SPATIO-TEMPORAL INTERACTIONS IN IMMEDIATE SERIAL RECALL

by

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Abstract

In an immediate serial recall task, participants are asked to recall lists of items in order. In the Hebb repeating-list variant of the task, subjects are read a series of lists, and every third list is repeated. Performance improves across repetitions but is stable for the non-repeated trials. The repetition advantage—the increased accuracy for the repeated list—is known as the Hebb effect. Several models have been advanced to explain how participants order successive items, but how participants take advantage of the repetition has largely been ignored. Although the task is usually discussed in terms of recall of verbal items, the Hebb effect has been observed with sequences of visuo-spatial positions.

The present work assesses whether immediate serial recall of verbal material benefits from visuo-spatial context. Sequences of letters were presented in different spatial positions in a visual version of the Hebb task. Presenting lists in random spatial positions on the periphery of an imaginary circle did not boost performance, but if the sequence was predictable, overall accuracy increased. The spatial path of successive items influenced the Hebb effect. When the distance between successive positions was minimized, participants were able to exploit the repetition early in practice. The results deny an account based on item distinctiveness. I discuss the results in terms of contemporary models of ISR.
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In an immediate serial recall (ISR) task, participants are presented lists of items and asked to recall them in order shortly after presentation. By what mechanisms do people maintain order in memory? Perhaps the first documented study of this question was by Nipher (1878). He reported that when recalling ordered lists, recall was most accurate at the beginning and at the end of a list. His work was followed, independently, by Ebbinghaus in 1885. Since these pioneering studies, researchers have produced a considerable literature detailing the nuances of human performance on the task (see Neath, 1998 for a review).

Several mechanisms have been proposed to account for the ability to report in order. The theories fall broadly into three categories: (a) Chaining/associative theories suppose that successive list items are linked together. When one item is recalled, it prompts recall of the next item because the two were linked. (b) Gradient/ordinal theories order recall by ranking items based on their relative level of activation. The activation is developed during study and reflects the subject’s rehearsal of the items. (c) Positional/context models propose that time becomes a context cue that is associated with each list item. To order recall, the initial time is reinstated, and the successive contexts prompt recall of the associated items.

The various accounts of ISR ignore visuo-spatial information. Paradoxically, visuo-spatial information is known to be an important contributor to serial recall in the clinical literature concerning memory disorders. The Corsi asks patients to recall a series of positions in order; that is, the Corsi task is a visuo-spatial analogue of the verbal ISR task (see Corsi, 1972; Milner, 1971). Performance is used as a diagnostic test of memory disease. This paper attempts to bridge the gap between the technical and clinical literatures. In the present studies, I assess the role of visuo-spatial information in ISR by introducing spatial information in various degrees of predictability. I will use the results to assess the various technical theories of ISR.
A second focus of the current work concerns learning across the series of ISR trials. Hebb (1961) showed that participants can take advantage of repeated lists, but current theories of ISR have not taken such learning into account. Therefore, the second focus of my work concerns how learning can be best handled within current theory.

In the next section I will review the three classes of theory, with some early examples, and then discuss some recent implementations. Chapter 2 introduces the Hebb task. I will discuss some procedural variations that allow me to introduce visuo-spatial context into that task. I shall also speculate about how the various theories might address learning in the modified paradigm.

Chapter 3 presents the empirical work. In the final chapter, I discuss the impact of the results for the various theories.

Three Classes of Theory

Associative Theory

Chaining theory, the first, and most intuitive theory was proposed by Ebbinghaus (1885/1964). According to chaining theory, the list of items is chained together by direct item-to-item associations. The idea is that people rehearse overlapping pairs (e.g., AB, BC, etc.) of items so that successive items in the list are associated, the recall is driven by the inter-item associations. In its simplest form ordered recall is driven solely by associations between adjacent items (e.g., Wickelgren, 1965).

Figure 1 introduces schematic of each class of theory. Simple chaining models are represented in Figure 1 (i). In the figure successive items (A, B, C) are represented by circles and associations are represented by arrows. Hence, Figure 1(i) represents the items and the associations that drive recall.

In simple chaining theory, report starts with the first items, and each report becomes the cue for recall of the next item in the list. Because report of each list element derives from the
prior response, any error will disrupt recall of all subsequent items. An obvious objection to chaining theory is that, unlike human subjects, it can not recover from an error. A second criticism is that chaining cannot handle repeated items within a list. If, for example, the sequence ABCADE were presented, A is associated with both B and D but simple chaining theory provides no mechanism for multiple associations. Both problems are serious.

Compound-chaining theory has been advanced to solve the problems (e.g., Ebbinghaus, 1885/1964). It introduces remote associations that allow report to continue if the initial chain is broken (see Slamecka, 1985 for a review).

Figure 1 (ii) illustrates a basic compound chaining model. Like Figure 1 (i), list items are shown in circles but, in Figure 1 (ii), associations link item A to item C as well as to item B.

In compound-chaining models, the cue for a particular item includes all preceding items, not just the immediately preceding item. As I will discuss later, recurrent neural networks implement the multiple-cue trick (Elman, 1990; Jordan, 1986). A recurrent neural network allows chaining models to recover from errors because, unlike the simple variant, the associations from preceding list items allow recall to proceed.

**Ordinal Theory**

Ordinal theories do not use associations between list items. Instead, order is derived from an ordinal dimension: item activation. Figure 1(iii) shows a schematic representation of item selection in an ordinal model. The figure shows three items (A, B, & C) with activation indicated by the height of the column. The left panel of Figure 1 (iii) indicates that item A will be reported because it has the greatest activation. The right panel indicates that item C will be reported after items A and B because they have been suppressed.

In Grossberg's (1978) account, each item in the study set begins with a base level of activation. Studying an item increases its activation level. Rehearsal, occurs while items are being studied, and increases each item’s activation. Because the first item in the list is rehearsed
more times than any other item in the list, it will have the highest level of activation. Recall proceeds by iteratively selecting item that has the strongest activation. After each item is reported, its activation is suppressed to its original base level of activation. Suppressing activation of an item as soon as it has been reported guarantees that it is not repeated.

Ordinal theories escape some of the criticisms levelled at chaining theory (such as recovery from errors), but the simple activation based mechanism has its own problems. Learning between lists, for instance, would be difficult to characterize because it is unclear what would be stored from one trial to another.

**Context Theory**

Models in this class depend on a specification of an item's position in time. Unlike chaining models, items are not associated directly with one another. Instead, they are associated with temporal information, and recall is driven by the order of the associated information. Hence if the temporal information can be reinstated properly, the list elements will be recalled in order. The major differences among models in the category lie in their formalization of context and how order is reinstated at recall.

Conrad's Box Model (1965) is the simplest example. Short-term memory (STM) is represented as a series of *boxes*, each of which represents a position in a series. Studied items are placed in the appropriate box, and the order of the boxes is known. Hence recall proceeds in order. The model is an obvious oversimplification. It implies a strict definition of storage capacity, and it does not offer a principled account of errors. It was, however, the inspiration for several more complete models.

Rather than casting context as a static set of placeholders, as in Conrad’s Box Model (1965), Bryden (1967) forms context by encoding external events. Bryden (see also Lashley, 1951), proposed that list elements are associated with spatial and/or as temporal *tags*. The combination comprised the
Figure 1. Schematics of: (i) a simple chaining model (e.g., Wickelgren, 1965), (ii) a compound chaining model (e.g., Ebbinghaus, 1885/1964), (iii) item activations in a simple gradient model (e.g., Grossberg, 1978), (iv) context-item associations in a context model (e.g., Brown, et al., 2000).
context. Depending on the spatio-temporal details of the list’s presentation—Bryden discussed dichotic stimuli that included both space and time—recall could proceed in either spatial or temporal order. Bryden was more concerned with what dimension is used as constitutes context rather than a formal definition of context. More recently, however, Brown, Preece, and Hulme (2000) have advanced a formal definition of how time is generated in a biological system.

Figure 1 (iv) illustrates a the general form of context models. In the figure, list elements are shown in labelled circles and the contexts are indicated in boxes. The associations between time and list elements are represented by arrows. As indicated in the figure, time-one proceeds naturally to time-two and so forth, so that recall proceeds in order.

Context models escape some problems associated with the other models. For example, context models can handle repeated list elements. Unlike chaining models, context models can recover from errors because recall of one item does not hinge on correctly recalling the prior item.

Recent Implementations

The three classes of model sketched in the foregoing are prototypes for the mechanisms of interest. Of course variants on all three are possible and the variants may allow the various models to escape the criticisms associated with their class. In the following section, I will introduce some recent concrete implementations of the ideas.

Associative Models

TODAM. TODAM (Theory of Distributed Associative Memory) is an influential associative memory model (Lewandowsky & Murdock, 1989; Murdock, 1983; Murdock, 1995). TODAM represents a list item as a vector of Gaussian values. The set of values is drawn randomly from a zero centered Gaussian distribution with a standard deviation of $1/\sqrt{n}$, where n is the dimensionality of the vector. As a consequence, a set of TODAM vectors is orthonormal in
expectation. That is, the expected value of the dot product of each vector with itself is 1, and the expected value of the dot product between arbitrary pairs of vectors is 0.

The identity of each item is distributed over the set of numbers in the corresponding vector. Each value can be thought of as a partial descriptor of the item represented by the vector as a whole. Such a distributed representation allows list items to have a unique identity, but, because each item is represented by a unique pattern of values, there will be incidental similarities (assessed by dot product) among list items. As a result the vectors map nicely onto standard sets of verbal stimuli.

In TODAM, a stimulus item is represented by a vector $F$ of features:

$$F = (\ldots, 0, f_{(n-1)/2} \ldots f_1, f_0, f_1, \ldots f_{(n-1)/2}, 0, \ldots)$$

Memory in TODAM is a vector of the same dimensionality as the item vectors. When items are encoded in memory, item and order information are encoded differently. Items are encoded by adding their vectors to the memory vector. Order information is computed by forming overlapping pair-wise associations. Hence if the list includes items ABC … pair-wise associations of A with B, B with C, and so forth are computed. Association is constructed by convolving the vectors for the associated items.

Convolution (represented by *) is a method for collapsing the outer-product matrix computed from the associated vectors. Linear convolution is defined as:

$$(A * B)_x = \sum_{i=-L}^{L} A_i B_{x-i}$$

Where $L = (n-1)/2$, and $x$ ranges from $-L$ to $L$. The resulting vector does not directly resemble either parent vector.

Correlation (represented by #) is the approximate inverse of convolution. It is used to retrieve items from memory. Linear correlation is defined by:
\[(A\#B)_x = \sum_{i=-L}^{L} A_i B_{x+i}\]

By approximate inverse, I refer to the ability to recover one parent from its convolution with the other parent. Hence, if \(A*B = C\), \(B\#C \approx A\), and \(A\#C \approx B\).

To encode the bigram \(AB\) into memory, I would first add \(A\) and \(B\) to memory, and then add their convolution \(A*B\). Associative information is assigned a weight \(w_a\) that decreases exponentially across serial position. The associative weight decreases the strength of the associative information as more items are studied. To simulate a limited-capacity system, associative and item weights sum to one, i.e., \(w_i = 1 - w_a\).

So, to represent all aspects of the bigram \(AB\) in memory I would add the weighted elements to the memory vector \(M\).

\[M_j = M_{i(j-1)} + w_{i(j-1)} A + w_{ij} B + w_{aj}(A*B),\]

Where \(j\) represents the position in the study list. Now if I probe memory with the first letter (\(A\#M\)), it will yield a noisy version of \(B\).

In an ISR task, order is driven solely by pair-wise associations (i.e., only associative information is used) and, as in all chaining models, each item acts as a cue for the next item. The first item in the list is always associated with a recall cue. Once a list has been encoded into memory, recall begins by probing memory with the recall cue to select the first item in the list. The first response is used to probe for the next item, and so forth. In each case the facsimile vector produced by the cue is compared to the possible items (using dot product), and, if the facsimile is similar enough to a known item, that item is reported. If not, recall stops because there is no clear probe for subsequent items.

The inability to recover from an error is a major criticism of the original TODAM (Murdock, 1983). To allow the model to recover from errors, Lewandowsky and Murdock (1989) changed the way it probes during recall. In the new version, when an item cannot be recalled, the
facsimile is used to probe memory for the next response, effectively approximating the correct cue. The approximation mechanism was thought to allow the model to recover from errors. Mewhort, Popham and James (1994) argued, however, that their use of the facsimile vector was confounded with a chance factor. The number of possible responses matches the number of items left to recall, so, as recall proceeds the number of response competitors is reduced. Mewhort et al. showed that the reduction of response competitors was the effective factor driving recall when errors were made. Furthermore, the model still does not allow for repeated items within a list.

**Franklin and Mewhort.** Franklin and Mewhort (2002) extended TODAM in two important ways: (a) They assumed that subjects know all of the materials to be used in the experiment. Hence rather than thinking of studying as transferring new items into memory, they view encoding as re-enforcing information that is already present. They start a simulation by pre-loading a full vocabulary of items and associations in memory. Studying a list strengthens the relevant items and associations. (b) They changed the control mechanism by acknowledging that the strength of items includes both item information and information derived from associations. Hence to decide on report of an item they first combined pair-wise associations with item activation to produce momentary item activation. Decision about reporting is based on the momentary activation. Whereas TODAM used only associative information to order report, Franklin and Mewhort use both item and associative information to order report.

In the Franklin and Mewhort (2002) model, items and associations are coded in the same way as TODAM, but they are weighted differently. Recall that TODAM set the item and associative weights so they sum to one. Franklin and Mewhort argue, by contrast, that associative information—the pair-wise associations between successive items—will be strongest at the beginning of the list where rehearsal is easy. Later, because rehearsal becomes overwhelmed as new items are introduced, the strength of inter-item associations drops off. Their assumption was confirmed by a study of overt rehearsal (Rundus & Atkinson, 1970). Item information, by
contrast, is subject to interference and should be strongest at the end of a list because the final
items are not subject to as much interference as initial items. Accordingly, in their model, after
study, item information will have weights from a geometrically increasing function, and
associative information will have weights from a geometrically decreasing function. The
weighting means that there are two sources of information, each with opposing trends. Item
weights are defined by:

\[ w_i = w_{imax} x b^p \]

Where \( w_{imax} \) is the maximum value of any studied item, \( b \) is a scaling parameter, and \( p \) runs from
0 to list length (LL). And associative weights are defined by:

\[ w_a = w_{amax} x a^{(i-1)} \]

Where \( w_{amax} \) is the maximum strength of association, \( a \) is a scaling parameter, and \( i \) runs from LL
+ 1 to 1.

At recall, each item in the vocabulary (I\(_j\)) is compared to memory (M) to assess the item
strength (S\(_j\)) using the dot product (\( S_j = (I_j \cdot M) \)), and the associative strength (A\(_s\)) by correlating
the prior response (I\(_p\)) with memory and comparing the result to each item in memory
(\( As_j = (I_p \# M) \cdot I_j \)). The two scalar values that are summed to represent item activation for every item in
memory. The item with activation closest to a criterion value is reported. After report, the
response item and the probe are convolved and the resulting vector is added to memory to
simulate response interference. Recall ceases when no item in memory has a momentary
activation close enough to criterion.

Because Franklin and Mewhort’s (2002) model uses item strength and associative strength
to select successive items for recall, it can recover from errors. TODAM (Murdock, 1983) orders
recall solely on associative strength. By contrast, in Franklin and Mewhort’s model, when an
error is made, although the associative information will be compromised, the item information
can make up for it and recall can proceed.
The Franklin and Mewhort model (2002) has only been applied to free-recall data. And although the decision mechanism seems promising, it has yet to be applied to a serial recall task so its competency in this realm is uncertain.

**Simple Recurrent Neural Network.** Botvinick and Plaut (2006) have implemented the compound chaining idea in a simple recurrent neural network (SRN) model of ISR (e.g., Elman, 1990). In their model, they implement a localist item representation. That is, list items are represented as single units called nodes. Unlike a distributed representation, items are not represented by a set of descriptors; instead each node is an arbitrary placeholder that is either active or not (for instance A = 10000, B = 01000, C = 00100, ...).

Figure 2 is a schematic of Botvinick and Plaut’s (2006) model. Input, output and hidden layers are represented by rectangles, and open circles represent nodes within each layer. Connection weights dictate how activation spreads between nodes in adjacent layers; they are represented in Figure 2 by arrows.

The architecture of the SRN is straightforward: there are three layers of nodes, one for input, output, and a hidden layer in the middle. The model uses discrete time; that is, each event takes a step in time. At each time step, adjacent layers of nodes affect the states of one another. As shown in Figure 2, there are two directions of influence, forward and backward. Activation from each item in the input layer feeds forward to activate nodes in the hidden layer. The resulting pattern of activation in the hidden layer provides a distributed representation of the item. Activation in the hidden layer, in turn, feeds forward to item representation in the output layer. Feeding activation from one layer to the next takes place in one time step. The backward connections constitute the recurrent part of the SRN, and their influence is delayed by one time step (e.g., Elman, 1990). By delaying the recurrent connections, the state of the hidden layer is determined both by the state of the input layer from the current time step, combined with state of the output layer, and from the hidden layers, at the previous time step.
Sets of weights dictate how activation spreads between layers. Each node in the input layer affects the state of each node in the hidden layer, and the extent of their influence is determined by a set of weights. The weights for forward connections are initially random values between +1 and -1, and weights for recurrent connections are initialized to random values between -0.5 and 0.5.

Before the SRN can perform an ISR task, it must be trained to perform the task. It is trained by providing a large number of practice lists. On each practice list, the network attempts to recall in order, and the weights are adjusted to reduce errors. The adjustments are based on a version of recurrent backpropagation through time, adapted to the SRN architecture (William & Zipser, 1995). To facilitate learning, a method called teacher forcing is used. Teacher forcing indicates that activation sent from the output to the hidden layer is based on the correct value rather than what the network actually output for that trial. Training proceeds until the SRN achieves a criterion level of accuracy. After reaching the criterion level of accuracy, the weights are set and are not altered during testing.

Once the model has been trained, it can perform ISR and is prepared to be tested. The SRN studies each list by providing one list item per time step (Botvinick & Plaut, 2006). As a list is studied, the input layer's activation feeds forward to the hidden layer: each list item will have a unique pattern of activation at the hidden layer that reflects the weights developed when the network was trained. The activation of the hidden layer is also influenced by the state of the output as well as hidden layers from the preceding list item. The feedback from the preceding output and hidden layers constitutes the recurrent part of the SRN and encompasses the adjacent and remote associations that drive recall.
Once a list has been studied, the model is ready to recall. The input layer includes a special recall node that is reserved as a cue to begin recall. After the list has been studied, the recall node is activated externally, and it is the only node held active in the input layer. The network selects an item by assessing which is the most activated element\(^1\) in the output layer. The selected element is reported, and the activation is fed back to the hidden layer before selecting another item. Feedback from the output node has the effect of inhibiting the recall of the same item. The sequence of events is repeated until the requested number of items (a constant set by the list length) is recalled.

Because of the remote associations, a consequence of the recurrent connections in the network, Botvinick & Plaut's (2006) SRN is able to recover from errors, and it can accommodate

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\(^1\) Nodes in the output layer aren't binary (as in the input layer) but are variably activated by the pattern of activation in the hidden layer.
repeated items within a list.

**Ordinal Models**

**The Primacy Model.** Page and Norris’s (1998) Primacy Model, is the only current model to apply the ordinal logic to ISR. In their model, each item is represented by a single node (i.e., they use a localist representation). Each node is associated with a level of activation that reflects rehearsal. As a list is presented, the nodes for successive items are activated. The first node receives the most activation and successive nodes receive decreasing amounts of activation. Hence across items there is a gradient of activation favouring initial items, a *primacy gradient* (see Figure 1(iii) for a schematic depiction). The initial activations assigned to each item begin to decay as soon as the stimulus is no longer present, and rehearsal of it has ceased. Page and Norris assume that rehearsal continues until recall begins. Decay, therefore, commences only after the list has been presented completely.

After the list has been studied, recall proceeds by iteratively selecting the most highly activated item, then suppressing its activation to base level (to avoid repeating the same item). Selection is assumed to be a noisy process. Gaussian noise is added to each node’s activation level before selection. As a result, list items that are close in activation level might be confused at recall. The noise is attributed to the selection mechanism, that is, it is not added to the primacy gradient. The gradient of activations itself does not get noisier as items are recalled.

Because the Primacy Model (Page & Norris, 1998) does not rely on item-to-item associations to drive recall, correct recall of successive list items does not rely on correct recall of preceding list items, so error recovery is not an issue.

**Context Models**

**OSCAR.** Brown, Preece, and Hulme’s (2000) context model focuses on how time can be used as a context for successive study items. At the heart of this model is a dynamic context
vector that represents time. They postulate that time, in a biological system, is generated by oscillators operating in the brain. The oscillators cycle at different rates. Hence by sampling the state of several oscillators simultaneously, time can be represented in a single vector. The idea that biological systems use yoked oscillators has ample behavioural and physiological support (e.g., Church & Broadbent, 1990; Klimesch, 1996).

OSCAR represents list items as vectors of normalized random values. When a list is studied, the items are associated with successive context vectors by taking the outer product of the item's vector representation and the state of the context vector. Memory is represented by a matrix (M). Item-context associations, that is, the outer product matrix for each event, are added to memory. At recall, the model reinstates the context vector by resetting the time back to the initial state and steps through time to reproduce subsequent contexts. At each step, memory is probed with the then-current context vector to produce an approximation of the list element originally associated at that time step. The approximation is compared to the representations for known list items (by vector cosine) and the closest match is issued as the response. The factor driving the order of recall is its ability to reinstate the context-signal properly; if it does so perfectly, recall will proceed in perfect order, so errors are a product of noisy reproduction of the context-signal.

OSCAR is the first model for ISR that provides a realistic account of context. Subsequent models lean heavily on their account. Because the organization is based on association of a unique context to each item, the model has no trouble handling repeated elements or recovering from errors. Unfortunately, OSCAR has not been applied to the Hebb repeating-list paradigm, and it is hard to imagine how it could be extended without introducing massive change to the architecture. The problem is it has no way of remembering the repetition.

**The Phonological Loop Model.** Burgess and Hitch’s (1992; 1999; 2006) Phonological Loop model is the last model I will discuss, and it is the first to have addressed learning in the
Hebb repeating-list paradigm. It was created as a mathematical formalization of the phonological loop portion of Baddeley’s Working-Memory (WM) model (Baddeley, 1986; Baddeley & Hitch, 1974).

Baddeley’s original model proposed that WM is comprised of two isolated stores called the phonological loop and the visuo-spatial sketchpad. The phonological loop is responsible for storing and maintaining phonological information. Information in the phonological loop is assumed to decay with time; therefore information must be continually refreshed via rehearsal. The visuo-spatial sketchpad is responsible for visuo-spatial information and can be further broken down into a spatial subsystem (dealing with location information), and a visual subsystem (dealing with characteristics such as colour and shape). Later, Baddeley (2000) updated the theory to include yet another subsystem, called the episodic buffer, which binds visuo-spatial and phonological information to form a unitary (episodic) representation. Control over attention, selection, and general co-ordination of cognitive processes between the phonological loop, visuo-spatial sketchpad, and the episodic buffer is handled by what Baddeley termed the central executive\(^2\).

The cornerstone, and most well developed component of Baddeley’s WM model (Baddeley, 1986), is the phonological loop. It was conceived to account for data indicating that working memory is largely acoustic in nature: Phonemic similarity of list items reduces memory span, even for visually presented items (e.g., Baddeley, 1966; Conrad, 1964). Sequences of short words are easier to remember than longer words (e.g., Baddeley, Thomson & Buchanan, 1975). Articulatory suppression reduces memory span (see Baddeley, 1986 for a review) and removes the effect of word length (e.g., Baddeley, et al., 1975). Visually presented items are recoded phonologically by naming them. Articulatory suppression prevents phonological recoding and has the effect of removing word length effects for visually, but not aurally presented items (e.g.,

\(^2\) My description of the central executive is imprecise because its function has never fully specified.
Burgess and Hitch's (2006) implementation of the phonological loop is a simplified neural network model. Figure 3 (i) is a schematic of their model. Context, lexical, and input/output phoneme layers are represented by rectangles, and open circles represent nodes within each layer. The lexicon contains localist representation for items. The input/output phoneme layers contain localist representations of individual phonemes that combine to form a distributed representation for phonological information. The context layer contains a two layer, distributed representation of temporal position. The first layer reflects an item’s position within a list, and the second layer reflects an item’s position within a temporal group.

Figure 3 (ii) depicts the states of the two context layers at different times (time (t) = 1 through 6). The first context layer proceeds through successive states while a list is being studied while the second layer is sensitive to temporal grouping. If there is a pause while a list is being studied, the second layer resets and proceeds until the next pause or until the list is finished. The combination of these two context layers allows for hierarchical temporal encoding (i.e., subgroups, or chunks, can exist within a list).

Connection weights dictate how activation spreads between nodes in adjacent layers. These weights are represented in Figure 3 (i) by arrows. Dashed arrows indicate modifiable connection weights that are strengthened during learning. The solid arrow between the input and output phoneme layers indicates static, one to one connections between phonemes.
Figure 3. (i) The architecture of the phonological loop model (Burgess & Hitch, 2006). Rectangles indicate layers, circles indicate nodes, dotted- lines indicate full connectivity with modifiable weights, and solid lines indicate one-to-one connectivity with static weights. (ii) The two components of the context-signal at time-steps t = 1 through 6. The first component indicates the position in the list and the second component allows for hierarchical encoding of temporal subgroups within a list.

The Phonological Loop differentiates between visually and aurally presented items by how information enters the model. Aurally presented items activate their phonological representation in the phoneme input layer directly. Visually presented items, on the other hand, activate their lexical representation directly. Visual material must therefore be recoded phonologically. The model simulates phonological recoding by feeding activation from the lexicon to the output phoneme layer. The output layer, in turn, feeds to the input phoneme layer, and back to the lexicon. This means that the phonological representation for visually presented items will be dictated by the connection weights between the lexicon and the output phoneme layer.
The model simulates studying a list by first determining the initial state of the context-
signal. Then the first item in the list is presented, the effect of item presentation on the network
depends on the presentation modality, as just discussed. The node in the lexicon with the greatest
activation at this point is given an activation of 1 and the rest of the nodes in the lexicon are given
activations of 0. Once an item is selected, all modifiable weights are strengthened using a
Hebbian learning algorithm. There are two sets of weights: large-amplitude, fast-decaying and
short-amplitude weights that don’t decay, but saturate. The two components are intended to
simulate short-term and long-term memory respectively. The short-term weights are strengthened
according to:

\[ W_{ij}^s(t + \delta) = W_{ij}^s(t) + \alpha \kappa \{ a_j(t) - \theta \} a_i(t) \]

Where \( a_i \) and \( a_j \) are the activations of the two nodes in question, \( t \) is the current time-step, \( \delta \) is the
size of each time-step (the item’s spoken “word-length”, \( \theta \) is the presynaptic threshold value, \( \alpha \)
is the maximum size of a connection weight, and \( \kappa \) is the inverse of the number of units that are
active in the layer the connection comes from. At each time-step a small value is subtracted from
the short term weights to simulate decay.

The long-term weights are strengthened according to:

\[ W_{ij}^l(t + \delta) = \begin{cases} 
W_{ij}^l(t) + \epsilon \kappa \{ a_j(t) - \theta \} a_i(t) & \text{if } a_i(t) > 0; \\
W_{ij}^l(t) & \text{otherwise}
\end{cases} \]

Where \( \epsilon \) determines the learning rate and reduces as the connection weights approach their
maximum value.

Once a list has been encoded, recall begins by resetting the context-signal to its initial
state. At each time step (corresponding to each serial position in a study list), the context feeds
into the item layer. The item layer, in turn, feeds into the output (phoneme) layer, then back into
the item layer via the input (phoneme) layer. Following the feedback, the item node in the
lexicon that is most strongly activated is given an activation of one, and every other item node is
given an activation of zero. The one active item in the lexicon has now been selected for report, and, to simulate this, activation from the lexicon is fed into the output phoneme nodes. Burgess and Hitch (2006) assume that learning takes place at both study and report. So, before report continues, all modifiable weights in the network are strengthened. Then, the phoneme layers are reset, and the lexical node for the item that was selected for report is subject to decaying inhibition. Inhibition is simulated by changing the activation of the item node to a negative value which decays at the same rate as the short-term connection weights. Following this, the context-signal advances by one time-step and the next item in the series is recalled in the same way.

Up to this point, I’ve described the details of how the Phonological Loop model (Burgess & Hitch, 2006) encodes and recalls a single list. In order for the model to simulate learning in the Hebb repeating-list task (Hebb, 1961), however, it has another mechanism responsible for learning between lists. At the beginning of each list, all previously used context-sets, as well as a new context-set are active. Each item that is studied is compared to predictions from the previously used context-sets. If a previous context-set correctly predicts the item being presented, it gets a match score of one, otherwise the match score is zero. A sum of all the match scores, divided by the number of items presented so far, is maintained for each previous context-set. If the cumulative match for a previous context-set stays above a threshold value, it is reused. Otherwise the new context-set is used. If a context-set is used to recall the same list repeatedly, the weights connecting the context-set to the list items are strengthened. Repeatedly strengthening a set of weights has the effect of increasing recall accuracy. So if a list is repeated, as in the Hebb task, accuracy will increase over trials.

The Phonological Loop model is the only account to address the Hebb repeating-list effect (Hebb, 1961). Schwartz and Bryden (1971) introduced a variant of the Hebb task in which the initial items of the repeated lists were exchanged. In addition to dealing with learning in the repeating-list task, Burgess and Hitch (2006) also made a specific prediction for the Schwartz and
Bryden variant of the task. To understand the Schwartz and Bryden variant, we first have to understand Hebb’s perspective on learning.

Hebb (1961) introduced the repeating-list task to test his own theory of STM. The idea was that STM was represented structurally in terms of *reverberatory circuits* in the nervous system. The theory claimed that introducing two lists between repetitions would cause sufficient interference that no learning could possibly occur. To his surprise, Hebb found learning across repetitions separated by two other lists, and was forced to revise his theory.

In his revised account, Hebb (1961) conjectured that presenting a list creates a transient *reverberatory trace* that causes temporary structural changes to the synapses underlying memory for the list. Hebb called these structural changes *structural non-permanent intermediary traces*, and suggested that they might grant the neurons involved priority for firing. If the intermediate trace received reinforcement by means of repetition within a criterion time period, the structural changes would be consolidated and learning would occur. Schwartz and Bryden (1971) tested Hebb's conjecture by presenting subjects with a standard Hebb task, but with the first two items in the repeating list exchanged on alternate repetitions. This manipulation set up a condition in which most of the repeated list was left undisturbed.

Schwartz and Bryden (1971) found that changing the first two [or more] items in the repeated list disrupts the repetition advantage. Because much of the list was repeated, Hebb's (1961) revised theory predicted learning, so that Schwartz and Bryden’s results refuted Hebb's theory.

Burgess and Hitch (2006) accommodated Schwartz and Bryden’s (1971) result in terms of the way that context-signals are reused. In their model, switching the first two items on successive repetitions disrupts the cumulative-match mechanism. As a result, they predict null learning for the Schwartz and Bryden condition. In addition, if the Schwartz and Bryden manipulation is introduced after learning has occurred, because the learning advantage depends
on the cumulative-match mechanism, Burgess and Hitch anticipate that the manipulation should reduce performance to the no-repetition baseline.

**Space as an Ordering Principle**

The review of recent models in this chapter is not exhaustive of the models currently in the literature. The review does, however, cover the most influential models, and is representative of the classes of models that exist in the literature. Contemporary models of ISR focus on verbal ISR exclusively. The visuo-spatial aspect of stimulus presentation has not made its way into current theories of ISR. In fact, no current model of ISR has any representation for spatial events. The neglect is likely because the tasks that are generally used to examine verbal ISR don't include spatial manipulations; stimuli are all presented in one position or aurally. Although verbal materials are presented visually, their internal representation is thought to be phonological (e.g., Baddely, 1986). The phonological-loop model (Burgess & Hitch, 2006) is unique in that it deals differently with visually and aurally presented materials. It includes a step between perception and encoding in which the visual information is transcribed into its phonological representation. The transcription is thought to be needed to facilitate rehearsal. Because it is based on Baddeley's model (Baddeley, 1986), it is prepared to represent visuo-spatial information. However, Burgess and Hitch have not implemented the visuo-spatial sketchpad in their discussion of ISR.

**Visuo-Spatial ISR**

The Corsi block tapping task (e.g., Corsi, 1972; Milner, 1971) is a visuo-spatial ISR task. In the task, participants are given a set of blocks, and the experimenter tapped each block once forming a visuo-spatial sequence that the participant attempts to reconstruct. The factors that determine performance are hard to characterize. For instance, spatial clustering aids visuo-spatial memory span (De Lillo, 2004), but only if the sequence exhausts all positions within each cluster before continuing (Smyth & Scholey, 1994). Further, although path length (the physical distance
traveled from start to finish) does not affect performance (Orsini, Pasquadibisceglie & Picone, 2001), greater path complexity (roughly characterized by the number of path crossings) reduces overall performance (Busch, Farrell, Lisdahl-Medina & Krikorian, 2005). Performance, here, is not likely to be characterized by the mechanisms in the current models of ISR. Indeed before they could attempt any simulations, they would first need a way of representing visuo-spatial information. But, perhaps, the tasks are different enough that they should be left as separate exercises. Put another way: Is there any precedent to expect an interaction between visuo-spatial and temporal information in otherwise standard ISR tasks?

The answer is yes. Interestingly, the interplay between temporal and visuo-spatial information was at the heart of some of the earliest accounts of the sequential nature of behaviour (e.g., Bryden, 1967; Lashely, 1951). The early accounts were conceived as general models of the serial ordering of behaviour and were based on research about the interaction between spatial and temporal information. One popular technique involved memory span with dichotic presentation. In such tasks (e.g., Broadbent, 1954; Bryden, 1962), list items are presented in pairs arranged so that one member of the pair occurs at the same time in one ear that the other member of the pair occurs in the other ear. If the lists are presented quickly, subjects tend to report lists in spatial order (i.e., right ear then left ear). If lists are presented slowly however, participants generally report pairs of items in temporal order (i.e., first pair, second pair, and so forth).

Early accounts (e.g., Broadbent, 1958) focussed on how an ordering principle (spatial or temporal) is selected. Unlike contemporary models of ISR, however, they did not attempt to offer a principled mechanism for ordering recall once either space or time was selected. So, while they did not address the problem of ISR, the focus of this paper, they show that spatial aspects of stimulus presentation will affect the order and accuracy of recall.

Bryden (1967) reviewed how the order of report in free recall varies with spatial factors: e.g., the spatial arrangement of concurrently presented visual stimuli (e.g., Heron, 1957; Bryden,
1960; Kimura, 1959). He also discussed how the spatial distribution of concurrently presented visual stimuli affect order of report (e.g., Mewhort, 1966). Subsequent work emphasized the effects of spatio-temporal presentation on item localization (Hearty & Mewhort, 1975; Mewhort, 1974), and letter perception (Mewhort, Hearty & Powell, 1978). My conclusion is that the spatial aspect of presentation can affect the order and accuracy of report. Therefore, we can not leave the visuo-spatial tasks as a separate exercise.
Chapter 2: The Hebb Repeating-List Paradigm and Visuo-Spatial Context

To study ISR, I used a modified version of Hebb's (1961) repeating-list paradigm. Here, I will introduce the original paradigm and discuss its current status in the literature. Then, I will discuss the rational for the modifications to the task that I have introduced. Finally, I will discuss how visuo-spatial context might be implemented in various models of ISR and develop predictions for my experiments.

The Hebb Repeating-List Paradigm

In Hebb's (1961) study, 24 sequences of digits were presented aurally to participants at a rate of 1 digit per second. Each list was a random permutation of the digits one through nine. After listening to each sequence, the participants were asked to report the sequence in order. Every third list was exactly the same, but the participants were not told of the repetition. Performance on the repeated lists increased across the 24 trials, but performance for the other lists was flat. The advantage for repeated lists, over the non-repeated lists is known as the Hebb effect.

Learning in the Hebb (1961) task is often characterized as implicit learning (e.g., by Seger, 1994; Stadler, 1993). Implicit learning implies that subjects are unaware that they are learning, and indeed of the manipulation. The ability to learn contingencies without being able to explicate them has been explained in two very different ways. Reber (1967) suggested that learning is accomplished by two independent systems, an explicit and an implicit learning system. The implicit system works subconsciously to abstract rules that describe the contingencies, and this system alone is responsible for performance in an implicit-learning task. While this view remains popular (e.g., Goschke & Bolte, 2007; Khun & Dienes, 2005), there is mounting evidence that performance often thought to involve the implicit system can be explained without invoking separate systems for implicit and explicit learning (e.g., Dunn & Kirsner, 1988; Hintzman, 1990; Vokey & Higham, 2003). Models of ISR do not address implicit learning, but McKelvie (1987)
has shown that performance on the Hebb task is the unchanged for subjects who can articulate the repetition, relative to those who can not. Hence, for ISR, the distinction is moot.

Hebb's (1961) procedure has been replicated many times (e.g., Cunningham, Healy, & Williams, 1984; Fendrich, Healy, & Bourne, 1991; McKelvie, 1987; Melton, 1963) and has enjoyed renewed interest as a potential tool for assessing theories of ISR (e.g., Hitch, Fastame, & Flude, 2005; Oshea & Clegg, 2006; Page, Cumming, Norris, Hitch & McNeil, 2006; Cumming, Page & Norris, 2003).

The Hebb effect has been shown using aurally presented material (e.g., Hebb, 1961) as well as visually presented material (e.g., Hitch et al., 2005; Oshea & Clegg, 2006). Although most studies have used verbal material, many studies have shown a repetition advantage using visuo-spatial sequences (e.g., Couture & Tremblay, 2006; Turcotte, Gagnon & Poirier, 2005; Milner, 1971).

Until very recently no model had succeeded in simulating even basic learning in the Hebb paradigm. Presently only two models boast simulations of the task, a simple recurrent network (Botvinick & Huffstettler, 2006, discussed by Plaut & Botvinick, 2006)\(^3\) and the phonological loop model (Burgess & Hitch, 2006).

**Modifications to the Hebb Repeating-List Paradigm**

I used a modified version of the Hebb repeating-list task to explore the interaction between temporal and visuo-spatial aspects of list presentation. I modified the task in five ways;

1. In Hebb's (1961) original task, and all subsequent replications, lists comprised permutations of the digits 1-9 or 0-9, depending on the desired list length. Because the list length in these experiments is the size of the pool of potential items (or close to it), it is possible that digits naturally following one another in the number line (e.g., 1, 2, 3) were presented

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\(^3\) Plaut and Botvinick (2006) state that their model can reproduce the Hebb effect (Hebb, 1961) and promise the results in a forthcoming paper (Botvinick & Huffstettler, 2006) but the paper has not yet been published and is therefore impossible to discuss.
consecutively in an experimental list. As a result, some lists, including the repeating list, could be
made unintentionally easier. To minimize accidental selection of easy sequences, I used letters
rather than numbers. There are a sufficient number of letters to allow me to pick only non-
consecutive items as stimuli.

2. The Hebb task (1961) was designed to observe memory for order, not memory for
what items were presented. As such, uncertainty about which items were presented on any given
list is minimized by presenting the same items in every list. In his original task, Hebb had
participants report the lists verbally. In many modern variants of the paradigm, items are
displayed on a computer screen, and subjects reported by typing the items (e.g., Cumming et al.,
2003). To minimize item uncertainty, I provided all the letters at the end of every list in the form
of an interactive response palette (described later) so that participants were never concerned with
remembering what items they saw, only the order in which they appeared.

3. Pilot work indicated that using a response palette makes the task slightly easier than
Hebb's (1961) original task. To bring the difficulty of the task to a level comparable to Hebb's, I
used 10-item lists rather than nine.

4. Hebb (1961) presented lists aurally. In four of the five conditions, to observe the
interaction between visuo-spatial and temporal information, I provided each list element a unique
visuo-spatial position. The fifth condition was a replication of the standard Hebb effect; instead
of presenting the stimuli aurally, I presented them visually, one after another, at the same location.

5. As I discussed in the previous section, Burgess and Hitch (2006) predict that, if
participants are allowed to learn a repeating-list and then are given a perturbed repeating-list,
there will be no repetition advantage for the perturbed list. I tested their prediction: I repeated
the same list every third trial, but on the last repetition, the order of the first two items was
inverted (e.g., if the eighth repetition were $abcdef$, the ninth would be: $bacdef$.

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Predictions for Manipulations of Visuo-Spatial Context

How are the various models prepared to deal with visuo-spatial context? The next section explores that question and discusses how context might affect performance.

Ordinal models do not include a mechanism for expressing context and, so, are mute on the effect of adding visuo-spatial context. Likewise associative models encode order in terms of inter-item associations and, therefore, have no role for context. By definition, context models should be best suited to deal with visuo-spatial context.

All context models are, fundamentally, distinctiveness models. Successive temporal states are more or less distinct, depending on the temporal codes (i.e., how closely they were presented in time). Phonological distinctiveness is treated in the Phonological Loop model (Burgess & Hitch, 2006). And, although no context model has yet specified a mechanism for representing visuo-spatial context, visuo-spatial context would have to be treated as an extra dimension by which to distinguish list elements. Hence context models must predict that adding a unique visuo-spatial context will improve accuracy of report.

All context models rely on subjects’ ability to reinstate, when recalling, context information available at the time of study. From the literature on the Corsi task (Corsi, 1972), we know that several factors affect subjects’ ability to reinstate visuo-spatial sequences. For example, path complexity affects subjects’ ability to reinstate visuo-spatial context (e.g., Busch et al., 2005). This provides an interesting hypothesis: the complexity of the visuo-spatial path should affect how accuracy of recall. A simple path should aid recall, whereas, a complex path should reduce accuracy by making the visuo-spatial dimension difficult to recall.
Chapter 3: Testing for Spatio-Temporal Interactions in ISR

This chapter examines ISR under different spatio-temporal arrangements. If the results indicate that performance on the Hebb repeating list task (Hebb, 1961) is affected by visuo-spatial context then current theories of ISR will need to be extended to accommodate visuo-spatial information into their ordering mechanisms.

Methods

The specific conditions are described below, but the general method is the same for them all. Participants were presented with 27 lists of 10 letters and asked to reconstruct the temporal order of presentation. As in the original Hebb task (Hebb, 1961), every third list was exactly the same, and the participants were not informed of the manipulation. The details of the experimental design follow.

Participants

A total of 90 participants, with normal or corrected to normal vision, were randomly assigned to the four groups of 18. Participants were recruited from the Queen's undergraduate Psyc 100 class, and were granted course credit in exchange for their time.

Stimuli

Each list was a 10-item combination of the first 10 non-consecutive consonants in the alphabet (B, D, F, H, J, L, N, P, R, T). Vowels were excluded to discourage incidental similarities to words and non-consecutive letters were chosen to minimize effects of natural (alphabetic) ordering among stimuli.

Apparatus

The experiment was administered using a PC (Pentium IV, 2.0 Ghz, 1 Gig RAM) running Windows XP, using custom software written in Delphi. Delphi is a commercial application-
development tool, it does not support real-time work requiring time resolution greater than about 1/10 of a second. Stimuli were represented on a 17 inch CRT monitor in a dimly lit room.

**Procedure**

Participants were seated 40 cm in front of a computer screen with a mouse in front of them. They first received verbal instructions for the task, including instructions for responding with the response palette using a mouse. Figure 4 presents a schematic illustration of the response palette. As is shown in the figure, the palette comprised two rows of boxes. The bottom row held all the letters presented in each list, as well as a *backspace* and dash character. The top row represented serial positions within a list, when letters were clicked with the mouse they moved to the next available empty box in the top row. Each box listed a letter presented during the trial. Once the top row was full, a *thumbs-up* character was shown beside to the right, participants clicked on this character to submit the list and proceed to the next trial.

![Figure 4](image)

*Figure 4.* The response palette seen at the end of each trial. Participants clicked the letters one at a time (using the mouse) to reconstruct the temporal order of the list. As the letters were clicked they moved to occupy the next empty box in the sequence. The back arrow (far right) allows for corrections, and the dash character (second from right) was used rather than guessing.

Participants initiated each trial by pressing a button; the computer produced 10 grey circles on a black background. The circles were arranged on the periphery of an imaginary circle with a diameter subtending a visual angle of 22°. The circles indicated the positions in which the list items would appear. Before each letter was shown, the circle in which it was to be presented
would turn red and remain for 450 msec before being replaced by a letter. Letters were presented in white Arial font; each letter subtended a visual angle of $2.8^\circ$ (height) X $2.15^\circ$ (width). Each letter remained on the screen for 450 msec and was then replaced by a grey circle (see Figure 5 for an example).

The interval between successive trials was partially under the subject's control. On average, subjects initiated the next trial within two seconds and there was a mandatory three second pause before the next trial was presented, so in total the average inter trial interval was 5 seconds.

After studying each list, participants attempted to reconstruct the order of the list using a response palette that appeared at the bottom of the screen. They were instructed to use the dash character rather than guessing when responding.

Participants received a total of nine triples of trials (two non-repeated lists and one repeated list). The first eight triples were run in the standard Hebb fashion. The ninth reversed the first two items of the repeat sequence. The reversal was designed to test the specific prediction offered by Burgess and Hitch (2006).

At the end of each experimental session, the participants were asked how prepared they were by the practice and their awareness of the manipulation.

1. Was the practice sufficient and appropriate to prepare you for the task?

2. What strategies did you use to remember the lists?
   o Did you rehearse out loud or in your head?

3. Did you notice any patterns or regularities in the lists you saw?

---

*In the Hebb condition, the lists were presented in a single position. Successive letters followed the same time course, but all list items were presented in one position, at the centre of the screen.*
If yes – Please describe what you noticed and when approximately you noticed (give options ¼, ½, ¾ of the way through the experimental trials).

Figure 5. An example of the sequence of events in list presentation. In the actual experiment the background was black, light circles were grey, dark circles were red, and letters were white. The presentation of each letter was preceded by a red circle predicting its location.

Practice

The experimental sessions consisted of 9 practice trials followed by a block of 27 experimental trials. Practice trials followed the same procedure as experimental trials, except that in the practice trials all lists were random, whereas in the experimental session every third list was exactly the same.

Conditions

To establish baseline performance, I included a replication of the standard Hebb (1961) condition (referred to as the Hebb condition). In the Hebb condition I presented lists visually, and to replicate the standard Hebb effect with visually presented stimuli, all list elements were presented in the same position.

The remaining conditions were created to observe ISR under various spatio-temporal
arrangements. The display included multiple positions that were evenly spaced on the periphery of an imaginary circle so that all positions are equidistant from central fixation. The differences among the ensuing conditions lie solely in the spatio-temporal presentation of list items, or, more simply, in the path that each list took through the available positions.

I describe the conditions in terms of how structured the path is. Busch et al. (2005) quantified path complexity by counting the number of times the path crosses itself. I will describe an unstructured path as a random series of spatial positions, and a structured path as one that does not cross itself.

The conditions, and their underlying logic, are detailed individually below.

Condition 1 (Unstructured): Each list item had unique visuo-spatial coordinates, but the path was unstructured in the sense that the sequence of positions is determined randomly for each list (Figure 6(i)). This condition was meant to determine whether simply adding visuo-spatial context would improve performance by adding another unique dimension by which to differentiate list items.

Condition 2 (Unstructured-Reliable): The path was unstructured in that the sequences of visuo-spatial positions were determined randomly (Figure 6(i)), but reliably in the sense that each list followed the same path. In this condition, participants could learn the path by the time that practice was over. If participants’ expectation of the sequence of positions plays a role, performance should be better here than in the Unstructured condition.

Condition 3 (Structured-Reliable): Here, the path was counter-clockwise (Figure 6(ii)). The sequence was created so that each position was closest to the next position. Hence, this was the shortest structured path that could be taken. Because decreased path complexity makes it easier to remember a sequence of visuo-spatial positions, this condition assesses whether a structured path further facilitates the use of visuo-spatial contextual information. If it does this cell should yield the best performance.
Figure 6. Examples of the paths taken through the positions in the various trials: (i) an unstructured path (i.e., multiple path crossings), (ii) the shortest possible structured path.

Results

In response to the post-session questionnaire, all participants reported that the practice trials prepared them sufficiently for the experimental trials. In each group, approximately 50% of participants reported that they rehearsed lists out loud; the remainder reported that they rehearsed sub-vocally.

Accuracy scores were constructed by counting the number of items reported in the correct position within the list and then divided by list length (10) to produce the proportion correct. There were twice as many non-repeated lists (18) as repeated lists (9). To allow for one-to-one comparisons, data for non-repeated lists were averaged over pairs of consecutive trials to produce 9 data points. Therefore, all the data for non-repeated lists were averaged over accuracy data for two consecutive trials.

Learning

To assess the effect of repeating the list in the Hebb paradigm, the first eight pairs of data points were analyzed. Accuracy data were submitted to a 4 (Condition) X 2 (List-type: Repeated
Figure 7 summarizes the data for all conditions. For each condition, it shows accuracy as a function of trials and repetition condition. All conditions showed the classic Hebb effect: performance on the repeated lists increased with practice whereas performance on non-repeated lists stayed constant. The pattern of results was confirmed by a strong Trials by List-Type interaction, $F(7, 595) = 7.01, p < 0.0001$; the trials-linear component of the interaction explained 92% of the variance among the cells, $F(1, 85) = 70.7, p < 0.0001$.

The basic Hebb (1961) effect was replicated in all conditions; nevertheless, the results of conditions were not identical. To assess performance across the groups, I used a set of orthogonal comparisons. The comparisons are outlined in Table 1.

Table 1

*Orthogonal group comparisons used throughout the different analyses.*

<table>
<thead>
<tr>
<th>Comparison #</th>
<th>Hebb</th>
<th>Unstructured</th>
<th>Unstructured-R</th>
<th>Structured-R</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>1</td>
<td>-1</td>
<td>-1</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0</td>
<td>-1</td>
<td>1</td>
</tr>
</tbody>
</table>

Comparison 1 (The effect of unstructured space): The first comparison contrasts performance when stimuli were presented in the same visuo-spatial position (Hebb) to when each list element was given a unique random spatial position (Unstructured). The comparison assesses whether adding a unique visuo-spatial context to each list element affects performance.

Comparison 2 (The effect of reliable space): The second comparison contrasts performance when stimuli were presented in a series of reliable spatial positions (Structured-
Reliable, Unstructured-Reliable) to when there was no reliable spatial information (Hebb, Unstructured). It assesses whether presenting lists in a reliable series of spatial positions facilitates performance.

Comparison 3 (The effect of structure): The third comparison contrasts performance when lists were presented in a structured and reliable visuo-spatial path (Structured-Reliable) to when lists were presented in an unstructured-reliable visuo-spatial path (Unstructured-Reliable). It assesses whether the structure of the visuo-spatial path affects performance.

**Group Differences.** Comparison 2 indicated that the spatially reliable groups were more accurate (0.634) than the spatially non-reliable groups (0.545), $F(1, 68) = 6.1, p < 0.016$. None of the other group comparisons were significant, and there were no interactions with trials or list-type.

As is clear in Figure 7, all of the groups reached approximately the same asymptote. A statistical analysis with several groups at asymptote masks differences in learning because asymptotic performance shrinks variance. To get a sharper handle on the interactions, I looked at performance early in learning before asymptotic performance occurred. To investigate group differences early in learning, the analysis was repeated for the first three trials.
Figure 7. Mean number of items reported correctly in position, averaged across participants, for repeated and non-repeated lists over the first eight trials for the individual conditions.

Learning Early in Practice

To assess learning early in practice accuracy data for the first four trials were submitted to a 4 (Condition) X 2 (List-Type: Repeated vs. Non-Repeated) X 3 (Trial) repeated measures
ANOVA.

Figure 8 summarizes accuracy over the initial 3 trials as a function of repetition. Averaged across all four conditions there was a strong Hebb effect. The pattern yielded a strong Trials by List-Type interaction, $F(7, 476) = 9.24, p < .0001$; the trials-linear by repetition explained 91% of the variance among the means, $F(1, 85) = 57.13, p < .0001$.

Figure 8. Accuracy for repeated and non-repeated lists over the first four trials for the individual conditions with linear regression lines and their associated slopes.
**Group Differences.** Comparison 1 (The effect of unstructured space): The first comparison assessed the advantage for providing successive letters a unique spatial position. The main effect was not significant, $F(1, 85) < 1$. The null effect indicates that there was no overall advantage for providing successive letters with a unique spatial position. This confirms the analysis based on all eight trials. The visuo-spatial context was not enough to increase performance, a result inconsistent with a distinctiveness account.

Comparison 2 (The effect of reliable space): Figure 9 presents accuracy data averaged over list type for groups with reliable space and those without. Groups with reliable space showed greater accuracy overall than those without. The advantage supported by a significant main effect of group, $F(1, 68) = 5.83, p < .018$. Accuracy also increased over trials in the reliable space groups, but not for those without. The pattern resulted in a Trials (linear) X Group interaction, $F(1, 68) = 7.32, p < .009$, as well as a marginally significant quadratic trend, $F(1, 68) = 3.34, p < .072$. So, to provide a learning advantage, the visuo-spatial context must be reliable from trial to trial. Because there was no interaction with list type, the trend applies to both repeated and non-repeated lists; hence, the advantage seen in the data is not due to the repetition. It could be that the visuo-spatial context was more easily reinstated in the reliable groups because it was learned during practice. This cannot, however, be explained by a simple distinctiveness account without accounting for the effect of reliability.
Comparison 3 (The effect of structure): Figure 10 presents accuracy data for repeated and non-repeated lists over the first three trials for the Structured-Reliable and Unstructured-Reliable groups. The data show that while there is a large Hebb (1961) effect for the structured group, there is no clear separation between performance on the non-repeated and repeated lists in the unstructured group. The pattern of results was evident in a Trials (quadratic) X Group X List-Type interaction, $F(1, 68) = 3.99, p < .05$. There was virtually no difference between the overall accuracy for Structured and Unstructured-Reliable groups in the first three trials (each about 0.59) which highlights the fact that the Structured group was more accurate than the Unstructured-Reliable group on repeated lists but less accurate for non-repeated lists.

The pattern of results, thus far, indicates that providing reliable visuo-spatial context boosts overall accuracy but will not advantage learning. A large learning advantage is only achieved by structuring the reliable visuo-spatial context. Although perhaps not surprising on the surface, the boost to overall accuracy is not anticipated by any formal model of ISR. The only
difference between these two conditions is the structure of the visuo-spatial context, and no model has a way of representing path structure.

Participant Awareness of the Repetition

Following each experimental session, subjects were asked to indicate whether or not they noticed the repetition, and if so, when approximately during the session they noticed. Table 2 presents the proportion of participants who indicated that they recognized a repeating sequence and approximately when they noticed it. It is interesting to note that in the Structured-Rliable condition, 44% of participants noticed the repetition within the first quarter of practice, where most learning occurred for that group. Otherwise, the lowest proportion of participants who noticed the repetition was in the Unstructured-Unreliable group, but proportions in the other groups were essentially equal.
Table 2

The proportions of participants aware of the repetitions at different points during the trials: 1/4, 1/2, 3/4 of the way through experimental trials, or uncertain.

<table>
<thead>
<tr>
<th>Point of Awareness</th>
<th>Hebb Unstructured-Unreliable</th>
<th>Unstructured-Reliable</th>
<th>Structured Reliable</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/4</td>
<td>.22</td>
<td>0</td>
<td>.06</td>
</tr>
<tr>
<td>1/2</td>
<td>.28</td>
<td>.06</td>
<td>.28</td>
</tr>
<tr>
<td>3/4</td>
<td>.06</td>
<td>.11</td>
<td>.11</td>
</tr>
<tr>
<td>Uncertain</td>
<td>0</td>
<td>.11</td>
<td>.0</td>
</tr>
<tr>
<td>Total &gt;</td>
<td>.56</td>
<td>.28</td>
<td>.45</td>
</tr>
</tbody>
</table>

McKelvie (1987) performed a detailed analysis of learning in the Hebb (Hebb, 1961) task, and discovered that regardless of participants' awareness of the repetition, learning occurred. While group sizes in the present experiment were insufficient to perform a like analysis, groups were parsed based on their awareness into subgroups and submitted to an 8 (Trials) X 2 (List Type: repeated vs. non-repeated) repeated measures ANOVA. All groups showed significant, or marginally significant, Trial (linear) X List Type interactions which confirms McKelvie's finding that the advantage for the repeated list was independent of participant awareness.
Errors

The previous analyses considered how accuracy changed over trials but did not distinguish between the different types of errors. The experiment allowed for two types of error: Subjects could (1) indicate that they could not remember what letter was presented in a given position by issuing a dash character (an error of omission), or (2) they could put a letter in an incorrect position, making an error of substitution.

The number of each type of error was recorded; each score was divided by list length to get the proportion of errors for a given list. The data were submitted to a 4 (Condition) X 2 (Error-Type: Omission vs. Substitution) x 2 (List-Type: Repeated vs. Non-Repeated) X 3 (Trial) repeated measures ANOVA. Because this analysis repeats results reported from the accuracy data, I will not report effects that were evident in the prior analysis, only those that involve the new factor (Error Type).

Overall the proportion of omission errors made on Non-Repeated lists (.144) was virtually equal to the number made on Repeated lists (0.140). The proportion of substitution errors for Non-Repeated lists (0.345) was substantially greater than for Repeated lists (.280). Repeating a list reduced the proportion of substitution errors more than the omission errors. The pattern resulted in a List Type X Error Type interaction, $F(1, 68) = 19.7, p < .0023$.

To ascertain whether the List Type X Error Type interaction was local to the first 3 trials or if it persisted across learning, the analysis was repeated for all eight trials. There was no List Type X Error Type interaction, $F(1, 68) = 1.9, p < .17$. So, the difference in proportions of omission errors between repeated and non-repeated lists is significant only early in practice.

**Group Differences.** Comparison 1 (The effect of unstructured space): The proportion of substitution and omission errors for the Hebb group and the Unstructured-Reliable group are depicted in Figure 10. The Hebb group made more omission errors than the Unstructured-
Reliable group (0.202 & 0.116 respectively) but the opposite was true for substitution errors (0.312 & 0.369 respectively). The pattern resulted in a marginally significant Group X Error Type interaction, \( F(1, 68) = 3.8, p < 0.057 \). Given that there were no detectable differences between these groups when accuracy scores were analyzed, the result implies that adding an unstructured spatial element to the display doesn't affect learning but it does change the proportions of omission and substitution errors.

The analysis was repeated for all eight trials to see if the effect persisted across all eight trials. The same Group X Error Type interaction remained, \( F(1, 68) = 4.86, p < 0.031 \). The interaction confirmed that the difference in relative proportions of omission and substitution errors was evident across trials, not just in the first three.

Figure 11. The relative proportions of the substitution and omission errors made by the Hebb and Unstructured groups over the first 3 trials.
Comparison 3 (The effect of structure): The proportions of omission and substitution errors over the first three trials for the Structured-Reliable and Unstructured-Reliable groups are depicted in Figure 11. The graph indicates that while the proportion of errors made were reduced in both Unstructured and Structured groups, the proportion of substitution errors was reduced in the Structured group while the proportion of omission errors was reduced in the Unstructured-Reliable group. The pattern resulted in a significant Trials (quadratic) X Group X Error Type interaction, $F(1, 85) = 15.7167, p < .036$.

The analysis was repeated for all eight trials to see if the interaction persisted across practice. The analysis yielded the same Trials (quadratic) X Group X Error Type interaction, $F(1, 68) = 5.46, p < .023$. This confirmed that the interaction persisted across all eight trials.

Figure 4. Omission and substitution errors for Reliable-Structured (Structured Short, Structured Long) and Reliable-Unstructured groups over the first four trials.
Cost of the Perturbation

Up to this point, I have discussed how subjects learned under the various conditions but have not mentioned the effect of the perturbation that was introduced on the very last repeated list; the first two letters in the list were inverted. The perturbation was included in the experiment to measure the cost of changing an element of the repeated list after learning had already taken place.

To assess the effect of the perturbation, I compared the proportions of omission and substitution errors made on the well-learned repeated list (trial eight) to the perturbed list (trial nine). The comparison gave me a detailed picture of the effect of changing the beginning of the repeated list.

Error data for the eighth and ninth repeated lists were submitted to a 4 (Condition) X 2 (Error-Type: Omission vs. Substitution) X 2 (Trial: 8th vs. 9th) repeated measures ANOVA.

There was an increase the proportion of errors from trial eight (0.106) to trial nine (0.162) in all groups, this was evident in main effect of Trials, $F(1, 68) = 12.7, p < .0001$.

**Group Differences.** The analysis revealed only one significant group interaction:

Comparison 2 (The effect of reliable space). Figure 13 presents the proportions of omission and substitution errors for the last unperturbed list (trial eight) and the perturbed list (trial nine) for groups with and without reliable space. The cost of the perturbation to performance is clearly not evenly distributed over the types of errors; groups with reliable visuo-spatial context showed an increase in errors of substitution while groups without reliable visuo-spatial context showed an increase in errors of omission. The pattern resulted in a Trials X Group X Error Type interaction, $F(1, 68) = 5.17, p < .0261$.

The fact that all groups suffered a drop in performance is not surprising, but did the perturbation completely nullify the effect of the repeating list as predicted by the Phonological Loop model (Burgess & Hitch, 2006)? To answer, the accuracy data for the perturbed repeated
list were compared to accuracy data for the ninth non-repeated lists in a 4 (Group) X 2 (List Type: Repeated vs. Non Repeated) repeated-measures ANOVA. The results indicated, contrary to the prediction developed by the Phonological Loop model, that participants in every group were more accurate at recalling the perturbed repeated list (0.675) than the non-repeated list (.544). The difference resulted in a main effect of list type, $F(1, 68) = 17.4, p < .0001$.

Figure 5. The effect of the perturbation on the proportions of omission and substitution errors under conditions of Reliable-Space (Structured-Reliable, Unstructured-Reliable) and without Reliable-Space (Hebb, Unstructured-Unreliable).

Because the repeated list is so well learned by the eighth repetition, one might expect that such a small perturbation would lead the majority of errors to be at the location of the perturbation, i.e., in the first two serial positions. Accuracy as a function of serial position on the eighth and ninth repeated lists, as well as the ninth non-repeated list, is presented for all groups in Figure 14. Interestingly the data show that the drop in accuracy was not at the locus of the perturbation: Errors induced by the perturbation for the Structured-Reliable group were found
mainly in the last four serial positions, and in the rest of the groups the errors were relatively evenly distributed over the serial positions.

Figure 64. Serial position curves depicting the effect of the perturbation on accuracy for the last repeated list (trial 9) under conditions of Reliable-Space (Structured-Reliable, Unstructured-Reliable) and those without Reliable-Space (Hebb, Unstructured).
The Effect of Visuo-Spatial context on learning

The effect of adding visuo-spatial context to the Hebb repeating list task (Hebb, 1961) is not straightforward. Adding unreliable unstructured visuo-spatial context did not increase performance nor provide any learning advantage. Making the unstructured visuo-spatial context reliable increased in accuracy, but did not yield a learning advantage. Finally, structuring the reliable sequence of visuo-spatial contexts increased both accuracy and learning early in practice.

In the first chapter, I noted that no model is currently prepared to represent visuo-spatial information. I discussed some simple ways in which visuo-spatial context could be implemented context based models. The simplest way to introduce visuo-spatial context into is to assume that it makes list items more discriminable. This idea is akin to Bryden's (1967) notion of associating list items with spatial tags as they are encoded. Unlike Bryden's account, however, I do not wish to cast spatial information and temporal information as separate ordering principles. The predictions developed from discriminability theory are straightforward: adding unique visuo-spatial contexts to successive list elements should result in an overall increase in accuracy. The current study denies, this prediction. Adding visuo-spatial context increased performance only when the path was reliable.

Reliability, in the present work, meant that participants knew the series of visuo-spatial positions because they were allowed to practice. So, when the experimental trials began, participants had a good idea of the sequence of visuo-spatial positions. It seems reasonable to suggest that reliable context is easier to reinstate at recall than unreliable context. Perhaps the effect of including visuo-spatial information is not to make items more discriminable but to make successive contexts more discriminable. Although this suggestion may seem straightforward, context models such as OSCAR and the Phonological Loop model (Burgess & Hitch, 2006)
would need to be revised in at least 2 major ways.

Firstly, a mechanism for learning sequences of visuo-spatial information would have to be specified. The learning mechanism would allow the model to distinguish novel series of visuo-spatial context from those that have been practiced. Secondly, a mechanism by which temporal and visuo-spatial information can be combined would have to be specified. By integrating the two kinds of information, the second mechanism would allow the contexts, associated with list items, to be more discriminable. This added discriminability would predict an increase in performance.

If a context model were to incorporate the mechanisms I have outlined, it could account for the increase in overall accuracy achieved upon including reliable visuo-spatial context. It could not, however, account for the drastic learning advantage observed when the reliable sequence of visuo-spatial context was structured. The fact that path complexity affects performance adds a layer of difficulty to the problem.

From a modeling perspective, the issue of path complexity is intimately tied to the choice of representation for visuo-spatial positions. OSCAR (Brown et al., 2000) and the Phonological Loop model (Burgess & Hitch, 2006), have distributed representations for temporal context. The Phonological Loop also has a distributed representation for phonological information. There is no compelling reason not to suggest a distributed representation for visuo-spatial information as well. The most obvious way of representing visuo-spatial locations is to invoke a Cartesian coordinate system. Locations in the visual field could be assigned a representation based on their x-y coordinates. Such a formalization, regardless of how distinctiveness itself is quantified (see Murdock, 1960; Neath, 1993 for examples), would mean that visuo-spatial positions would be more similar the closer they are in space. If, as I have suggested, visuo-spatial information is somehow integrated into the context-signal, then the reinstatability of the context at recall would benefit from greater discriminability (i.e., distance) between successive visuo-spatial locations.

In the present work, I have demonstrated that presenting lists in a structured series of
visuo-spatial positions produces the fastest learning and the best overall performance. The structured path was created by following the shortest possible path through the available positions, a counter-clockwise path. Therefore, in the structured condition successive positions were as close, spatially, as they could have been. If each position were represented by a set of Cartesian coordinates, a counter-clockwise path would produce a series of visuo-spatial coordinates in which successive states were as similar as possible. Therefore, under this representation scheme, a counter-clockwise path would produce the least discriminable set of contexts possible. Because less discriminability means worse performance, better accuracy would be predicted in the Unstructured-Reliable group than in the Structured-Reliable group. In the present experiment, the reverse was true. So the question remains: How should a model represent visuo-spatial information? At the present there is no clear answer, but the results presented in this paper argue strongly against a simple Cartesian based representation system.

Before anyone can account for any effect of path complexity, we first need to be able to quantify it. While the difference between a simple path (e.g., Figure 6(ii)) and a complex path (e.g., Figure 6(i)), might be obvious to the eye, it is not obvious how to quantify the difference.

The best *measure* of path complexity that is currently available appears to be the number of path crossings (e.g., Busch et al, 2005). It has had reasonable success at predicting participants' performance on a visuo-spatial span task, but it is not diagnostic of why participants remember simple paths better than complex ones. We need to understand why some visuo-spatial sequences are more difficult to remember than others. Armed with that understanding we will know what aspects should be represented in a formal model.

**The effect of perturbing the final list**

Inverting the first two elements in the repeating list after learning reduced accuracy. Burgess & Hitch (2006) predicted that the manipulation would remove any advantage provided by the repetition. I tested this prediction and found that accuracy on the perturbed list was only
slightly disrupted. Participants were still more accurate at recalling the perturbed list than random lists.

The Phonological Loop model (Burgess & Hitch, 2006) over-predicts the disruptive effect of perturbing a repeated list post-learning. Over-prediction is caused by the same mechanism that is responsible for correctly simulating the disruptive effect of altering the first two elements in a repeated list during learning (Schwartz & Bryden, 1971). The model is too rigid to yield the kind of partial disruption shown in the present experiment.

When two adjacent items in a repeated list are inverted, one of two things can happen. (a) The match remains above threshold, and an old context-signal is recruited. If so, accuracy for the perturbed items should drop below accuracy for non-repeated lists, and accuracy will gradually recover for the remaining list items. (b) A new context-signal is recruited, and performance should be identical to that on a non-repeated list. Switching the first two items in a repeating list is sufficient to disrupt the matching process. If not, the model would not be able to simulate the disruptive effect of perturbing the beginning of the repeating list during learning, as in Schwartz and Bryden's (1971) experiment.

Regardless whether the context-signal from the repeated list is reused or not, the current data contradict the prediction. Hence, my results argue strongly against the Phonological Loop model as a general explanation for ISR.

So far I have discussed the effect of the perturbation on the Hebb group. The effect of the perturbation was the same for all groups. The pattern of errors, however, was not identical among the groups. Further, the bulk of the errors induced in the Structured-Reliable condition occur in the last four serial positions, after the perturbation. In all other conditions, the errors are evenly distributed across serial positions. No current theory offers predictions for the pattern of errors, but the results will constrain future models of ISR.
**Future Research**

The difference between the Structured-Reliable and Unstructured-Reliable groups' performance is perhaps the most surprising result in the present work. What is not clear from the present design is how well the participants knew the unstructured visuo-spatial sequence by the time the experimental trials began. It is possible that the nine practice trials were not sufficient for participants to completely learn the sequence of positions. If this is the case, the observed differences between Structured and Unstructured-Reliable groups could reflect insufficient experience with the unstructured path. To investigate this possibility, I could extend the current design to include more time for participants to learn the visuo-spatial sequence. It might be useful to implement a Corsi task (Corsi, 1972) for this purpose. This would allow participants to fully learn the unstructured visuo-spatial sequence before being asked to recall letters in the series of positions.

While the result would not change my discussion of the steps that current models of ISR would have to make in order to accommodate visuo-spatial context, it would give us a better understanding of the conditions under which visuo-spatial context can benefit performance.

If it turns out that structure is key to taking advantage of visuo-spatial context when the sequence of positions is well learned, it would be instructive to vary the structure of the visuo-spatial path systematically. It would, for instance, be interesting to know if the learning advantage seen in the Structured-Reliable group is *all or nothing* or if it varies continuously with the amount of structure in the path. Another question, similar to that asked by Schwartz and Bryden (1971), is whether I can disrupt the learning advantage by making the visuo-spatial context unstructured at the beginning of the list.

The answers to these questions would tell us a great deal more about the role structure plays in the *usability* of visuo-spatial context and offer further constraints for future models of ISR.


