidence for the monotonic decline in precision is also provided by Bays and Husain (2008). Unlike typical change detection tasks, the tested object always changed, and participants were asked to report the direction of change. In their task, participants studied arrays of colored squares and were tested on whether the square moved left or right (see Figure 1.7A). Their results are shown in Figure 1.8A, with the observed proporiton of outward (positive)-movement judgments plotted against movement. Perfect, errorless, performance for this task is indicated by proportions of 0 and 1 for inward (negative) and outward (positive) movements, respectively. By comparison, the worst-case performance is indicated by a constant proportion for all movements (see Figure 1.7B for an illustration of the perfect and worst-case performances).

Figure 1.7C and Figure 1.7D illustrate the predictions made by the distributed-resources and discrete-slots models, respectively. As can be seen, neither model predicts absolutely perfect performance and allows for some noise in participant judgments. This similarity aside, these models make markedly different predictions. The distributed-resources model predicts that participants judgments will become less accurate as set size increases, but still eventually reach perfect performance with large enough displacements. The discrete-slots model, on the other hand, predicts that participants judgments won't change until an item is not in memory, whereupon they will never reach perfect accuracy.

Figure 1.8A shows the results of the Bays and Husain experiment. As can be seen, participants become less accurate as set size increases, even when the increase is only from 1 item to 2 items. This result supports the distributed-resources model and does not support the discrete-slots model without the allowance for items to occupy multiple slots in Working Memory.

1.2.4 Storage of Items that Require Few Resources

The fourth consequence of the model concerns stimuli that require a very small amount of resources. One example is simple stimuli that change greatly, such as large movements in the Bays and Husain paradigm of Figure 1.7A. These large movements are easy to detect

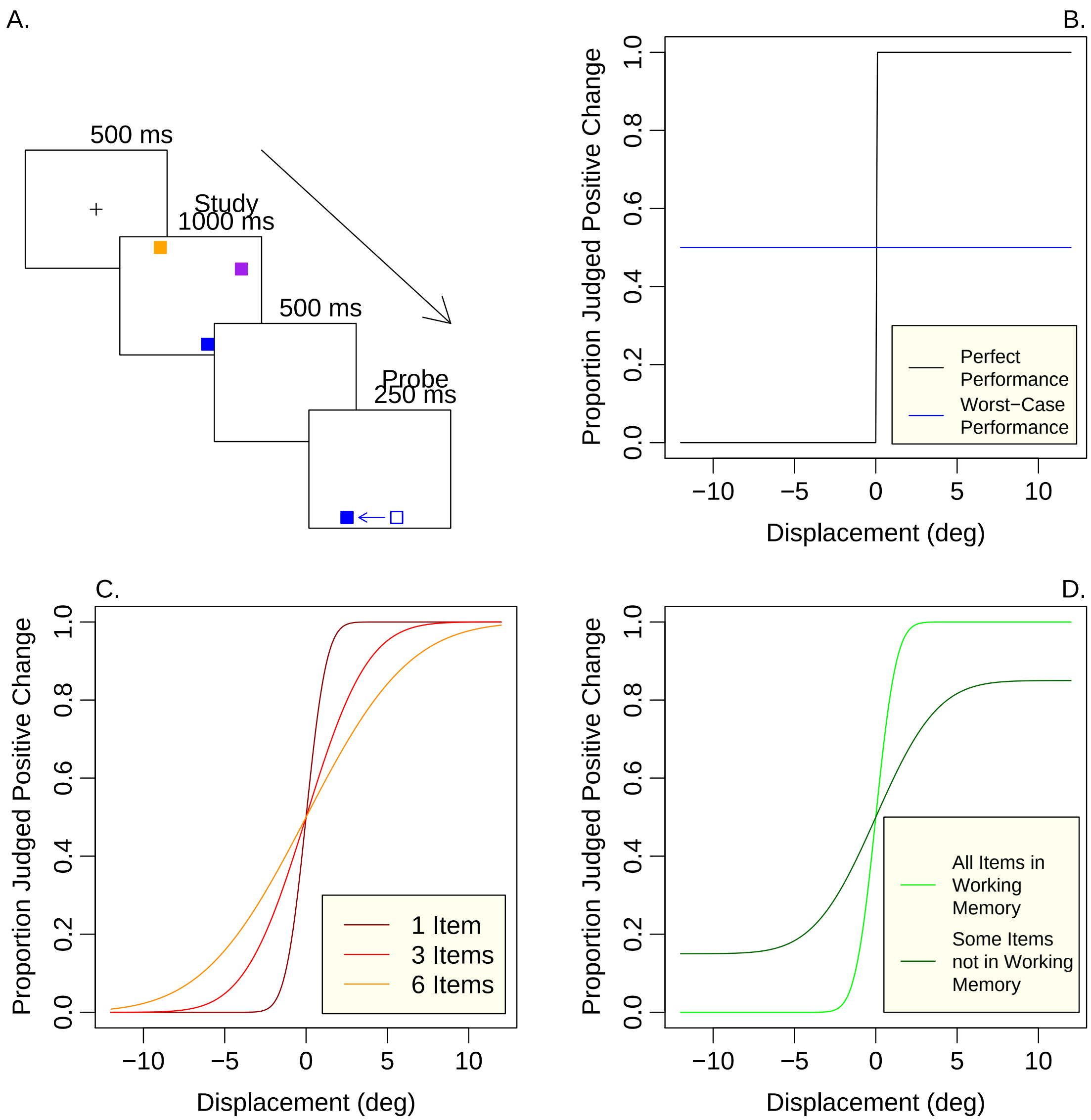

Figure 1.7: **A.** Trial layout for Simple Square Displacement Test **B.** Examples of perfect performance and worst-case performance, with proportions of outward judgments of 0 and 1 for inward (negative) and outward (positive) displacements, respectively, on perfect performance and a constant proportion of outward judgments for all displacements on worst-case performance (.5 here). **C.** Examples of performance predicted by the distributed-resources model for array sizes of 1, 3, and 6. **D.** Examples of performance predicted by the discrete-slots model for all items in Working Memory (in black) and some items not in Working Memory (in blue).

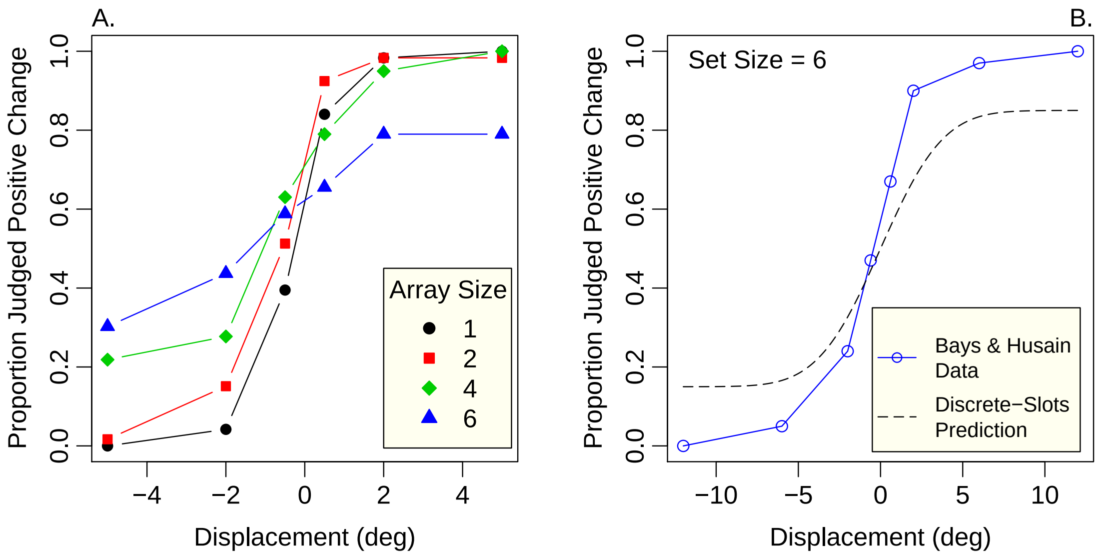

Figure 1.8: **A.** Distributed-Resources Model fitting from Cowan and Rouder (2009) to accuracy data from Bays and Husain (2008). As can be seen, accuracy for equivalent displacements declines as set size increases, even when increasing array size from 1 to 2. This decline in accuracy is indicative of a decline in the precision of items in memory. **B.** Results, adapted without permission, from Bays and Husain (2009). As can be seen in blue, participants reach perfect performance on the task for large displacements. This improved performance cannot be accounted for by the discrete-slots model, whose prediction is shown here by the black dashed line.

without taxing Working Memory. In the limit of large movements, it is expected that performance will approach perfection, and this statement holds even for large array sizes. This consequence of the distributed-resources model is in stark opposition to the prediction of the discrete-slots model. According to the discrete-slots model, performance will never be greater than that dictated by the capacity limit.

To test this consequence, Bays and Husain (2009) moved items several degrees of visual angle. They found perfect performance when movements were greater than about 6°, even for array sizes as large as 6 items (see Figure 1.8B). Their results are incompatible with the discrete-slots model and indicate that memory can be finely divided across many items.

1.3 Description of Projects

Out of the evidence provided above, two instances stand out as being particularly informative. The first is the Bays & Husain task (2008; 2009), in which participants were asked to determine whether a square had moved left or right. The second is the Zhang & Luck task (2008), in which participants were asked to state the color of a given square. I will refer to the above two experimental paradigms as the *identification paradigm* and the *production paradigm*, respectively, for the remainder of this paper.

The results from these two paradigms produced opposite conclusions, with the identification paradigm supporting the distributed-resources model and the production paradigm supporting the discrete-slots model. This is problematic, as these models are contradictory – they cannot both be correct. Therefore, the goal of this research is to settle and determine which model provides a more accurate description of visual working memory.

In order to settle this contradiction, I have investiagted both of these perspectives and will go into detail regarding them in the following chapters. Chapter 2 covers one experiment and subsequent data analysis that investigate the perfect-performance result obtained in the identification paradigm and illustrate why it cannot be used to support one model of working-memory capacity over the other. Chapter 3 covers five experiments from the production paradigm. Chapter 4 covers the model-based analysis of the data from the experiments described in Chapter 3. Overall, the results suggest that visual working memory is more accurately described by a discrete-slots model than by a distributed-resources model, though some qualifications must be made.

Chapter 2

Testing of the Perfect-Performance Result

2.1 Motivation

The purpose of this experiment is to explore the Bays and Husain perfect-performance result. The discrete-slots model cannot account for perfect performance on an identification task, suggesting that the distributed-resources model provides a better description of working-memory capacity. However, some trials in identification tasks might provide information in addition to that which is given in the study array. Consequently, participants might have used such information to make a response without recourse to working memory.

We believe that the identification task used by Bays and Husain suffers from this flaw. Recall that Bays and Husain moved one of several items and asked participants to identify the direction of motion: either leftward or rightward. Information at test is especially apparent in cases like Figure 2.1, where a test item is placed near the edge of the screen. In this case, where the test item is to the far left, it is clear that direction of movement must have been leftward. Hence, position at test provides information about the direction of movement, even in the absence of working-memory storage. Most importantly, this

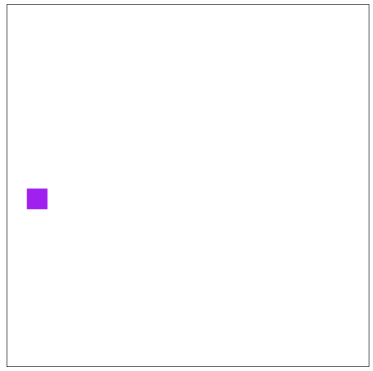

Figure 2.1: There is significant correlation between direction of movement and position at test. As seen here, a test item positioned at the edge of the screen suggests to participants that it had moved towards the edge of the screen.

correlation between position and movement increases with the size of movement. Without careful planning, large leftward or rightward movements tend to place the test item closer to the edge than smaller movements. We fear that the Bays and Husain perfect-performance result is more an artifact of this correlation than a correlate of working-memory dynamics.

To assess whether the perfect-performance result is driven by an artifact, we experimentally broke the correlation between test position and direction-of-movement. To do so, we simply had all test items be positioned in the center of the screen. In this case, there is no information about the direction of movement that may be obtained from the test-item position without recourse to working memory. In the experiment below, we refer to the original Bays and Husain testing procedure as the *test-anywhere* condition. We refer to our new testing procedure as the *test-at-center* condition. The main question is whether we can replicate perfect performance in the test-anywhere condition while observing error-prone performance in the test-at-center condition.

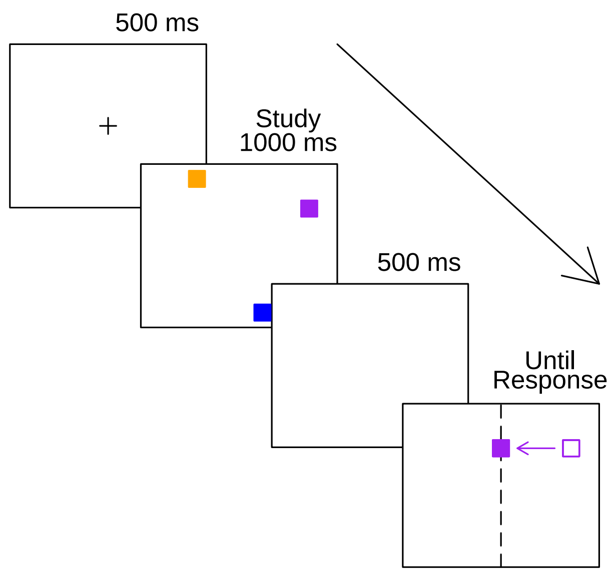

Figure 2.2: Trial layout for the test-at-center condition.

2.2 Experiment

2.2.1 Participants

Thirty-six students (21 female and 15 male) a the University of Missouri completed the experiment as part of an Introduction to Psychology course requirement.

2.2.2 Design & Stimuli

Factors of array size (either 1,3 or 8 items), displacement (10 levels), and testing condition (test-anywhere vs. test-at-center) were manipulated in a mixed design. Array size and displacement were varied in a within-subjects manner; test condition was varied in a between-subjects manner with 18 participants per test condition level.

In the test-anywhere condition, the position of the studied squares were selected at random from a $12^\circ \times 22.5^\circ$ region centered on the display. One item was displayed at test, and it was displaced from the study position as follows. To ensure that people were not always as ceiling, we used the following displacements. When one items was studied, the ten levels of displacement were $\{\pm 0.4^\circ, \pm 0.8^\circ, \pm 1.2^\circ, \pm 1.6^\circ, \pm 12^\circ\}$. Displacements for the three-item and eight-item arrays are $\{\pm 0.8^\circ, \pm 1.6^\circ, \pm 2.4^\circ, \pm 3.2^\circ, \pm 12^\circ\}$ and $\{\pm 1.6^\circ, \pm 3.2^\circ, \pm 4.8^\circ, \pm 7.2^\circ, \pm 12^\circ\}$, respectively. Note that in all conditions, the largest absolute displacement was 12° of visual angle.

In the test-at-center condition, the position of all studied items that were not to be tested were selected at random from a $26.4^\circ \times 15^\circ$ region centered on the displace. The tested item was studied at a point such that the test was always at the center (at the negative value of the displacement level). Levels of displacement were $\{\pm 0.6^\circ, \pm 1.2^\circ, \pm 1.8^\circ, \pm 2.4^\circ, \pm 12^\circ\}$ for one-item study arrays, $\{\pm 1.2^\circ, \pm 2.4^\circ, \pm 3.6^\circ, \pm 4.8^\circ, \pm 12^\circ\}$ for three-items study arrays, and $\{\pm 2.4^\circ, \pm 4.8^\circ, \pm 7.2^\circ, \pm 9.6^\circ, \pm 12^\circ\}$ for the eight-item arrays. Note that in all conditions, the largest absolute displacement was 12° of visual angle.

Items in each display were squares that subtended $.9^\circ$ of visual angle on a side. Items were drawn at one of either 13 (test-anywhere) or 11 (test-at-center) fixed vertical positions on the screen and with horizontal positions chosen such that the total distance between the centers of any two squares subtended at least 1.75°. Each square on a trial was a unique color, with the colors drawn randomly from a palette of eight primary colors. Participants were seated 50 cm and 72.5 cm for the test-anywhere and test-at-center conditions, respectively. The screen itself, a 17" Apple iMAC display, subtended a $42.4^\circ \times 26.5^\circ$ region in the test-anywhere condition and a $28.8^\circ \times 18^\circ$ region in the test-at-center condition. Displays were presented with the Psychophysical Toolbox (Kleiner, Brainard, & Pelli, 2007).

2.2.3 Procedure

Trials began with 500 ms of fixation, followed by the study array presented for 1000 ms. Following study, a blank screen was presented for 500 ms, followed immediately by the test item which remained visible until a response was made. Following response, a 1000 ms blank screen preceded the start of the next trial. Participants indicated that the test item moved left or right using the "z" and "/" keys with the left and right index fingers, respectively. Participants received positive auditory feedback following correct responses, and no feedback following incorrect ones. Sessions began with a practice block of six trials. This was followed by 7 experimental blocks of 60 trials each.

2.3 Results

2.3.1 Empirical Results

Data from one participant in the test-at-center condition were discarded because responses were exceedingly fast. For the remaining participants, responses faster than 200 ms and slower than 10 s were discarded. These trials comprised less than .1% and .4% of total trials for the test-anywhere and test-at-center conditions, respectively. Other reasonable choices of response windows, such as from 250 ms to 2 s, did not change the results appreciably.

Figure 2.3 shows the proportion of rightward responses as a function of displacement across testing and array size conditions. In these plots, the value 0.0 and 1.0 serve as perfect performance limits for leftward (negative) and rightward (positive) displacements, respectively. The left and right columns show data from the test-anywhere and test-at-center conditions, respectively. As can be seen, performance in the test-anywhere condition is nearly perfect for a range of displacements for arrays sizes of 1, 3, and even 8 items. These findings replicate Bays and Husain's result that performance can reach ceiling with sufficiently large displacements, even for numbers of items that exceed typical capacity estimates. Performance in the test-at-center condition, displayed on the right in Figure 1.5, is perfect or nearly perfect for arrays of 1 and 3 items with large displacements. In the 8-item condition, however, average performance never reaches ceiling with large displacements. Instead, performance asymptotes at about 80%, and the vast majority of participants do not achieve near perfect performance.

2.3.2 Model-Based Analysis

It seems natural to ask if the test-at-center data provide better support for the discrete-slots model or the distributed-resources model. This paradigm is not well-suited to answering this question for several reasons. First, the test-at-center condition may encourage participants to remember whether a square was to the left or right of center instead of remembering where the square was located like they would need to do in the test-anywhere condition. These "left" and "right" categories use fewer mnemonic resources than an exact location. These categories may also encourage chunking and grouping because of their meager information requirements (Cowan, 2001; Miller, 1956). If participants chunked or grouped, then the constant capacity assumption would likely be violated. There are other test procedures, such as the production experiments in Zhang & Luck (2008), that are better candidates for model comparison, as they discourage chunking and grouping. Second, the task was designed to assess perfect performance. The specific choices of displacements are not ideal for differentiating between the two models. In particular, this design does not employ enough small displacements in the eight-item condition nor does it employ enough large displacements in the one-item condition to assess changes in slope across array size in the response functions.

Despite these limitations, a model-based assessment can point out the misfit of both models and illustrate the reasons for misfit. As such, some model-based analysis was conducted on the data from this experiment. The models used are developed as follows:

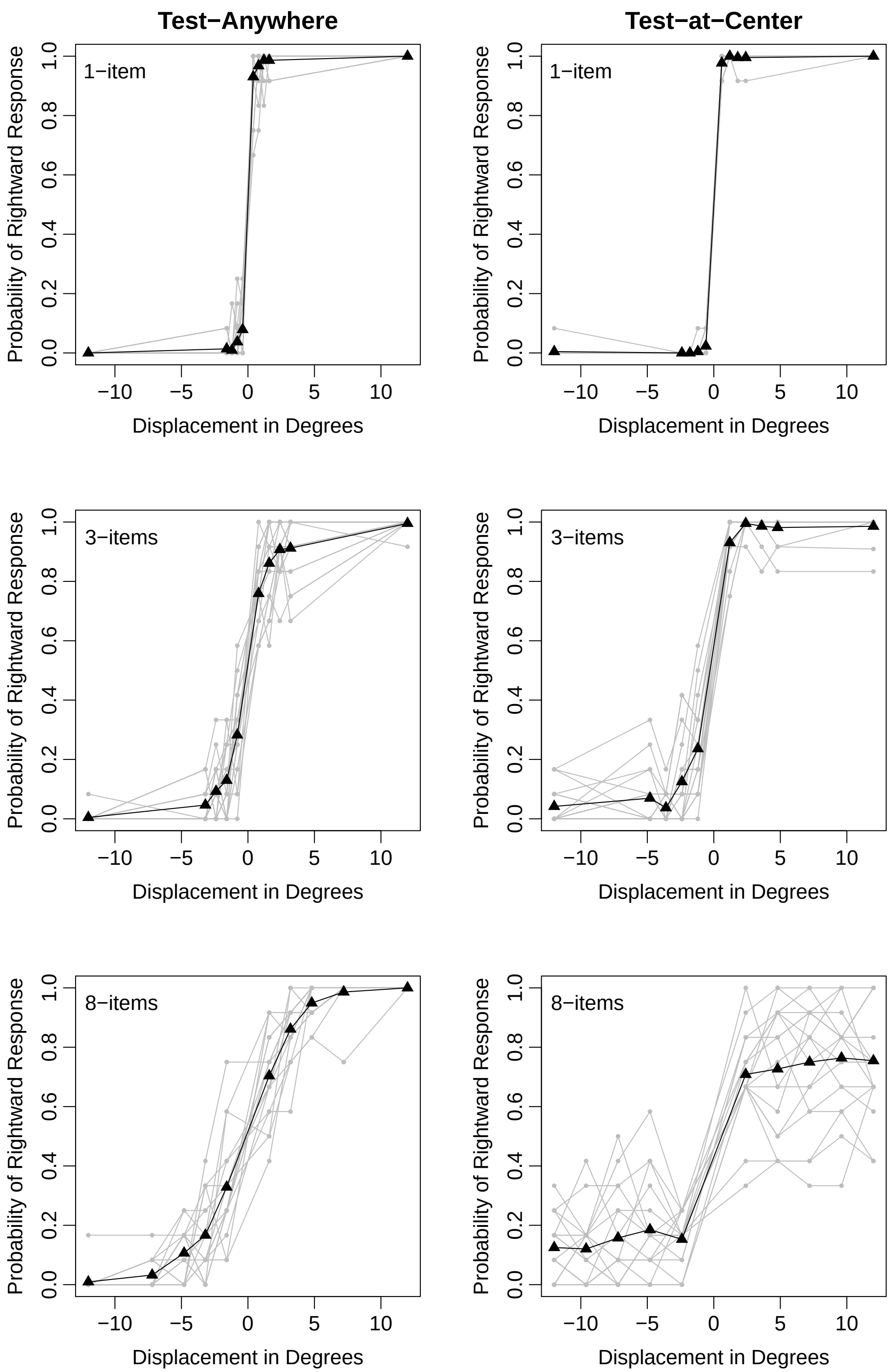

Figure 2.3: Proportion of rightward responses as a function of displacement across array size and testing conditions. The grey and black curves denote individual and averaged proportions, respectively. Performance approaches ceiling levels in the test-anywhere condition, but remain error-prone in the test-at-center condition.

Let I denote the total number of trials for a particular subject in the experiment. Let z_i, for $i \in \{1, \ldots, I\}$ denote the response on the ith trial with $z_i = 0$ if the response is leftward, and $z_i = 1$ if the response is rightward. We model each response as a Bernoulli trial:

$$z_i \overset{ind}{\sim} \text{Bernoulli}(p_i), \tag{2.1}$$

where p_i is the probability of responding rightward. In the implemented distributed resources model, participants' remembered location for any item is assumed to vary as a normal centered on the true study location. Let x_i denote the true study location, and x_i is centered such that $x_i = 0$ corresponds to the center of the screen. The remembered location is

$$y_i \overset{ind}{\sim} \text{Normal}(x_i, \sigma_i^2).$$

The variance of the normal reflects the amount of resources available for each item. Hence σ_i^2 is a function of n_i, where n_i is the number of items in the study array, referred to throughout as the *array size*. We write $\sigma_i^2 = \sigma_{n_i}^2$ to denote this dependency. A leftward or rightward response is made if the remembered location is less than or greater than zero, respectively. Consequently,

$$p_i = \Phi\left(\frac{x_i}{\sigma_{n_i}}\right),$$

where Φ is the cumulative distribution function (CDF) of the standard normal distribution. There are three free parameters in this model: a variance parameter for each of the three array-size conditions.

The discrete slots alternative is based on two mental states. Equation (2.1) holds, but p_i reflects this alternative structure. If the tested item is in working memory, then the distribution of the location of the remembered item is

$$y_i \overset{ind}{\sim} \text{Normal}(x_i, \sigma_i^2).$$

There are two different modeling choices for σ_i^2, which are discussed subsequently. When the tested item is not in working memory, then the participant simply guesses whether the item moved left or right, and guesses "right" and "left" with probabilities g and $1-g$, respectively. These assumptions yield the following:

$$p_i = \alpha_i \Phi\left(\frac{x_i}{\sigma_i}\right) + (1-\alpha_i)g,$$

where α_i is the probability that the item on the ith trial is in working memory. With constant capacity k,

$$\alpha_i = \min\left(1, \frac{k}{n_i}\right).$$

Remaining is the issue of the variance of mnemonic precision σ_i^2. One approach is to assume that items in working memory take up only one slot no matter how many slots may be free. In this case,

$$\sigma_i^2 = \sigma_0^2, \tag{2.2}$$

where σ_0^2 is a constant across all array sizes. Zhang and Luck (2008) recommend an alternative approach where items can be stored multiple times if the number of slots exceed the array size. This approach allows for flexibility in the model by reducing the effective variance for small array sizes. This constraint can be expressed as

$$\sigma_i^2 = \beta(k, n_i)\sigma_0^2 \tag{2.3}$$

where $\beta(k, n_i) = \max\left(1, \frac{k}{n_i}\right)$ is a constant that adjusts the variance to account for the possibility of items occupying more than one slot. For this experiment, only the Zhang and Luck variance in equation 2.3 is used, but both models of variance are considered in later experiments. There are three free parameters in this model: a base variance parameter σ_0^2, a capacity parameter k, and a guessing probability parameter g.

Both this model and the distributed-resources model were fit by maximizing likelihood (Myung, 2003). Neither model fits the data well, but each misfits for different reasons. The distributed-resources model misfits in the eight-item condition because it cannot account for asymptotic performance that is not perfect. This misfit is indicated by arrows in the plot of model residuals, Figure 2.4A, with the residuals defined as the difference between predicted and observed proportions of rightward responses. The systematic pattern in the plot of residuals illustrates this failure to account for asymptotic performance, which is hard to explain if working-memory resources may be distributed arbitrarily finely across items.

The discrete-slots model misfits the relation of performance across array-sizes. A generalized version of the discrete-slots model with spearate capacity parameters for each array size was fit in addition to the two basic models. The plot of capacity estimates is shown in Figure 2.4C. As can be seen, capacity estimates are substantially greater in the eight-item condition than in the three-item condition. A simple explanation for this pattern is that the test-at-center condition encourages categorical encoding and similar phenomena, such as chunking. Overall, the misfit of the discrete-slot model seems more easily explained as reflecting tertiary factors. The misfit of the resources model, however, reflects primary factors, and is not as easily dismissed.

2.4 Discussion

The primary goal of this experiment was to show that the perfect-performance result in Bays & Husain (2009) is most likely due to an artifact in the original experimental design. Specifically, there is a correlation between displacement and test position that provides information about displacement direction. Participants are able to use this information to make responses without recourse to memory, as removing this correlation produces less-than-perfect performance. Thus, the perfect-performance result does not reflect a charac-

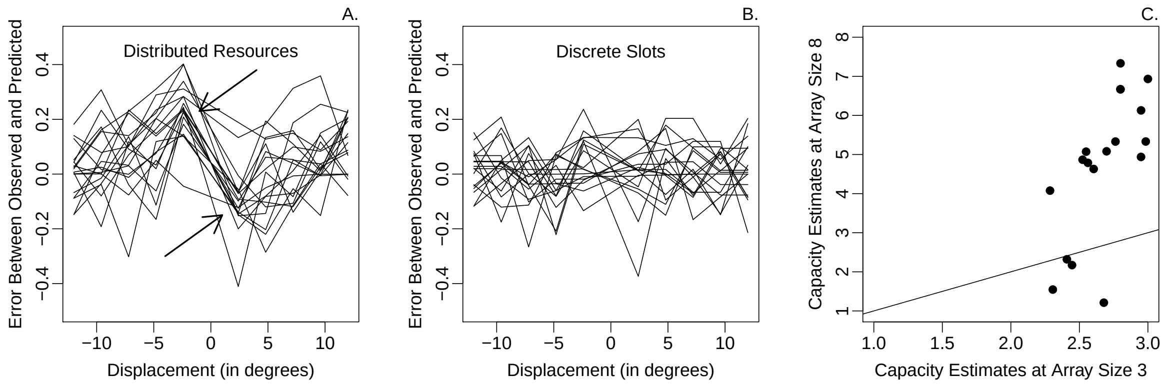

Figure 2.4: **A.** Difference between predicted and observed proportions of rightward responses as a function of displacement for the Simple Distributed-Resources Model. The arrows mark the misfit of this model. **B.** Difference between predicted and observed proportions of rightward responses as a function of displacement for the Discrete-Slots Model. **C.** Capacity estimates for the Free-Capacity Discrete-Slots Model for array sizes 3 and 8.

teristic of working-memory capacity and cannot be used to falsify the discrete-slot model. These results now appear in press in Psychonomic Bulletin & Review as Thiele, Pratte, & Rouder (2011).

In addition, model fits to the data in the test-at-center condition reveal shortcomings in both models. The distributed-resources model cannot account for stable imperfect performance, as this pattern is characteristic of the discrete-slots model. However, the discrete-slots model misfits the data because the constant capacity assumption seems to be violated. This violation is expected and likely reflects a problem with the experimental design as opposed to a flaw with the model. In the next chapter, I adopt more discriminative paradigms for head-to-head testing of the discrete-slots and distributed-resources models.

Chapter 3

Competitive Testing of The Discrete-Slots and Distributed-Resources Models

In the previous chapter, I investigated the perfect performance result of Bays & Husain (2009), the biggest threat to the discrete-slots model. I found that the observed perfect performance was actually an artifact of the experiment, and cannot be used to refute the discrete-slots model. However, the identification paradigm is not well suited for competitive testing of the two models because it asks participants to produce a binary response. Binary responses are not diagnostic of model accuracy, as they provide a poor characterization of participant errors. A better characterization of errors can be provided by the production paradigm used by Zhang & Luck (2008) and subsequently adapted by Rouder, Cowan, & Cusumano, as participant responses are graded. These gradations allow for better estimation of the precision at which items are stored in working memory, which makes the production paradigm well suited for testing these models.

In this chapter, I present five experiments from the production paradigm: the original

Rouder, Cowan, & Cusumano experiment and four other experiments adapted from it. It is important to note that, though I did not conduct the original experiment myself, I provide substantial novel analysis of the resulting data in the next chapter. The original experiment also provides important context for the later experiments. As such, I will provide a detailed description of the original experiment here.

In the following sections, I will cover each experiment individually. First, I will provide additional motivation for the particular experiment. Then, I will describe the methods unique to the given experiment. After that, I will show the results and derive some basic conclusions. While the empirical results of these experiments suggest that the discrete-slots model is the better description of working-memory capacity, the full conclusion is deferred to the following chapter on model-based analysis.

3.1 Experiment 2

Experiment 2 was executed by Rouder, Cowan, and Cusumano to comeptitively test the discrete-slots and distributed-resources models. The main structure of the paradigm is provided in Figure 1.5 on page 10. Because I provide substantial novel modeling, and base the subsequent expeirments on Experiment 2, I present Rouder, Cowan, and Cusumano's method in detail here.

3.1.1 Method

Participants

Twenty-four students (13 female and 11 male) at the University of Missouri completed the experiment as part of an Introduction to Psychology course requirement.

Design & Stimuli

The independent variables of this study were array size (either 1, 3, or 6 items), side of displacement, and angular displacement (finely graded between $\pm 60^\circ$), all of which were manipulated in a within-subjects design. Array sizes were evenly distributed, with 1, 3, and 6 items at study appearing one-third of the time each. The angular displacement of studied items was drawn randomly from either a uniform distribution with endpoints of -60° and -1° or $+1^\circ$ and $+60^\circ$.

Stimuli consisted of colored circles with a small dot located at one point on the edge of each circle. Each circle was located at one of eight points arranged in a ring centered on the center of the screen (see Figure 1.5A and Figure 1.5B on page 10 for an example). The colors used for the stimuli were red, green, blue, yellow, magenta, cyan, grey, and light blue.

Procedure

Trials began with 500 ms of fixation, followed by the study array, presented for 1000 ms. Following study, a fixation was presented for 500 ms, followed immediately by the test item, which remained visible until a response was made. The test item was shown with the dot at the top of the circle. Participants were asked to state the original location of the dot on the tested circle. This response was made by using the left and right arrow keys on a keyboard to move the dot to where they believed it was studied, with responses restricted to between -75° and $+75^\circ$. Sessions began with a practice block, and was followed by 6 experimental blocks of 60 trials each.

3.1.2 Results and Discussion

The empirical results for Experiment 2 can be seen in Figure 1.5C on page 10. The responses seem to follow one of two patterns: participants either respond close to the original studied angle, which appears as a diagonal cluster, or respond towards one of two "stereotypical" positions, producing horizontal bands. These trends are formally assessed in the next chapter.

3.2 Experiment 3

Experiment 3 is a replication of Experiment 2. The main difference is how participants produced their responses. In Experiment 2, they used a keyboard to move the dot to where they believed it was at study. In this study, participants used a mouse instead. This change was made in order to check the pattern observed in Experiment 2 for robustness to method of response.

3.2.1 Method

Participants

Twenty-six students (16 female and 10 male) at the University of Missouri completed the experiment as part of an Introduction to Psychology course requirement.

Design & Stimuli

The independent variables of this study were array size (either 1, 3, or 6 items) and angular displacement (finely graded between $\pm 60^\circ$), both of which were manipulated in a within-subjects design. Unlike in Experiment 2, it was possible in this experiment for the studied angle to be exactly 0°. The rest of the design is the same as in Experiment 2.

Stimuli consisted of colored circles measuring approx. 1.1° of visual arc in diameter with a small dot measuring approx. 0.14° of visual arc in diameter located at one point on the edge of each circle. Each circle was located at one of eight points arranged in a ring at a distance of 4.3° of visual arc from the center of the screen (see Figure 1.5A and

Figure 1.5B on page 10 for an example). The colors of the stimuli were the same as in Experiment 2, except that orange and violet were used instead of magenta and light blue.

Procedure

Trials began with 500 ms of fixation, followed by the study array, presented for 1000 ms. Following study, a fixation was presented for 500 ms, followed immediately by the test item, which remained visible until a response was made. The test item was shown with the dot at the top of the circle. Participants were asked to state the original location of the dot on the tested circle. This response was made by using the mouse to move the dot from the center to the edge and clicking when the participant believed the dot was in the correct position. Responses were not restricted between $-75°$ and $+75°$, as in Experiment 2, but instead could be made over the entire circle. Following response, participants received both visual feedback, in the form of a white dot measuring approx. $0.19°$ of visual arc in diameter in the original study position, and auditory feedback, in the form of one of three tones that played depending on how close the participant was to the original study position. Sessions began with a practice block of 12 trials. This was followed by 7 experimental blocks of 60 trials each.

3.2.2 Results and Discussion

The results for Experiment 3 can be seen in Figure 3.1. Despite the changes in response range and manner of response, the response pattern observed in this experiment matches the response pattern in Experiment 2, though the bands aren't as clear. Participants seem to either recall an item correctly or guess around one of two stereotypical positions. However, the guessing pattern is not as clearly visible in this experiment as it was in the last experiment. This would suggest that if the discrete-slots model still provides a better description of participant responses, then the participants in this experiment were less likely to guess than in Experiment 2 and may have even exhibited a different guessing pattern.

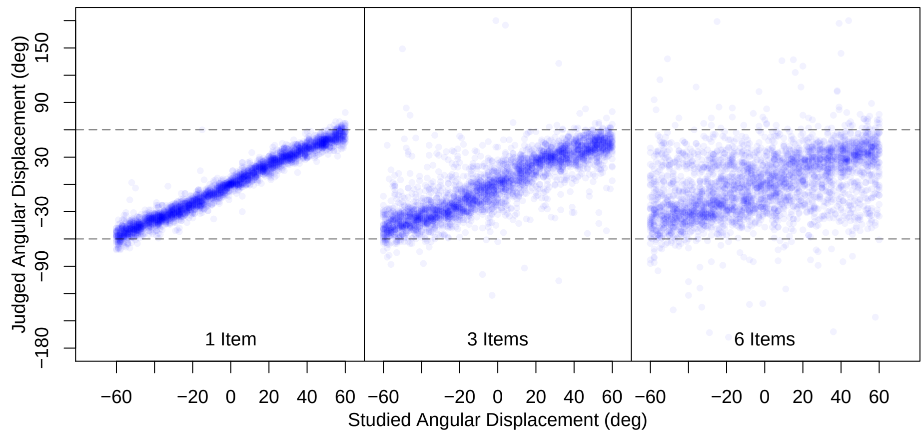

Figure 3.1: Participant responses in Experiment 3 plotted as a function of study angle and study array size. The two dashed black lines denote angles of $\pm 80°$, the furthest displacements from the top that were possible in the study arrays.

3.3 Experiment 4

Experiments 2 and 3 both seemingly indicate that participants tend to guess in structured patterns, and guess toward two stereotypical positions. Experiment 4 is an attempt to confirm this pattern. We used two types of trials, termed *veridical* and *false-probe* trials. Veridical trials were identical to those in Experiments 2 and 3; that is participants were asked to recall an item that was studied. In false-probe trials, however, participants were asked to recall an item they never studied, that is the position was unoccupied at study. In Figure 1.5A on page 10, there are two positions without items, as indicated by dots. On a veridical trial the probe would never appear at one of these empty positions, instead appearing in one of the studied positions; on a false-probe trial, the probe would always appear at one of these empty positions. The discrete-slot prediction is that the distribution of responses on these trials would be identical to the structured patterns we attribute to guessing in the veridical trials.

3.3.1 Method

Participants

Twenty-seven students (7 female and 20 male) at the University of Missouri completed the experiment as part of an Introduction to Psychology course requirement.

Design & Stimuli

The independent variables of this study were array size (either 1, 3, or 6 items), side of angular displacement for test item (left or right), angular displacement (finely graded between $\pm 60^\circ$), and type of test item (veridical or false), all of which were manipulated in a within-subjects design. False probe items were only used when the study array consisted of 6 items, and consisted of half of those trials. All other design characteristics are identical to those in Experiment 2.

Stimuli consisted of colored circles measuring approx. 0.71° of visual arc in diameter with a small dot measuring approx. 0.14° of visual arc in diameter located at one point on the edge of each circle. Each circle was located at one of eight points arranged in a ring at a distance of 3.8° of visual arc from the center of the screen (see Figure 1.5A and Figure 1.5B on page 10 for an example). The stimuli are otherwise identical to those used in Experiment 3.

Procedure

Trials began with 500 ms of fixation, followed by the study array, presented for 500 ms. Following study, a fixation was presented for 1000 ms, followed immediately by the test item, which remained visible until a response was made. The test item was shown with the dot at the top of the circle. Participants were asked to state the original location of the dot on the tested circle. This response was made by using the mouse to move the dot to the place they believed it was studied and then clicking. Unlike in Experiment 3, there was no feedback after each trial. Sessions began with a practice block of 8 trials. This was followed by 5 experimental blocks of 80 trials each.

3.3.2 Results and Discussion

The results for Experiment 4 can be seen in Figure 3.2. For veridical items (left three panels), the response pattern for this experiment is similar to that in the previous two experiments. For false items (rightmost panel), responses appeared to match the horizontal bands produced in veridical item tests, suggesting that the bands on veridical trials reflect uninformed guesses.

However, the middle region around 0° is even more sparse than in the previous two experiments. In addition, there is an overrepresentation of data in the array size 6 condition, illustrated by the circled portions of Figure 3.2. This pattern is observed in all three experiments, but is most pronounced in this experiment.

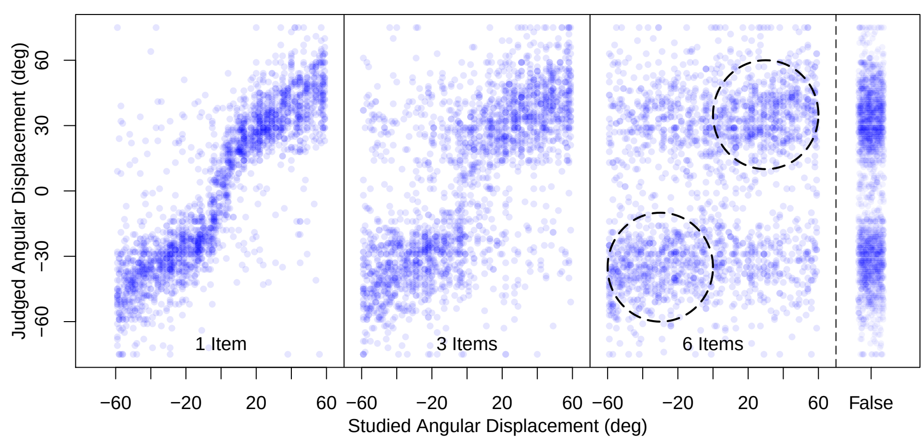

Figure 3.2: Participant responses in Experiment 4 plotted as a function of study angle and study array size. The responses on the far right are responses to false probes and, as such, do not have a "correct" study angle. The dotted circles outline the over-representation of coarse encoding in this task.

Experiments 2 through 4, designed to competitively test the discrete-slots and distributed-resources models, provide two important regularities: First, participant responses form horizontal bands that are centered around one of two stereotypical angles. These bands are indicative of uninformed guessing, as suggested by Experiment 4, and provide support for the discrete-slots model. Second, participant responses become more error prone as array size increases. This can be seen as an increase in the variance of the data as the array size increases. Although an increase in variance would be definitive evidence supporting the distributed-resources model, the fact that most of this increase is occurring in the guessing bands suggests that participants might be changing the way they store items as the array size increases instead of simply becoming less precise. Specifically, participants might be remembering the direction towards which the items are oriented instead of trying to remember the exact angles, a strategy I will refer to as *coarse encoding* throughout.

This prediction is illustrated in Figure 3.3. According to this prediction, responses come from one of three regions: a diagonal cluster in which responses are close to the studied angle, one of two horizontal bands centered on a stereotypical angle, or one of two shorter bands corresponding to the stereotypical angle on the same side as the studied angle. This third region corresponds with the use of a coarse-encoding strategy, as it would suggest that participants focus less on the actual angle and more on the side towards which it was oriented. This region is also of particular note as it is where the data in the last three experiments is overrepresented. Greater use of coarse encoding would also explain the lack of mass in the center of these plots, as participants would tend to respond close to the stereotypical angles and avoid the middle.

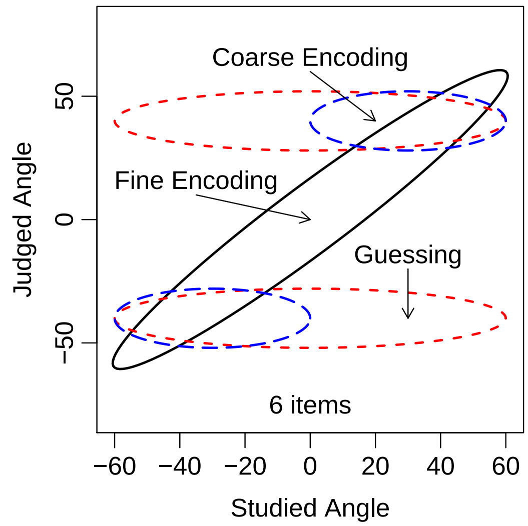

Figure 3.3: General response pattern, as predicted by the discrete-slots model, for Experiments 2, 3, and 4. The diagonal ellipse represents the general pattern of responses expected when the participant finely encoded the to-be-tested item. The long horizontal ellipses represent the pattern of responses expected when a participant is guessing. The shorter horizontal ellipses represent the pattern of responses expected when a participant coarsely encoded the to-be-tested item.

3.4 Experiment 5

In the previous three experiments, the patterns observed suggest that participants may be using an alternative coarse-encoding strategy when presented with larger array sizes. This posibility is a nuisance to competitive testing of the discrete-slots and distributed-resources models. As such, it is important to see if coarse encoding can be eliminated in order to provide a fair comparison. Eliminating coarse encoding may be done by removing the motivation to encode coarsely. The best way to eliminate coarse encoding would be to force all items in the study array to be oriented either leftward or rightward. Forcing all items to one side will discourage coarse encoding, as remembering any one item as being oriented "leftward" or "rightward" will provide no advantage beyond simply guessing. In

Experiment 5, all of the items at study were oriented either left of vertical or right of vertical.

3.4.1 Method

Participants

Twenty-one students (13 female and 8 male) at the University of Missouri completed the experiment as part of an Introduction to Psychology course requirement.

Design & Stimuli

The independent variables of this study were array size (either 1, 3, or 5 items), side of angular displacement (left or right), and magnitude of angular displacement (finely graded between $-80°$ and $-10°$ or between $+10°$ and $+80°$), all of which were manipulated in a within-subjects design. Study arrays sizes were evenly distributed, with 1, 3, and 5 items at study appearing one-third of the time each. The side of displacement was counterbalanced with study array size. The angular displacement of studied items was drawn randomly from either a uniform distribution with endpoints $-80°$ and $-10°$ or a uniform distribution with endpoints $+10°$ and $+80°$.

The stimuli in this experiment were identical to those used in Experiment 3.

Procedure

Trials began with 500 ms of fixation, followed by the study array, presented for 1000 ms. Following study, a fixation was presented for 500 ms, followed immediately by the test item, which remained visible until a response was made. The test item was shown with the dot at a randomly drawn position on the bottom of the circle no more than $\pm 80°$ away from the bottom. Participants were asked to state the original location of the dot on the tested circle. This response was made by using the mouse to to move the dot from the bottom half of the circle to the top half and clicking when the participant believed the dot was in the correct position. The rest of the test procedure is identical to that in Experiment 3. Sessions began with a practice block of 12 trials. This was followed by 7 experimental blocks of 60 trials each.

3.4.2 Results and Discussion

The results for Experiment 5 can be seen in Figure 3.4. Unlike the three previous experiments, the pattern exhibited is largely inconclusive. As can be seen, participant responses are very noisy at large array sizes. This noise is substantial enough to suggest that the distributed-resources model provides a more accurate description of the data. It is also possible that the observed pattern is the combination of a diagonal cluster and a horizontal band, which would support the discrete-slots model, but this combination is not immediately apparent and requires additional analysis to be confirmed. This additional analysis is covered in the following chapter.

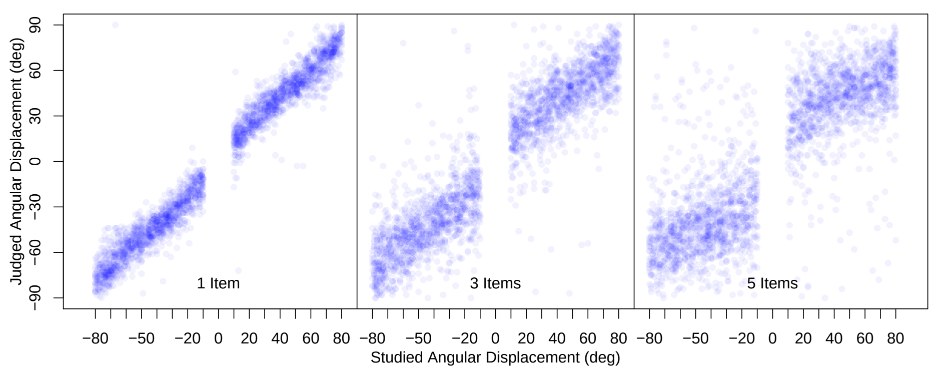

Figure 3.4: Participant responses in Experiment 5 plotted as a function of study angle and study array size.

3.5 Experiment 6

In Experiment 5, we attempted to eliminate coarse encoding by orienting items leftward or rightward. The results, however, were inconclusive at best and seemed, if anything, to provide support for the distributed-resources model. Clarity could be obtained by knowing what happens when participants guess and assessing whether this guessing pattern accounts for the increase in variance in Experiment 5. We replicated Experiment 5 with a slight change for this purpose. We used two types of trials, *veridical* and *false-probe* trials, which are as described earlier in Experiment 4.

3.5.1 Method

Participants

Twenty-one students (13 female and 8 male) at the University of Missouri completed the experiment as part of an Introduction to Psychology course requirement.

Design & Stimuli

The independent variables of this study were array size (either 1 or 6 items), side of angular displacement (left or right), magnitude of angular displacement (finely graded between -80° and -10° or between $+10^\circ$ and $+80^\circ$), and type of test item (veridical or false), all of which were manipulated in a within-subjects design. Study arrays consisting of 1 or 6 items were studied one-third and two-thirds of the time, respectively. False probe items only appeared when the study array consisted of 6 items, and trials with false test items comprised only one-third of all trials with study arrays of 6 items. All other design characteristics are identical to those in Experiment 5.

The stimuli in this experiment were identical to those used in Experiment 3.

Procedure

Trials began with 500 ms of fixation, followed by the study array, presented for 1000 ms. Following study, a fixation was presented for 500 ms, followed immediately by the test item, which remained visible until a response was made. The test item was shown with the dot at the center of the circle. Participants were asked to state the original location of the dot on the tested circle. This response was made by using the mouse to move the dot from the center to the edge of the circle and clicking when the participant believed the dot was in the correct position. The rest of the test procedure is identical to that in Experiment 5. Sessions began with a practice block of 13 trials. This was followed by 6 experimental blocks of 72 trials each.

3.5.2 Results and Discussion

The results for Experiment 6 can be seen in Figure 3.5. For veridical items (left two panels), the response pattern is similar to that seen in Experiment 5. For false items (rightmost panel), the responses formed a horizontal band on the same side as the other items in the array. This suggests that participants generally knew which side the items were on when guessing, and typically guessed towards a stereotypical position. Although these guesses are quite noisy, the pattern observed in this experiment does seem to be a combination of a diagonal cluster and a horizontal band, implying that the discrete-slots model provides a better description of the data.

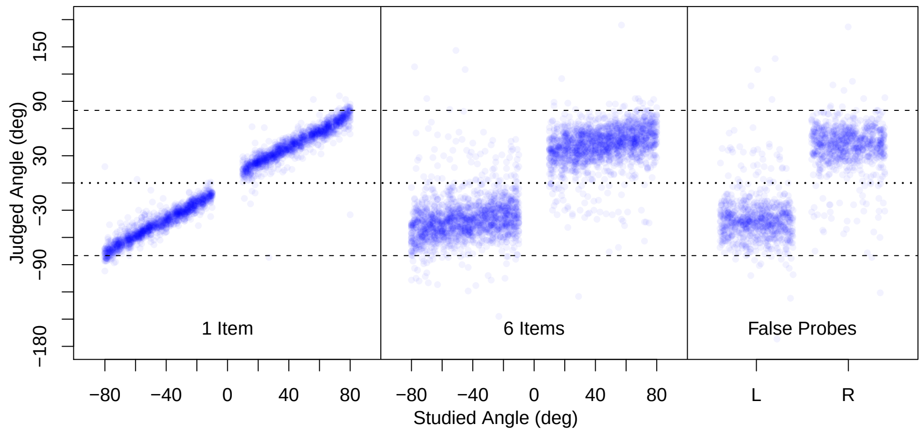

Figure 3.5: Participant responses in Experiment 6 plotted as a function of study angle and study array size. The responses in red are responses to false probes and, as such, do not have a "correct" study angle. These false probe responses are categorized as "leftward" or "rightward" based on the direction of orientation of all other studied items.

3.6 Summary

In this chapter, we covered 5 experiments using the production paradigm from Zhang & Luck (2008). In the discussed experiments, participants studied circles with dots at various locations on their edges, and then were asked to recall the location of one of the dots. We plotted the responses of participants against the study angles. The data from these experiments suggests that the discrete-slots model is a more accurate representation of working memory than the distributed-resources model, as responses in all experiments appeared to be a mixture of a diagonal cluster and horizontal guessing bands. This mixture result is especially important, as the guessing bands observed were not restricted to the same side as the studied angle in Experiments 2, 3, and 4. This lack of restriction in these three experiments is incompatible with a distributed-resources model. However, these conclusions are based on informal, visual inspections of the data and do not provide sufficient support for the discrete-slots model on their own. As such, additional analysis is necessary to determine which model more closely fits the data. This analysis will be covered in the following chapter.

Chapter 4

Model-Fitting for the Discrete-Slots and Distributed-Resources Models

In the previous chapter, I described five experiments and presented their emprical results. While the patterns in the first three experiments seemed to support the discrete-slots model, the lack of mass in the middle made this interpretation difficult. The pattern in the data from Experiment 5 was also troubling, as it seemed to provide support for a distributed-resources model rather than a discrete-slots model. However, there is still the possibility that the discrete-slots model is a more accurate description of participant responses, which is supported by the pattern of responses to false-probe items in Experiment 6.

In order to assess these issues, I fit 10 formal models to the data from the above experiments a total of 40 times by maximizing the likelihood of each model given the observed data. I then compared the models using Bayesian Information Criterion (BIC) scores to determine which model performed the best. Overall, the BIC scores strongly support the discrete-slots model over the distributed-resources model.

4.1 Specification

Ten formal models were developed in an attempt to describe the data and to determine whether the discrete-slots model or the distributed-resources model provided a better description. These models are developed as follows: Let I denote the total number of trials for a single participant in the experiment with $i \in \{1,\ldots,I\}$ indexing the trial for that participant. Let $\mathscr{I}_V(i)$ be an indicator function for the ith trial with $\mathscr{I}_V(i) = 1$ if the test item was veridical, and $\mathscr{I}_V(i) = 0$ if the test item was false. In Experiments 2, 3, and 5, all items were veridical, meaning that $\mathscr{I}_V(i) = 1$ for all trials. $\mathscr{I}_V(i) = 0$ was only possible in Experiments 4 and 6. Let n_i denote the array size, let x_i denote the studied angle for trials where the tested item was in the study array, and let y_i denote the response provided by the participant. Each model is described for a single participant, with each participant having their own estimates for each set of model parameters.

4.1.1 Distributed-Resources Models

Four of the models used in the analysis are classified as Distributed-Resources models. Distributed-Resources models suggest that a person engaged in a working-memory task will remember every item that was studied, but will only remember a portion of each item in large study arrays.

$\mathscr{M}_1$: Simple Distributed-Resources Model with Power-Law Variance

In the simple distributed-resources model, responses follow a normal distribution:

$$y_i \overset{ind}{\sim} \text{Normal}(x_i, \sigma_i^2). \tag{4.1}$$

The variance of the normal distribution reflects the amount of resources available for each item. Hence, σ_i^2 is a function of n_i. In model $\mathscr{M}_1$, this relation is described with a power-law:

$$\sigma_i^2 = \sigma_0^2 (n_i^{2r})$$

where σ_0^2 and r are free parameters estimated for each participant.

$\mathscr{M}_2$: Simple Distributed-Resources Model with Free Variance

Model $\mathscr{M}_2$ follows Equation (4.1), as model $\mathscr{M}_1$, but does not place a power-law constraint on variance. Instead, model $\mathscr{M}_2$ assumes a variance parameter for each array size:

$$\sigma_i^2 = \sigma_{n_i}^2$$

where each $\sigma_{n_i}^2$ is a free parameter estimated for each participant.

$\mathscr{M}_3$: Nearest-Neighbor Distributed-Resources Model with Power-Law Variance

The Simple Distributed-Resources model assumes that all items in the study array are encoded in memory. Consequently, the simple model cannot account for the possibility of a participant not knowing the angle for a test item and, thus, cannot account for guessing. However, Bays, Catalao, & Husain (2009) posited that participants might incorrectly recall another item in the study array. This incorrect recollection could mimic guessing on some trials.

In the Nearest-Neighbor Distributed-Resources model, this incorrect recollection is considered by allowing participants to occasionally respond as though they were tested on a "nearest-neighbor", another stimulus in the study array that was located next to the test item. Using the study array in Figure 1.5B on page 10 for an example, if the orange circle on the bottom is presented at test, then the green and red circles would be the nearest-neighbors.

Using a latent variable q_i to denote the item that was recalled, where $q_i = 0$ implies that the test item was correctly recalled, $q_i = +1$ implies that the item located in the position clockwise to the test item was incorrectly recalled, and $q_i = -1$ implies that the item located in the position counter-clockwise to the test item was incorrectly recalled:

$$q_i \overset{ind}{\sim} \text{Multinomial}(\vec{p}),$$

where $\vec{p}$ is a vector of probabilities. These probabilities are derived from a latent "strength" associated with the test item and the nearest-neighbors. The strength of the test item is described by a free parameter, ν, and the strength of each nearest-neighbor is assumed to be 1. These individual strengths are then divided by the total strengths to produce the probabilities in $\vec{p}$. For example, if both positions next to the test item had items at study (i.e. there are two nearest-neighbors), then the probability that the test item will be correctly recalled is $\frac{\nu}{\nu+2}$, and the nearest-neighbors will be incorrectly recalled with a probability of $\frac{1}{\nu+2}$ each. If there is only one nearest-neighbor, then the test item will be recalled with probability $\frac{\nu}{\nu+1}$ and the nearest-neighbor will be recalled with probability $\frac{1}{\nu+1}$. Naturally, because there would only be one nearest-neighbor, an "item" in the other nearest-neighbor position would be recalled with a probability of 0. Similarly, if there are no nearest-neighbors, then an "item" in a nearest-neighbor position would be recalled with probability 0. This implies that the test item would be correctly recalled with a probability of 1.

From these examples, the general form of the probability vector can be defined as

$$\vec{p} = \left\{ \frac{\mathscr{I}^-(i)}{\upsilon + m_i}, \frac{\upsilon}{\upsilon + m_i}, \frac{\mathscr{I}^+(i)}{\upsilon + m_i} \right\},$$

with $\upsilon = \nu \times \mathscr{I}_V(i)$, ν is the strength parameter mentioned earlier, $m_i \in \{0, 1, 2\}$ is the number of nearest-neighbor items, and $\mathscr{I}^-(i)$ and $\mathscr{I}^+(i)$ are indicator functions that are equal to 1 only when there was an item in the study array in the position counter-clockwise and clockwise to the test item, respectively, and are otherwise equal to 0.

With this, participant responses follow these distributions:

$$y_i | q_i \overset{ind}{\sim} \begin{cases} \text{Normal}(x_i^-, \sigma_i^2) & \text{if} \quad q_i = -1 \\ \text{Normal}(x_i, \sigma_i^2) & \text{if} \quad q_i = 0 \\ \text{Normal}(x_i^+, \sigma_i^2) & \text{if} \quad q_i = +1 \end{cases} \tag{4.2}$$

where x_i^- and x_i^+ are the angles at study of the items in the study array in the positions counter-clockwise and clockwise to the to-be-tested item, respectively.

The variance of the normal distributions reflects the amount of resources available for each item. Hence, σ_i^2 is a function of n_i and does not change with respect to the exact item recalled. In model $\mathscr{M}_3$, this relation is described with a power-law:

$$\sigma_i^2 = \sigma_0^2 (n_i^{2r})$$

where σ_0^2 and r are free parameters. These are estimated along with ν for each participant.

$\mathscr{M}_4$: Nearest-Neighbor Distributed-Resources Model with Free Variance

Model $\mathscr{M}_4$ is the same as model $\mathscr{M}_3$ with the exception that it does not place a power-law constraint on variance. Instead, model $\mathscr{M}_4$ assumes a variance parameter for each array size:

$$\sigma_i^2 = \sigma_{n_i}^2$$

where each $\sigma_{n_i}^2$ is a free parameter. These are estimated along with ν for each participant.

4.1.2 Discrete-Slots Models

Six of the models used in the analysis are classified as Discrete-Slots models. Discrete-Slots models describe working memory as being composed of a fixed number of slots, each of which can store one item from the array. According to this model, a person engaged in a working-memory task will study and remember as many items as their capacity will allow. When tested, this person will either recall the item correctly if the item was stored in a slot or guess if the item was not stored in a slot.

$\mathscr{M}_5$: Simple Discrete-Slots Model with Constant Variance

The Simple Discrete-Slots model is based on two mental states: in-memory and out-of-memory. Using an indicator variable z_i to denote the state of memory on trial i, where $z_i = 1$ implies that the test item is in memory, and $z_i = 0$ implies that the test item is not in memory:

$$z_i \overset{ind}{\sim} \text{Bernoulli}\left(\min\left(1, \frac{k}{n_i}\right) \times \mathscr{I}_V(i)\right), \tag{4.3}$$

where k is a free parameter representing the number of slots in working-memory. It is important to note that, in the experiments that use false test-items, $\mathscr{I}_V(i) = 0$ implies that $z_i = 0$.

If the tested item is in working memory, then the distribution of responses is

$$y_i|(z_i = 1) \overset{ind}{\sim} \text{Normal}(x_i, \sigma_i^2). \tag{4.4}$$

The variance of the normal distribution is a measure of the mnemonic precision at which items are stored. In typical descriptions of the discrete-slots model, this precision is assumed to be constant regardless of the number of items stored in memory. Model $\mathscr{M}_5$ follows this assumption:

$$\sigma_i^2 = \sigma_0^2,$$

where σ_0^2 is a free parameter.

If the tested item is not in working memory, then the response must be a guess. Normally, guessing is described as being without information and, as such, is usually assumed to be uniformly distributed over the entire response range (Zhang & Luck, 2008). However, due to the results observed in the previous chapter, we make a different assumption about the way participants guess. Specifically, we assume that participants tend to center their guesses around one of two stereotypical positions, denoted here as α_L and α_R. Using a latent variable s_i to denote the side towards which a participant responds, with $s_i = 1$ implying that they respond rightward and $s_i = 0$ implying that they respond leftward, participants guesses are distributed as follows:

$$y_i|(z_i = 0, s_i) \overset{ind}{\sim} \text{Normal}(s_i(\alpha_R) + (1 - s_i)(\alpha_L), \sigma_g^2), \tag{4.5}$$

where σ_g^2 is a free parameter that describes the variability of a participant's guesses. For the purposes of model estimation, α_L and α_R are both treated as free parameters.

Due to the differences in design between Experiments 2, 3, and 4 and Experiments 5 and 6, participant guesses are modeled differently in each case. In Experiments 2, 3, and 4, participants were shown items whose orientations varied across the top third of the circle. As each item was equally likely to be oriented leftward or rightward, participants were assumed to make their guesses similarly:

$$s_i \overset{iid}{\sim} \text{Bernoulli}\left(\frac{1}{2}\right).$$

The assumption that participants guess leftward or rightward with equal likelihood is made for simplicity. Adding a free parameter to account for bias would make this model overly flexible and would likely interfere with the estimation of the other free parameters.

In Experiments 5 and 6, participants studied items that, on any given trial, were all oriented leftward or rightward. Figure 3.4 and Figure 3.5 suggest that participants noticed this and used it to inform their responses in all cases. Even in the false-probe trials in Experiment 6, participant responses were on the same side as the other items in the study array 97% of the time. Given that participants could remember the side of the study array so clearly, assuming that they would guess toward either side with equal likelihood is unreasonable. As such, guesses in Experiments 5 and 6 are distributed as in Equation (4.5), but with:

$$s_i = \mathscr{I}_S(i),$$

where $\mathscr{I}_S(i)$ is an indicator function with $\mathscr{I}_S(i) = 1$ if all studied items were oriented rightward at study, and $\mathscr{I}_S(i) = 0$ if all studied items were oriented leftward at study.

Given the above, the overall description of participant responses is:

$$y_i | z_i, s_i \overset{ind}{\sim} \begin{cases} \text{Normal}(x_i, \sigma_i^2) & \text{if} \quad z_i = 1 \\ \text{Normal}(s_i(\alpha_R) + (1 - s_i)(\alpha_L), \sigma_g^2) & \text{if} \quad z_i = 0 \end{cases} \tag{4.6}$$

with k, σ_0^2, σ_g^2, α_L, and α_R as free parameters estimated for each participant.

$\mathscr{M}_6$: Simple Discrete-Slots Model with Zhang & Luck Style Variance

Model $\mathscr{M}_6$ follows Equation (4.4), as model $\mathscr{M}_5$, but does not assume a constant variance across array sizes. Instead, model $\mathscr{M}_6$ assumes that variance is a function of array size:

$$\sigma_i^2 = \frac{\sigma_0^2}{\max\left(1, \frac{k}{n_i}\right)},$$

where σ_0^2 and k are free parameters. This equation was initially used by Zhang & Luck (2008) as a correction for the change in variance with array size observed in their experiments. According to this correction, participants might store multiple copies of an item if the number of slots in memory exceeds the array size. By “doubling” slots in this manner, the variance of the item decreases when the array size is smaller than capacity.

The rest of model $\mathscr{M}_6$ is identical to model $\mathscr{M}_5$.

$\mathscr{M}_7$: Simple Discrete-Slots Model with Free Variance

Model $\mathscr{M}_7$ follows Equation (4.4), as models $\mathscr{M}_5$ and $\mathscr{M}_6$, but does not assume a constant variance across array sizes nor does it assume the correction for changes in variance used by Zhang & Luck (2008). Instead, model $\mathscr{M}_7$ assumes a variance parameter for each array size:

$$\sigma_i^2 = \sigma_{n_i}^2,$$

where each $\sigma_{n_i}^2$ is a free parameter. Allowing variance to vary freely with array size causes this model to lose its process interpretation, as the discrete-slots model assumes that items are stored as whole objects at a set precision. However, by adding this model to the analysis, we hope to test the constraints on variance used in the other models that satisfy the above assumption.

The rest of model $\mathscr{M}_7$ is identical to models $\mathscr{M}_5$ and $\mathscr{M}_6$.

$\mathscr{M}_8$: Coarse-Encoding Discrete-Slots Model with Constant Variance

Although the simple discrete-slots model can account for the banding found in the first three experiments, the pattern of responses suggests that participants might have encoded items coarsely. As such, additional flexibility must be added to the models to account for coarse encoding. The following model includes this additional flexibility.

It is important to note that, due to the potential for coarse encoding in the first three experiments and the differences in design between them and the latter two experiments designed to eliminate the above potential, the coarse-encoding models cannot be informatively applied to the data from Experiments 5 and 6. Specifically, because of the way guessing in these latter two experiments was described, there would be no way to distinguish between guessing and coarse encoding, making coarse-encoding models too flexible for those data sets.

The coarse-encoding discrete-slots model extends Model $\mathscr{M}_5$ by splitting the in-memory state into two states: finely-encoded memory and coarsely-encoded memory. Depending on how memory is encoded, participants will provide answers to the task in one of two ways: they will center their responses either on the actual studied angle or on the stereotypical angle for the side toward which the test item was oriented.

For an indicator variable z_i, $z_i = 1$ implies that the test item is in memory and $z_i = 0$ implies that the test item is not in memory. This variable follows the distribution described in Equation (4.3), where k is a free parameter representing the number of slots in working-memory. It is important to note that, in the experiments that use false test-items, $\mathscr{I}_V(i) = 0$ implies that $z_i = 0$.

Assuming that $z_i = 1$, there is a second indicator variable m_i where $m_i = 1$ implies that the item was finely encoded and $m_i = 0$ implies that the test item was coarsely encoded:

$$m_i|(z_i = 1) \overset{ind}{\sim} \text{Bernoulli}(p_f),$$

where p_f is a free parameter. If $z_i = 0$, then m_i has no value.

If an item in working memory is finely encoded, then the distribution of responses is

$$y_i|(z_i = 1, m_i = 1) \overset{ind}{\sim} \text{Normal}(x_i, \sigma_i^2). \tag{4.7}$$

The variance of the normal distribution is a measure of the mnemonic precision at which items are stored. In typical descriptions of the discrete-slots model, this precision is assumed to be constant regardless of the number of items stored in memory. Model $\mathscr{M}_8$ follows this assumption:

$$\sigma_i^2 = \sigma_0^2,$$

where σ_0^2 is a free parameter.

If an item in working memory is coarsely encoded, then the participant will produce a response on the same side as the test item, but will center their responses on a stereotypical angle for that side instead of centering on the angle of the test item. Participant responses in this instance are distributed as described in Equation (4.5), with:

$$s_i|(z_i = 1, m_i = 0) = \mathscr{I}_S(i).$$

where $\mathscr{I}_S(i)$ is an indicator function with $\mathscr{I}_S(i) = 1$ if the tested item was oriented rightward at study, and $\mathscr{I}_S(i) = 0$ if the tested item was oriented leftward at study.

If the tested item is not in working memory, then the response must be a guess. Using Equation (4.5), participant responses are equally likely to be drawn from either of the two normal distributions:

$$s_i|(z_i = 0) \stackrel{iid}{\sim} \text{Bernoulli}\left(\frac{1}{2}\right). \tag{4.8}$$

The assumption that participants guess leftward or rightward with equal likelihood is made for simplicity. Adding a free parameter to account for bias would make this model overly flexible and would likely interfere with the estimation of the other free parameters.

Given the above, the overall description of participant responses is:

$$y_i|z_i, m_i \stackrel{ind}{\sim} \begin{cases} \text{Normal}(x_i, \sigma_i^2) & \text{if} \quad z_i = 1 \text{ and } m_i = 1 \\ \text{Normal}(\mathscr{I}_S(i)(\alpha_R) + (1 - \mathscr{I}_S(i))(\alpha_L), \sigma_g^2) & \text{if} \quad z_i = 1 \text{ and } m_i = 0 \\ \text{Normal}(s_i(\alpha_R) + (1 - s_i)(\alpha_L), \sigma_g^2) & \text{if} \quad z_i = 0 \end{cases} \tag{4.9}$$

with k, p_f, σ_0^2, σ_g^2, α_L, and α_R as free parameters estimated for each participant and s_i as a latent variable distributed as in Equation (4.8).

$\mathscr{M}_9$: Coarse-Encoding Discrete-Slots Model with Zhang & Luck Style Variance

Model $\mathscr{M}_9$ follows Equation (4.7), as model $\mathscr{M}_8$, but does not assume a constant variance across array sizes. Instead, model $\mathscr{M}_9$ assumes a Zhang & Luck-style Variance:

$$\sigma_i^2 = \frac{\sigma_0^2}{\max\left(1, \frac{k}{n_i}\right)}$$

where σ_0^2 and k are free parameters. The rest of model $\mathscr{M}_9$ is identical to model $\mathscr{M}_8$.

$\mathscr{M}_{10}$: Coarse-Encoding Discrete-Slots Model with Free Variance

Model $\mathscr{M}_{10}$ follows Equation (4.7), as models $\mathscr{M}_8$ and $\mathscr{M}_9$, but does not assume a constant variance across array sizes nor does it assume the correction for changes in variance used by Zhang & Luck (2008). Instead, model $\mathscr{M}_{10}$ assumes a variance parameter for each array size:

$$\sigma_i^2 = \sigma_{n_i}^2$$

where each $\sigma_{n_i}^2$ is a free parameter. Allowing variance to vary freely with array size causes this model to lose its process interpretation, as the discrete-slots model assumes that items are stored as whole objects at a set precision. However, by adding this model to the analysis, we hope to test the constraints on variance used in the other models that satisfy the above assumption.

The rest of model $\mathscr{M}_{10}$ is identical to models $\mathscr{M}_8$ and $\mathscr{M}_9$.

4.2 Model Comparisons

BIC values were calculated, by participant, for each model. These values were then compared within participants to identify the models that provided the best and worst fit to the data for each participant, termed here as “wins” and “losses”, respectively. The wins and losses for each model were then counted, and are listed in Table 4.1. In Experiments 2 and 4, the coarse-encoding model $\mathscr{M}_9$ won most frequently by participants. This is likely because of the guessing bands that were observed in the data for those experiments. The data in experiment 3 also exhibited guessing bands, but model $\mathscr{M}_7$, a discrete-slots model, had the largest participant count. In Experiments 5 and 6, the discrete-slots models won over the distributed-resources models, with model $\mathscr{M}_6$ winning in Experiment 5 and model $\mathscr{M}_7$ winning in Experiment 6.

BIC values were also summed across participants to produce an overall score for each model within each experiment. The differences in these scores relative to the lowest BIC score for each experiment are presented in Table 4.1 as BIC Differences. The results from BIC Differences are similar to those observed by participant counts, with the main difference being that a coarse-encoding model, model $\mathscr{M}_{10}$, won in Experiment 3 instead of a discrete-slots model. Model $\mathscr{M}_7$ also won in Experiment 5, instead of model $\mathscr{M}_6$, but this difference is relatively minor given that both models are discrete-slots models.

	Distributed-Resources				Discrete-Slots			Discrete-Slots + Coarse-Encoding		
	$\mathscr{M}_1$	$\mathscr{M}_2$	$\mathscr{M}_3$	$\mathscr{M}_4$	$\mathscr{M}_5$	$\mathscr{M}_6$	$\mathscr{M}_7$	$\mathscr{M}_8$	$\mathscr{M}_9$	$\mathscr{M}_{10}$
Exp. 2										
BIC Difference	3060	*3103*	2705	2748	633	446	533	323	**0**	135
# of Winners	0	0	0	0	1	4	2	2	**13**	2
# of Losers	6	*17*	0	1	0	0	0	0	0	0
Exp. 3										
BIC Difference	*1680*	1640	1022	1049	1013	50	59	1068	89	**0**
# of Winners	0	0	2	0	0	5	**11**	0	5	3
# of Losers	6	*12*	1	0	0	0	0	7	0	0
Exp. 4										
BIC Difference	-	-	5814	*5891*	748	741	940	36	**0**	192
# of Winners	-	-	0	0	1	1	0	9	**15**	1
# of Losers	-	-	4	*23*	0	0	0	0	0	0
Exp. 5										
BIC Difference	1184	*1195*	1046	1055	316	117	**0**	-	-	-
# of Winners	1	0	0	0	2	**12**	6	-	-	-
# of Losers	3	*10*	2	3	3	0	0	-	-	-
Exp. 6										
BIC Difference	-	-	*1931*	*1931*	273	242	**0**	-	-	-
# of Winners	-	-	0	0	1	6	**14**	-	-	-
# of Losers	-	-	10	*11*	0	0	0	-	-	-

Table 4.1: BIC statistics for Project 2. The values above describe the differences in BIC scores between each model and the best model for each experiment along with the number of subjects where each model was either the best or the worst by BIC. The models included are Simple Distributed-Resources with Power-Law Variance ($\mathscr{M}_1$), Simple Distributed-Resources with Free Variance ($\mathscr{M}_2$), Nearest-Neighbor with Power-Law Variance ($\mathscr{M}_3$), Nearest-Neighbor with Free Variance ($\mathscr{M}_4$), Simple Discrete-Slots with Constant Variance ($\mathscr{M}_5$), Simple Discrete-Slots with Zhang & Luck-style Variance ($\mathscr{M}_6$), Simple Discrete-Slots with Free-Variance ($\mathscr{M}_7$), Coarse-Encoding with Constant Variance ($\mathscr{M}_8$), Coarse-Encoding with Zhang & Luck-style Variance ($\mathscr{M}_9$), and Coarse-Encoding with Free Variance ($\mathscr{M}_{10}$). Numbers in bold denote the winning models both in relative BIC and in largest number of individual wins by BIC. Numbers in italics denote the losing models both in BIC difference and in the largest number of individual losses by BIC. Models that were not run for a given experiment are marked with a hyphen. Despite the lack of a signle-best model overall, the winning models are generally from the Discrete-Slots class and the losing models are generally from the Distributed-Resources class.

4.3 Comparison of Estimates

As a way to understand why certain models performed better, additional analyses of parameter estimates were conducted. Some key findings are presented here.

4.3.1 Estimates for Probability of Fine Encoding

In Experiments 2, 3, and 4, coarse-encoding models were fit to the data. These models include a parameter that describes the probability of finely-encoding the studied angle. Estimates for these probabilities from model $\mathscr{M}_{10}$ are plotted by experiment in Figure 4.1. Estimates from models $\mathscr{M}_8$ and $\mathscr{M}_9$ are highly correlated with the estimates from model $\mathscr{M}_{10}$ and, as such, are not presented.

These results support the use of coarse encoding in Experiments 2 and 4, and to a lesser degree in Experiment 3. This conclusion is also supported by the fact that coarse-encoding models won in BIC by both relative totals and participant counts in the above experiments. The data also support the use of coarse encoding by some participants in Experiment 3. However, as seen in Figure 3.1, the guessing bands aren't nearly as clear in Experiment 3 as in the other experiments, suggesting that participants didn't use coarse encoding often, as evidenced by the high probability of fine-encoding estimates. It is also important to note that a discrete-slots model won in BIC by participant count in Experiment 3, even though a coarse-encoding model won by relative total. As such, coarse encoding does not seem to be a universal strategy, and might stem from a specific difference in the experimental designs.

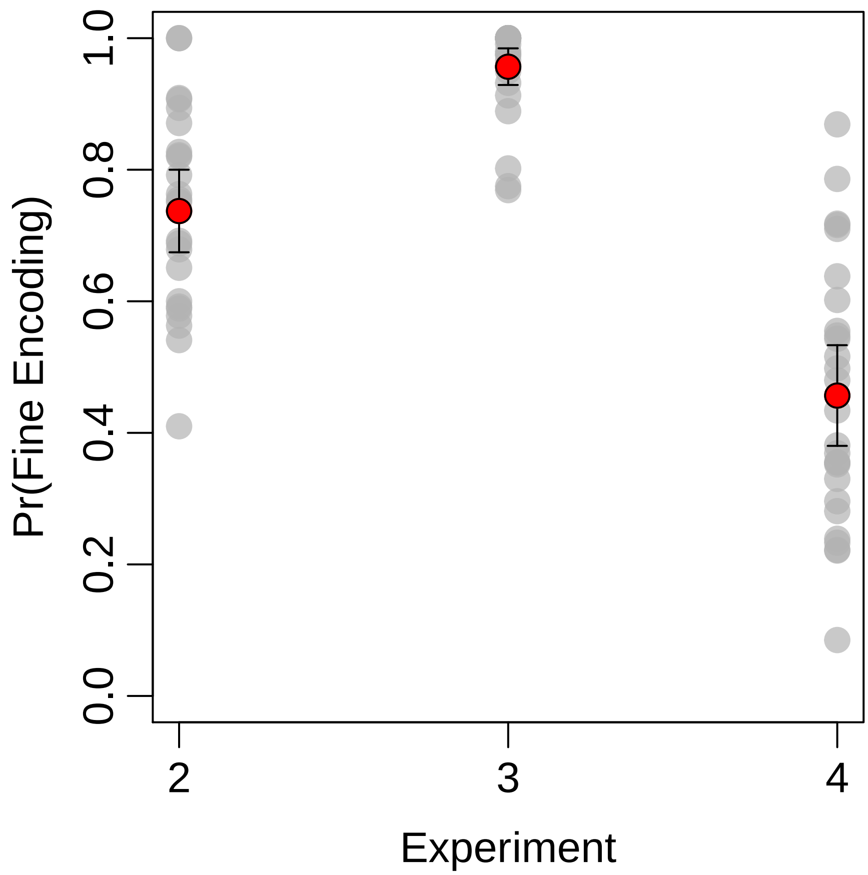

Figure 4.1: Estimates for the probability of fine-encoding from model $\mathscr{M}_{10}$ for Experiments 2, 3, and 4. The red dots indicate the average estimate with error bars extended out to 2 standard errors. Participants coarsely-encoded some study arrays in all experiments, but seemed to do so the least in Experiment 3.

4.3.2 Effectiveness of the Zhang & Luck 'Doubling of Slots'

In order to test the effectiveness of the Zhang & Luck (2008) models of variance (models $\mathscr{M}_6$ and $\mathscr{M}_9$), effective standard deviations were calculated from model estimates

$$\sigma_p = \sqrt{\frac{\sigma_0^2}{\max\left(1, \frac{k}{n_i}\right)}}.$$

These effective standard deviations were then compared with the standard deviation estimates from the free variance models (model $\mathscr{M}_7$ and $\mathscr{M}_{10}$) by dividing the effective standard deviations estimates by the corresponding free-variance model standard deviation estimate. If these ratios are close to 1, then the constraint provided by "doubling" slots is an accurate description of the relation between variance and array size. The averages of these ratios for models $\mathscr{M}_6$ and $\mathscr{M}_7$ are plotted in Figure 4.2. The ratios between models $\mathscr{M}_6$ and $\mathscr{M}_7$ and the ratios between models $\mathscr{M}_9$ and $\mathscr{M}_{10}$ are largely similar, so the latter ratios will not be reported.

In a few instances, where the ratios are close to 1 for all array sizes, the Zhang & Luck-style estimates are concordant with free variance estimates. However, the general form of these ratios suggest that the Zhang & Luck-style models are ineffective in estimating the variance of responses in larger arrays. In particular, the Zhang & Luck-style model of variance tends to underestimate the variance of responses in large arrays, with the size of the error increasing as array size increases. This undercorrection by the Zhang & Luck-style model casts some doubt on the assumption that the variance of individual slots in working memory is constant with respect to array size.

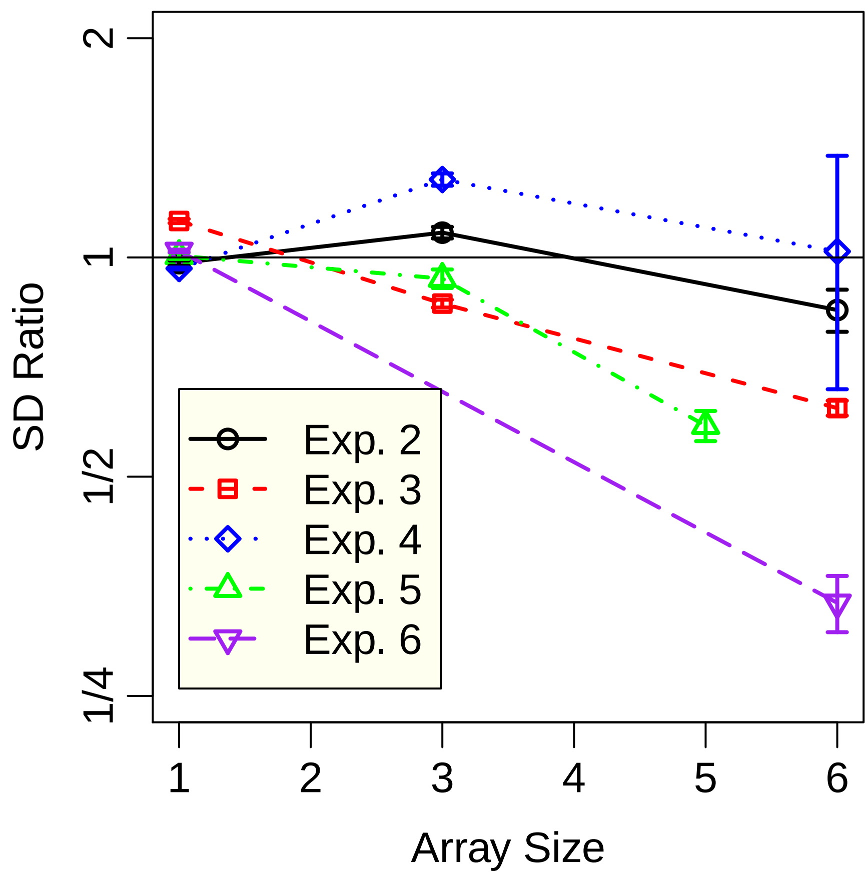

Figure 4.2: Means of the ratios of standard deviation estimates between models $\mathscr{M}_6$ and $\mathscr{M}_7$ for all five experiments with error bars extended out to 2 standard errors. Overall, Zhang & Luck (2008) models of variance tend to underestimate the true variance for larger arrays.

4.4 Discussion

Between the discrete-slots and distributed-resrouces models of working memory, discrete-slots models provide a better description of how people will respond to working-memory tasks. Discrete-slots models did better overall in BIC than distributed-resources models. However, some of the assumptions of the discrete-slots models did not seem to hold with this data. In particular, neither constant variance nor Zhang & Luck-style variance appear to hold. While additional constraints are typically posited by discrete-slots models, the constraint on variance is one of the more critical assumptions. It is important to note, though, that model $\mathscr{M}_9$, which assumed Zhang & Luck-style variance, did win in BIC for both Experiment 2 and Experiment 4, both of which showed average standard-deviation ratios close to 1 for all array sizes in Figure 4.2, which provides some support for the possibility of constant precision within individual slots across array sizes. Thus, with some qualifications, the data support the discrete-slots model of working memory over the distributed-resources model.

Chapter 5

Overall Conclusions

In conducting the research for this thesis, I have attempted to resolve the conflict between two different models of visual working memory, described as the discrete-slots and distributed-resources models. Out of several experimental paradigms that have been used in prior attempts to settle this dispute, I have focused on the results of two: the Bays & Husain identification task and the Zhang & Luck production task as used by Rouder, Cowan, & Cusumano.

For the first project, I investigated the perfect-performance result from the Bays & Husain paradigm. By making a slight modification to the task, I have shown that the perfect performance result is likely due to an artifact in the experiment's design. As such, the results from the original Bays & Husain (2008; 2009) experiments cannot be used as evidence for the distributed-resources model and against the discrete-slots model. Empirical modeling of the data suggests that the Bays & Husain paradigm is not well-suited to testing the accuracy of these models, which may also hold true for similar tests.

In the second project, I looked at the Rouder, Cowan, & Cusumano experiment and conducted four replications of their original experiment. The data from these five experiments seem to support the discrete-slots model, as participant responses tended to fit into one of two patterns: either they closely matched the studied angle or were centered around one of two stereotypical reference points. However, the lack of data in the middle of the diagonal and the abundance of data in the bands in the first few experiments was worrisome, as neither model could effectively describe this pattern without substantial modification. I suggested that participants might have employed a different strategy and coarsely encoded items in larger arrays, and both experimental control and model-based analysis seemed to support this suggestion. And though the data from Experiment 5 seemed to support the distributed-resources model more than the discrete-slots model, the responses to false targets in Experiment 6 suggest that participants could have produced a different guessing pattern.

The experiments in the second project also provided substantial amounts of data for direct model comparisons. Using BIC, the discrete-slots class of models consistently outperformed the distributed-resources class of models, though no single discrete-slots model won consistently over any other model. However, the model analysis also suggested that some of the assumptions of the discrete-slots model do not necessarily hold in all cases. In particular, the assumption that the precision of an item stored in a slot is constant with respect to array size does not seem to hold. The analysis of the first three experiments also suggests that a constant precision may be unfeasable, as participants frequently used coarse encoding in experiments 2 and 4.

This constraint on variance is an important part of the discrete-slots model. However, there are other important constraints provided by the discrete-slots model that are supported by this research. Specifically, the limit on the number of items that can be held in memory and the provision that participants guess when tested on an item not in memory, seem to hold quite well. This success is largely due to the mixture result observed in the data, as the distributed-resources model is unable to account for uninformed guessing. As such, the discrete-slots model provides a better description of the observed results than the distributed-resources model.

Despite the results of this thesis, several assumptions from both models remain in need of testing. In particular, there is still an issue regarding the discrete-slots assumption that stimuli with multiple features, such as color, shape, and orientation, are bound into unitized wholes and, consequently, use no more mnemonic resources than stimuli with fewer features (Luck & Vogel, 1997; Wilken & Ma, 2004; Awh, Barton, & Vogel, 2007; Wheeler & Treisman, 2008). Earlier research produced mixed results, with studies both supporting and refuting this assumption, while recent research by Bays, Wu, and Husain (2011) provided additional evidence refuting this assumption. More analysis of mnemonic resources used by feature binding is needed to settle this issue. Another assumption in need of testing is the distributed-resources assumption that attentional resources can be finely allocated across arbitrarily many items in a study array (Bays & Husain, 2008). While flexible allocation of resources has substantial support from both eye-tracking research and from tests over sequentially-presented arrays (Gorgoraptis et al., 2011), it seems inaccurate to claim that there is no finite limit on the number of items to which attentional resources may be allocated. Our own research suggests that only some items can be held in memory, even if those items were encoded coarsely. Even intuitively, it seems natural to assume that there would be some finite limit on the number of items that can be held in memory, even if that limit isn't necessarily constant across all types of items. However, the research from Bays & Husain and from Gorgoraptis etal. produce strong enough results to warrant additional inquiry. Consequently, this thesis can only conclude in favor of the discrete-slots model in cases where items only varied in one feature and where items were studied simultaneously, with additional research needed on stimuli that vary in more than one feature and on sequentially presented stimuli.

Bibliography

[1] G. A. Alvarez and P. Cavanagh. The capacity of visual short-term memory is set both by visual information load and by number of objects. *Psychological Science*, 15:106–111, 2004.

[2] E. Awh, B. Barton, and E. K. Vogel. Visual working memory represents a fixed number of items regardless of complexity. *Psychological Science*, 18:622–628, 2007.

[3] P. M. Bays, R. F. G. Catalao, and M. Husain. The precision of visual working memory is set by allocation of a shared resource. *Journal of Vision*, 9(10):7–7, 2009.

[4] Paul M. Bays and Masud Husain. Dynamic Shifts of Limited Working Memory Resources in Human Vision. *Science*, 321(5890):851–854, 2008.

[5] Paul M. Bays and Masud Husain. Response to Comment on "Dynamic Shifts of Limited Working Memory Resources in Human Vision". *Science*, 323(5916):877d–, 2009.

[6] P.M. Bays, E.Y. Wu, and M. Husain. Storage and binding of object fatures in visual working memory. *Neuropsychologia*, 49:1622–1631, 2011.

[7] N. Cowan. The magic number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral and Brain Sciences*, 24:87–114, 2001.

[8] N. Cowan, E. M. Elliott, J. S. Saults, C. C. Morey, S. Mattox, A. Hismjatullina, and A.R.A. Conway. On the capacity of attention: Its estimation and its role in working memory and cognitive aptitudes. *Cognitive Psychology*, 51:42–100, 2005.

[9] Nelson Cowan. *Attention and memory: An integrated framework*. Number 26 in Oxford Psychology Series. Oxford University Press, 1995.

[10] Nelson Cowan and Jeffrey N. Rouder. Comment on "Dynamic Shifts of Limited Working Memory Resources in Human Vision". *Science*, 323(5916):877c–, 2009.

[11] J. P. Egan. *Signal detection theory and ROC analysis*. Academic Press, New York, 1975.

[12] N. Gorgoraptis, R.F.G. Catalao, P.M. Bays, and M. Husain. Dynamic updating of working memory resources for visual objects. *The Journal of Neuroscience*, 31(23):8502–8511, June 2011.

[13] M Kleiner, D Brainard, and D Pelli. What's new in Psychtoolbox-3? *Perception*, 36, 2007. ECVP Abstract Supplement.

[14] S. J. Luck and E. K. Vogel. The capacity of visual working memory for features and conjunctions. *Nature*, 390:279–281, 1997.

[15] G. A. Miller. The magical number seven plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, 63:81–97, 1956.

[16] J. N. Rouder, N. Cowan, and M. C. Cusumano. Discrete-slots model of working memory accounts for bimodalities in human performance. In Preparation, 2010.

[17] J. N. Rouder, R. D. Morey, N. Cowan, C. E. Zwilling, C. C. Morey, and M. S. Pratte. An assessment of fixed-capacity models of visual working memory. *Proceedings of the National Academy of Sciences*, 105:5976–5979, 2008.

[18] G. Sperling and M. J. Melchner. The attention operating characteristic: Examples from visual search. *Science*, 202:315–318, 1978.

[19] J.E. Thiele, M.S. Pratte, and J.N. Rouder. On perfect working-memory performance with large numbers of items. *Psychonomic Bulletin and Review*, 2011. Online Publication.

[20] M. E. Wheeler and A. M. Treisman. Binding in short-term visual memory. *Journal of Experimental Psychology: General*, 131:48–64, 2002.

[21] P. Wilken and W. J. Ma. A detection theory account of change detection. *Journal of Vision*, 4:1120–1135, 2004.

[22] Weiwei Zhang and Steven J. Luck. Discrete fixed-resolution representations in visual working memory. *Nature*, 453:233–235, 2008.