Computational Cognitive Sciences (2021)
Prof. Nisheeth Srivastava ,IIT Kanpur

Models of Memory Search

Naiza Singla[1] and Shivam Malhotra[1]

[1] Dept of EE., Indian Institute of Technology, Kanpur

Abstract

Cognitive Science typically postulates unconscious mental phenomenon, computational or otherwise, to explain cognitive capacities. Memory has always been a salient area of interest in this regard, for man must rely on his memory for most of the daily routine work. Storing and retrieving the memory is fundamental, and many great neurobiologists and cognitive scientists have proposed different models for the same. Once we understand the importance, it becomes essential to study, compare and understand the differences between them to develop a base area for further scientific research.
This paper provides a comprehensive review and insight into several computational models of memory search. We first start with a brief description of the early developments made in the field of memory and then we present a detailed review of various models along with the crucial experiments that led to their proposal.
We then compare the ways the various models predict certain basic findings in memory research, both qualitative and quantitative. We also discuss the key theoretical ideas that have emerged from these model studies and the loose ends left by them which need to be answered by future research.

1. Introduction

Research on learning and memory has been driven by models since at least the 1940s. It is hard to imagine how understanding memory could not be necessary for the field and humanity: Memory is what we are and defines us as individuals. The three main stages of memory are encoding, storage and retrieval. We will be discussing the retrieval stage of the memory in this paper, which, in fact, is one of the oldest concepts in psychology. We search for a forgotten idea in our memory, just as we rummage our house for a lost object. In both cases, we visit what seems to us the probable neighbourhood of that which we miss. We turn over the things under which, or within which, or alongside which, it may be, and if it lies near them, it soon comes to view. Hence, we cannot imagine our survival without thinking/searching in our minds because this is only how we can use our knowledge in the real world. Therefore, theoretical and empirical explorations of retrieval processes in memory have taken a considerable upsurge in the last several years. Hence, in our paper, we will start with a brief description of recall and recognition and other few paradigms important in memory retrieval. We will then proceed by throwing some light on what memory models are, and then we shall discuss the critical past developments made in the field of memory encoding and its retrieval. After this, we will discuss the most important models that have been propounded over the years. We shall also talk about their applications, successes and failures and how they are essential for understanding memory search in a better sense. We will then finally conclude the article by exploring the loose ends of these models and the questions which need to be addressed in future work.

2. Preliminaries

Let us first understand few of the important terms necessary to learn and interpret the paper.

2.1. Encoding

Encoding is the act of getting information into our memory system through automatic or effortful processing. It allows a perceived item of use or interest to be converted into a construct that can be stored within the brain and recalled later from long-term memory.

2.2. Paradigms related to memory search

- **Recall & Recognition :** It is crucial to understand the meaning of recall and recognition to truly understand the theories and the mathematics behind the models of memory search. In a retrieval process like recall, the information must be retrieved from the encoded memories, whilst in recognition, the presentation of a familiar outside stimulus provides a cue to the information that has been seen before. A cue might be an object or a scene—any stimulus that reminds a person of something related. Recall may be assisted when retrieval cues are presented that enable the subject to access the information in memory quickly [GS84]. As we will see in the later sections, we will know that there have been few models that could successfully explain the mechanism of recognition but could not precisely justify how we can recall the test items.

- **Cued Recall :** A cued recall test is a procedure for testing memory in which a participant is presented with cues to aid retrieval. In a classic study conducted in 1966, Endel Tulving and Zena Pearlstone gave participants a written list of words to learn and observed that group who were given some cues recalled significantly more words than the group who were given the lists only [TP66]. Cues can be external stimuli, such as words, sentences, incomplete pictures, letters within a word, and so on, as long as they have some connection to the to-be-remembered (target) information. That connection might be a semantic or associative relationship, temporal co-occurrence of a cue and target, or the cue could be the target presented in an incomplete form.
- **Free Recall :** It is a common task in the psychological study of memory. In a free recall task, participants study a list of items on each trial and then are prompted to recall the items in any order. Items are usually presented one at a time for a short duration and can be several nameable materials, although words from a more extensive set are usually chosen. The recall period typically lasts a few minutes and can involve spoken or written recall. The standard test involves the recall period starting immediately after the final list item; this can be referred to as immediate free recall (IFR) to distinguish it from delayed free recall (DFR), wherein the recall is delayed, and some distracting activity may be introduced.
- **Serial Recall :** In serial recall, subjects study a list of randomly arranged items and subsequently recall the list in forward order. In early work concerning the task of serial recall, researchers asked subjects to learn long lists of randomly arranged syllables over repeated study test trials [You68]. In more recent work, researchers asked subjects to immediately recall a short list after a single presentation [FL12].
- **List Effects :** It has been found that if we add more items to the list, it causes memory for the other items to decrease (the list-length effect). On the other hand, strengthening (or weakening) some items on a list harms (helps) free recall of the remaining list items. This is termed the list-strength effect [RCS90].

All of the above-described paradigms have been very important in the memory retrieval studies, and a good model of memory search should be able to consider all these factors and explain the same as we will see in the following sections.

2.3. Information

If we are to understand human memory in any detail,we must distinguish three types of information:(1) Item information, which underlies the recognition of single objects ("items"); (2) associative information, which underlies the relation or association between two objects or items; and (3) serial-order information, which preserves the temporal order in a string of three or more items. These disctinction were developd by Murdock [McF75].

3. Early developments

3.1. Models of Memory

Ever since the earliest recorded observations concerning memory, scholars have sought to interpret the phenomena of memory in relation to some type of model.In 1682, Robert Hooke, described the first mechanistic model of human memory, which could address the questions of encoding, memory capacity, repetition, retrieval, and forgetting in a surprisingly modern way. However, it had drastic shortcomings which we will see in the later section. After this, scientists started conducting a lot of experiments to understand memory and its storage. By the end of the nineteenth century, experiments based on serial recall in which subjects learned a series of items and subsequently recalled or relearned the items presented a lot of data which mainly pointed towards the idea of "associations" being formed amongst the encoded items. Associative chaining and positional coding represented the two classic models used to account for data on serial learning [LW11]. Although the above descriptions hint at the theoretical ideas developed by early scholars, they do not offer a suficiently specific description to derive testable predictions from the models.
In the late 1950s and the early 1960s, the cognitive revolution developed hand-in-hand with the flourishing of mathematical modeling that allowed learning and memory findings to be explained elegantly using very simple assumptions. It contributed to what would become the Atkinson-Shiffrin theory,presenting a much more complete framework for learning and memory processes,and is now popularly known as "the modal model". A major element of this theory was the distinction between a temporary short-term memory and a relatively permanent long-term memory. Short-term store (STS) is the temporary store into which information about presented items is placed and in which control processes such as coding and rehearsal are carried out. Long-term store (LTS) is the permanent store, containing all prior information plus new information transferred from STS. SAM (see section 4.3) utilizes this two-phase memory system which has been described at a greater length in the later section. This theory had a strong influence on many prominent memory models developed since the 1970s. We will briefly highlight some of these models in the upcoming sections.

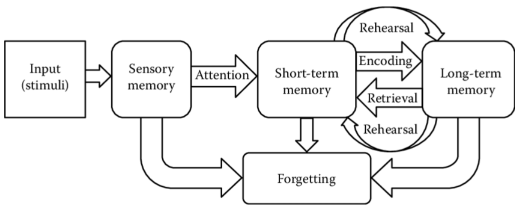


Figure 1: *The Atkinson-Shriffin Model of Memory*

3.2. Memory retrieval

How does our brain record a lasting impression of an encoded item or experience? What exactly does a brain do when we search for history/past episodes? Overall, the mechanisms of memory are not entirely understood. However, there are many theories concerning memory retrieval, which have been described below.

- During recognition, we compute the similarity for each comparison between the representation of the new experience with the stored memory and sum these similarity values to determine the global match between the test probe and memory contents. The Multi-Trace Distributed model and TODAM are based on this theory and are explained in length in the next part.
- However, the above-described theory is not entirely practical *(owing to biological concerns)* when it comes to cued recall. Hence it was then proposed that a better model might be required. One such model implemented using this idea was the Hopfield network (Hopfield 1982).
- Then, the development of the SAM theory (Search of Associative Memory) started in 1978. It uses probed cue for retrieval, but it also assumes that different types of information are stored together in the memory trace, which act as cues for retrieval, i.e. a critical aspect of the model was the notion that item and inter-item information, as well as the contextual information, is stored in the memory.
- SAM set the standard for future theories of memory search and remains a benchmark model to this day. Many other models, such as REM, have been inspired from the SAM model only (see section 4.3).

4. Memory Search

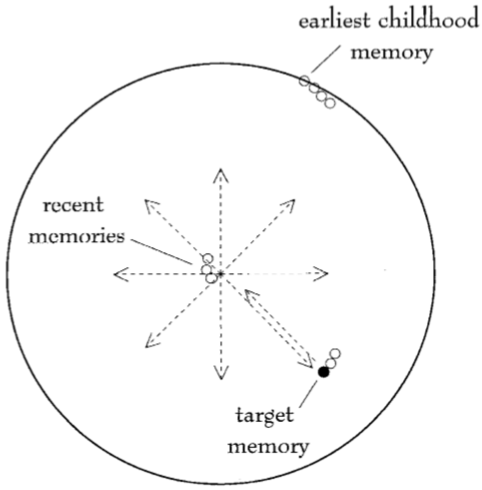
Although all classifications are to some degree unsatisfactory, we group current models into four categories: 1. Separate-Trace models involving spreading activation, or making no explicit activation assumptions–we term these neural network models; 2. Multi-trace models involving parallel activation, here termed distributed models; 3. Models based upon Atkinson & Shriffin's memory model; and 4. Differentiation models which involve the additional ability to improve upon the memory stored; and 5. Neural Network models that interpret the neurons as basic functional units of computation.

4.1. Hooke's Model of Memory

In 1682, the scientist and inventor Robert Hooke, described the first mechanistic model of human memory [Sin76]. Hooke adopts a version of Descartes' dualism [Ala89] , and conceives the creation of memory as an interaction of impressions from the five senses at fixed anatomical location, though unlike Descartes, he does not comment upon the location. At the point of interaction with the brain, the soul *(agent of thought)* is constantly constructing new memories, each of which is attached to the previous memory in an interlinked chain. Pressure from newly formed memories continually pushes against the older ones, in a sphere that expands outward from the center. In what follows, we will focus primarily upon memory retrieval.

For Hooke, retrieval was primarily a matter of resonance. Memories are serially chained, but the chain is coiled around the point where the soul interacts with the brain. A serial search of memory is not necessary because resonance provides parallel access to everything in the repository. Another assumption is that the soul is constantly radiating activity onto all the ideas in the store and can sense the ones that are resonating with its current activity. Such an interpretation is generally consistent with what has been called "global matching," as an explanation of the feeling of recognition or familiarity that surrounds an ongoing experience (Clark & Gronlund, [CG96]). In global matching models such as that of Gillund & Shiffrin (1984), such parallel activation can be followed up by recall of specific items, which corresponds to the soul's focus on particular ideas [GS84].

This model has severe shortcomings, which are difficult to cover in the context of this paper. However, the lack of strong mathematical and biological evidence devoids this model of much significance in today's research.



A schematic diagram of Hooke's model. The memory store is a growing sphere, shown in cross-section. The soul interacts with the brain in the center, where it is continually adding new memories to a coiling chain. The oldest memories are on the sphere's outer surface, and newly formed memories are at the center. Activity of the soul is broadcast throughout the sphere *(dashed arrows)*, and memories of similar past activity resonate in sympathy. A target memory of intermediate age *(black dot)*resonates its contents back to the soul.

Figure 2: *Hooke's representation of Memory. [Hin03]*

4.2. Distributed Memory Models

4.2.1. Multi-Trace Distributed Memory Model

The multi-trace distributed memory model (Hintzman, 1986; Hintzman & Block, 1971 ; Nadel & Moscovitch, 1997) suggests that the memories that are being encoded are converted to vectors of values, with each scalar quantity of a vector representing a different attribute of the item to be encoded [NM97]. Such a notion was first suggested by the early theories of Hooke (1969) and Semon (1923) [SET78]. A single memory is distributed to multiple attributes, or features so that each attribute represents one aspect of the memory that is encoded.

Suppose we encode a total of L attributes *(where a subset of the L attributes will be devoted to contextual attributes, a subset to physical attributes, and so on)* anytime we see an object. Then, when a memory is encoded, it can be written as m_1 with L total numerical entries in a column vector:

$$m_1 = \begin{bmatrix} m_1(1) \\ m_1(2) \\ \vdots \\ m_1(L) \end{bmatrix}$$

Such a vector of values is then added into the memory array or matrix, composed of different traces or vectors of memory.
Formally, one can represent the entire memory matrix M as concatenation of the individual memories $(m_1, m_2, m_3, ...)$ with multiple features.

$$M = \begin{bmatrix} m_1(1) & m_2(1) & m_3(1) & ... & m_n(1) \\ m_1(2) & m_2(2) & m_3(2) & ... & m_n(2) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ m_1(L) & m_2(L) & m_3(L) & ... & m_n(L) \end{bmatrix}$$

In this formulation, the n different memories appear to be independent of each other, thwarting the common consensus of the associativity and similarity. To account for it, items presented in memory matrix are associated by the similarity of their context vectors. When multiple items are made associated with each other and intentionally encoded in that manner, say an item a and an item b, then the memory for these two can be constructed, with each having k attributes as follows:

$$m_{ab} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_k \\ b_1 \\ b_2 \\ \vdots \\ b_k \end{bmatrix}$$

However, items are not always learnt in a similar context, and there will always be subtle variations in the context. Therefore, contextual attributes are often considered to be changing over time as modeled by a stochastic process.

Once memory traces corresponding to specific memory are stored in the matrix, to retrieve the memory for the recall process one must cue the memory matrix with a specific probe, which would be used to calculate the similarity between the test vector and the vectors stored in the memory matrix [GK04]. Mathematically, the probe p, is encoded as an attribute vector and is then compared one by one to all pre-existing memories *(trace)* in M by determining the Euclidean distance between p and each m_i. :

$$||p - m_i|| = \sqrt{\sum_{j=1}^{L}(p(j) - m_i(j))^2}$$

Because the memory matrix is constantly growing with new traces being added in, one would have to perform a parallel search through all the traces present within the memory matrix to calculate the similarity, whose result can be used to perform either associative recognition, or with the probabilistic choice rule, used to perform a cued recall. The similarity is represented as:

$$S(p, m_i) = e^{-\alpha||p-m_i||}$$

where α is a decay parameter and can be determined experimentally.
At this point, we would also like to momentarily broaden our horizon and remark that this model solves serveral boligical issues associated with *standard* model of memory (Squire et al). In this view, memory storage initially requires hippocampal linking of dispersed neocortical storage sites, but over time this need dissipates, and the hippocampal component is rendered unnecessary, which has been rendered false by recent evidence.However,in the view of MTT, hippocampal ensembles are always involved in storage and retrieval of episodic information. [NSRM00].

One of the biggest shortcomings of multiple trace theory is the requirement of some item with which to compare the memory matrix when determining successful encoding. As mentioned above, this works quite well in recognition and cued recall, but there is a glaring inability to incorporate free recall into the model. Free recall requires an individual to freely remember some list of items. Although the very act of asking to recall may act as a cue that can then elicit cued recall techniques, it is unlikely that the cue is unique enough to reach a summed similarity criterion or to otherwise achieve a high probability of recall.
It also has several other limitations . The notion of an ever-growing matrix within human memory sounds implausible [WLW03], and the idea of computational searches for specific memories among millions of traces that would be present within the memory matrix sounds far beyond the scope of the human-recalling process and is biologically beyond the capabilities of human nervous system.

4.2.2. Theory of Distributed Associative Memory (TODAM)

TODAM was developed by Murdock (1982) to deal with serial order information, since most of the models, including SAM, MINERVA2 *(MTT)* deal with item or associative information, and none have been extended to deal with serial-order information [Mur82].

The memory representation is similar to the Multi Trace Theory i.e. a N-dimensional vector describing the various features of each memory trace irrespective of information trace. Also, it uses composite storage *i.e. if there are two or more types of information,they are all stored in this same common memory vector*. However, the representation of association is quite different, and TODAM uses the convolution of item vectors to represent the association of two item vectors. TODAM also uses a forgetting parameter α.

Mathematically, the memory vector M, after addition of two new traces say f and g, after the j^{th} learning instance may be represented as:

$$M_j = \alpha M_{j-1} + f + g + f \circledast g$$

For serial recall, the equation is modified as :

$$M_j = \alpha M_{j-1} + f + f_{j-1} + f \circledast f_{j-1}$$

Both recall and recognition can also be explained mathematically. The comparison process for recognition *(similar to summed similarity)* is the dot product of memory vector with cue/probe. i.e. $f \cdot M$, while for associative memory it is simply the correlation *(opposite of convolution)* with memory i.e. $f \# M$. Though the retrieval process also involves deblurring †, we have omitted it to provide a simpler explanation. To account for serial recall, it proceeds sequentially. The first probe retrieves the first item, the first item retrieves the second item, the second item retrieves the third item, and so on.

TODAM has primarily three main models: the Chaining Model [LM89], the Chunking Model [Mur93] and the Power Set Model [Mur95] to account for specialized paradigms.

The deblurring assumptions used by TODAM, although appropriate for some aspects of serial-anticipation learning, provide an inadequate account of general serial recall and, in fact, predict several trends that are inconsistent with known data. [NN94] It also suffers from similar shortcomings of the Multi Trace Theory.

4.3. Dual-Store Memory Search Model (SAM)

Because SAM set the standard for future theories of memory search, and because it remains a benchmark model to this day, we provide an overview of the model's mechanisms. According to this model, items enter a limited-capacity STS during memory encoding. As new items are studied, they displace older items already in STS. While items reside together in STS, their associations become strengthened in a long-term store (LTS) [RS81]. At the time of test, items in STS are available for immediate report, leading to strong recency effects in IFR and the elimination of recency by an end-of-list distractor. Primacy emerges because the first few list items linger in STS, thus strengthening their LTS associations. The last few items spend the shortest time in STS, which accounts for the finding that subjects remember them less well on a post-experiment final free recall test [CGW70].

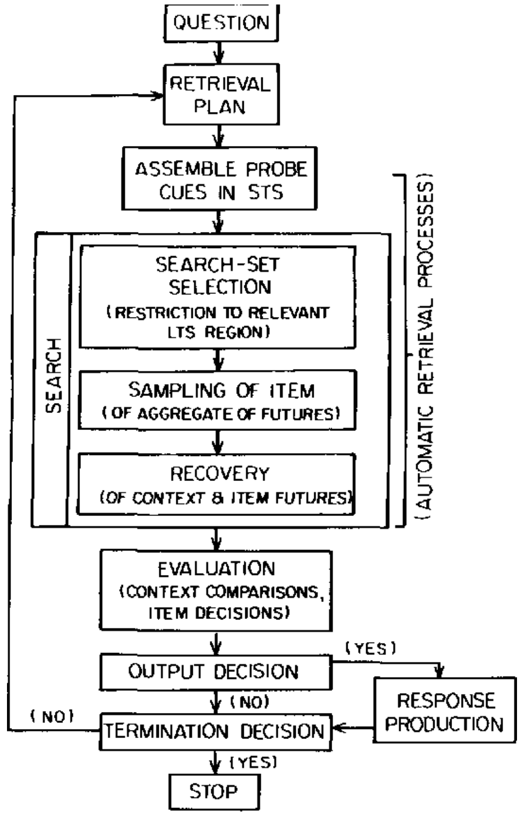


Figure 3: *Schematic Representation of recall process in SAM [RN82]*

We will try to give a mathematical interpretation of the model. Information from the sensory organs may be represented as Images I_i, which can contain several attributes in several different contexts pertaining to the newly studied object. The attributes are unitized i.e. there is a tendency for them to be retrieved as a group during memory search as in recall tasks.
The information in the LTS is retrieved using retrieval cues Q_j. These cues have properties similar to those of images, i.e. they are unitized and separate. Several ques can be used to probe the memory together with each being assigned a weight w_j. Retrieval is assumed to be a limited capacity process, therefore, it is not possibly to stack cues infinitely in a memory recall task.
Each cue has a tendency to activate a memory image, represented by a weighted strength:

$$S(Q_j,I_i)^{w_j} = A(j,i)$$

The strengths are determined by rehearsal and coding processes carried out in short terms store during study and by pre-existing relationships between cues and items. Total activation of image I_i is determined by the product of weighted strength across all cues.

$$A(i) = \prod_j A(j,i)$$

In a free or cued recall task, search of memory is carried out in several cycles. In each cycle, cues and weights are selected, a sample of one of the memory images is made, information is recovered from the image and assessed, a recall may be emitted, new information may be added to memory, and a decision is made whether or not to continue the search.
The probability of sampling a image I_i, given a set of cues and weights is just the ratio of I_i and the sum of activation of all images *(Luce Choice Rule)*.

$$P_s(I_i) = \frac{A(i)}{\sum_j A(j)}$$

Once an image has been sampled, it must be decoded to generate an appropriate decision and response i.e. the probability of image to generate the required result can be written as:

$$P_r(I_i) = 1 - e^{\sum_j w_j \cdot S(Q_j,I_i)}$$

Also, to prevent any form of over-sampling, only one recovery chance per cue is allowed for a given image.
Retrieval is also a function of both the relative and the absolute strength of the target item. That is, the probability of a successful

† If we look closely, a correlation with the memory vector, i.e. $f\#M$ would not yield back g, the required memory trace. Since, $f\#M \rightarrow f\#(f \circledast g) \approx g$‘, where g‘ is an approximation of g, and we must deblur it i.e. make it sharper, to obtain g

retrieval is decreased as the number of items on the list decreases (decreasing the relative strength) and it increases as the target item is studied longer or in a more elaborative way (increasing its absolute strength). Mensink and Raaijmakers [MR88] showed that this property enabled SAM to predict a number of otherwise hard to explain findings in the interference literature .

The SAM model faces serious problems in accounting for long-term recency data [BW74] and long-range contiguity data [LPK11] While both of these effects are observed, the short-term store cannot account for the effects. Since a distracting task after the presentation of word pairs or large inter presentation intervals filled with distractors would be expected to displace the last few studied items from the short-term store, recency effects [‡] *are still observed. According to the rules of the short-term store, recency and contiguity effects should be eliminated with these distractors as the most recently studied items would no longer be present in the short-term memory.*

4.3.1. SAM with Recovery Interference

In 2011, Kornell, Bjork, and Garcia, whilst studying recall latency effects, suggested that learning occurs not only from studying information repeatedly, but also from retrieving information [KBG11] .Incorporating these results, Huber, Tomlinson, Jang, and Hopper [HTJH15] proposed that learning in the recovery process can be decoupled from the learning that underlies the sampling process and that interference can occur in the recovery process when there are competing responses for a single memory i.e if a sampled memory involves recovery for more than one item or response, there will be interference and learning effects during the recovery process [Hub14]. Mathematically this can be represented as

$$p(recall) = p(sample)*p(recover|sample)$$

i.e. proportion of items recalled is the probability of sampling multiplied by the probability of recovery for any given item in that condition. Note that, this is not an assumption of independence, because recovery is expressed conditional upon sampling. The probability of recovery is defined similarly *(Luce choice Rule)* as :

$$\mathrm{p}(recover_i|sample_i) = \frac{S(T,R_i)}{S(T,R_i)+\sum S(T,R_j)+1}$$

where the terms represent recovery strength between the sampled target T and recovered responses R [RCKK12].
Next, we consider the possibility that some forms of learning selectively affects the recovery process, leading to a change in recall latency. To account for such learning, Hopper and Huber [HH18] proposed a model termed as PCR (Primary and Convergent Retrieval Memory) model that holds a similar idea of the sampling and recovery processes. However, the PCR model assumes that recall and recognition are inherently different paradigms, operate on different kinds of memory storage and have different learning processes. Additionally, the PCR model assumes that some forms of learning (e.g., repeated study practice) strengthen associations between retrieval cues and the target memory, supporting the sufficiency of memory. In contrast, other forms of learning (e.g., retrieval practice) strengthen associations between the features that comprise a target memory, resulting in fewer decoding steps and low recall latency [HH19].

Unlike most models, including the SAM and relative strength models, which provide specific predictions regarding only correct responses, PCR also provides prediction about error responses. Hopper and Huber recently found that after a failure to recall during test practice, failure to recall on a subsequent test was also faster, compared with restudy [HH19]. According to their PCR model, inter-item associations are learned even after retrieval failure (i.e., learning from the failure to recall), as the learning rule of the model concerns the temporal activation of features i.e. a dynamic recovery process leads to not only faster correct recall but also faster recall failure [§].

5. Differentiation Models

Differentiation is the idea that additional study of an item (e.g., through repetition or study time) results in further clarification of a single memory trace representing that study item [CM06]. This contrasts with the idea popularized by some strength-based models that additional study results in the storage of additional copies of the item. For example, suppose a word is presented for study three times. Strength-based models (e.g., Hintzman, 1988; Murdock, Smith, & Bai, 2001; Nosofsky, 1984) assume that three noisy copies of the concept are stored in the case of episodic memory. In contrast, differentiation models assume that a single trace will be stored and that trace will be updated with each repetition, forming a more complete and more accurate copy of the concept than if the word had been presented just once.

The two most important works in this regard are the Subjective Likelihood Model [MC98] and the Retrieving Effectively from Memory model [SS97]. They share the same core process involving the Bayesian decision process and differentiation during encoding. They are primarily suited to the task of episodic memory recognition [¶].

The early theories about episodic memory suffer from numerous

[‡] It is critically important to differentiate between two classes of recency. On the one hand, the recency observed in free recall, backward recall, and cued recall is associated with items that are recalled first. In these situations it is conceivable that recency reflects a contribution from some type of "short-term memory" or "rehearsal buffer". In forward serial recall, on the other hand, the terminal list items are necessarily recalled last. Moreover, ignoring omissions, the lag (i.e. the combined number of study and recall events) between study and report of an item is constant across all serial positions. This rules out any contribution of short-term memory to recency in forward recall, which renders it particularly theoretically interesting.

[§] It should be noted that Hopper and Huber measured failure latency, rather than error latency, which is the time taken to give a "can't recall" response

[¶] In this task, a list of items is studied followed by a short break, typically including some irrelevant task (e.g., adding a list of digits). After the break, the recognition memory test is administered where individual items are presented, and the participant is asked to say whether or not each item was presented on the list. The dependent measures are the hit rate(HR) and the false alarm rate (FAR) challenges and primarily from two experimental findings: the mirror effect ‖ [GAI91] and the null list strength effect ** [Den94]. Differentiation results in two major factors that combine to explain both the strength-based mirror effect and the null list strength effect.

Firstly, the match between the cue and the memory trace stored during the study of that item *(if that item was previously studied)* is more significant following multiple opportunities for encoding that study item. This is because it is a more accurate representation of the subject owing to several iterations of updates. Second, the match between any test probe *(target or foil)* and the memory traces stored during the study of other items will have more opportunities to mismatch and thus mismatch better following multiple opportunities for encoding the studied items. Thus, the degree to which a foil probe matches the contents of episodic memory decreases as study time increases, and the degree to which a probe matches the target memory increases, i.e. *differentiation naturally produces strength-based mirror effect as well as null list effect* [BHP09].

REM and SLiM were developed to account for these (and other) data and did so in part by incorporating the idea of differentiation. We will now look briefly into these models. Both REM and SLiM represent an item as a vector of feature values drawn from some standard distribution, and whenever an item is presented for study, an episodic memory trace is stored in the form of a vector that is a 'noisy' copy of the true, complete vector representing the item.

5.1. Retrieving Effectively from Memory (REM)

Shiffrin and Steyvers (1997) developed a more principled solution that assumed that the recognition decisions are based on a rational, Bayesian decision process. REM adopted multidimensional traces to represent past events and knowledge *(almost all the other global-matching models assumed multidimensional representations)* However, new theoretical power was created when they were combined with the Bayesian/rational architecture of REM.

REM assumes that the features of an item are drawn from a geometric distribution where some features *(i.e., those with low numerical values)* are more common than others *(i.e., those with high numerical values)* and standard features are less informative than uncommon features. The encoding of features into memory is discrete and independent and is guided by two parameters: u, the probability that a feature is stored, and c, the probability that a feature is correctly stored given that it is stored. The u parameter is typically assumed to vary as a function of study time, and the c parameter is assumed to be a fixed parameter of the system. However, it has also been argued that a variable c parameter may allow the system to account for several effects observed in Amnesia affected subjects [LM12]. Also, due to differentiation, the additional study would result in the storage of additional features.

During a recognition memory test, the complete set of features representing the test probe is compared to each of the noisy memory traces stored as described above to calculate the likelihood value, i.e. *the probability that the cue emerged from a given memory*. The decision of whether to call the test item "studied" is based on the mean of the likelihood ratio for all memory traces. Also, When matching the test probe to the contents of episodic memory, diagnosticity is taken into account, and diagnostic features provide much better evidence for recognition than no diagnostic features.

5.2. Subjective Likelihood Model (SLiM)

SLiM, in most regards, is quite similar to REM. In SLiM, noise or error arises in both the perception of the stimulus itself and the storage process. The stimulus can be modelled as a binary vector representing the features of the stimulus. The perception of the stimulus is subject to variability such that a given feature of a given stimulus might produce different feature values at different moments in time, i.e. the learning rate is variable. This is modelled using a time-dependent item generator, i.e. an item generator is simply a vector designating the probability that each feature will take the value of 1 during a presentation.

Another source of noise in SLiM occurs during the storage of the memory trace. The initial feature values are taken from the logistic-normal distribution with a mean equal to the average probability of any feature equal to 1. In contrast to REM, not all features participate in the learning process, i.e. only a subset of the features are learnable. A learning rate parameter decides given a parameter is learnable, up to what accuracy will it be stored [MC98].

Lastly, memory retrieval is quite similar to REM, with the notable exception of using maximum likelihood ratio as a means of comparison.

6. Neural Network Models

The neural network model assumes that neurons form a complex network with other neurons, forming a highly interconnected network; the activation value characterizes each neuron (how much energy it takes to activate that neuron), and the weight value characterizes the connection between two neurons (how strong the connection between those neurons is). In this model, connections are formed in-memory storage, strengthened through use, and weakened through disuse.

The first Neural Network model suited to Human Memory was the Ising model, proposed by William A. Little in 1974 [PZ17]. However, the primary purpose of the model was starkly different and was associated with microphysics. In 1982, J.J. Hopfield introduced an energy-based auto-associative memory ††, recurrent and

‖ The mirror effect is a strong regularity in recognition memory: If there are two conditions, A and B, with A giving higher recognition accuracy, then old items in A are recognized as old better than old items in B, and also new items in A are recognized as new better than new items in B.

** The null list strength effect in recognition memory is the finding that strengthening some items on a study list does not harm performance for other items on that list.

†† Auto Associative memory network means the trained network can recover full memorized information when given only partial information as input

biologically inspired attractor[‡‡] neural network model [Hop82]. The Hopfield model's dynamics are composed of a non-linear, iterative, asynchronous transformation of the network state. The process may also include stochastic noise. Unlike other neural networks that use backpropagation to learn the weight, Hopfield Network uses Hebbian Learning [Mor99]. The idea behind Hebbian Learning is that the connection between two neurons (synapse) will be stronger if the neurons at both ends are actively correlated. It can then recognize any of the learned patterns by exposure to only partial or even some corrupted information about that pattern, i.e., it eventually settles down and returns the closest pattern or the best guess.

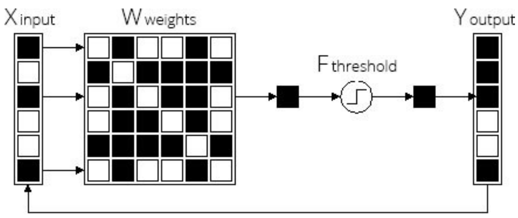


Figure 4: *Schematic Representation of recall process in Hopfield Network*

Following Hopfield, several new models were proposed, including Restricted Boltzmann Machines (RBM). Multilayer Perceptron (MLP) and Regulated Activation Networks (RAN) that can account for recall and recognition in Human Memory using slight modifications [SRPC21] [FSB17].

The above-proposed models, i.e. *(SAM SAM-RI, REM. . .)* with their increasingly complicated structure are characterized by a relatively large number of free parameters *(up to 6 in SAM)* that cannot be directly related to independent measurements of free recall and, thus, have to be tuned to account for the data obtained from experiments. This approach may become unrealistic in the long run because it does not generalize well for experimental data that was not used for parameter tuning. Also, Most previous Neural Network models have a glaring inability to account for proper free recall-based findings.

In accordance with the findings that associative information retrieval is a dominating factor that limits the number of recalled items during a free recall [RPRT13], Katkov & Romani introduced a new Neural Network memory model based upon a set of first principles [KRT17] :

- The encoding principle states that an item is encoded *(represented)* in the brain by a specific group of neurons in a dedicated memory network. When an item is retrieved *(recalled)*, either spontaneously or triggered by an external cue, this specific group of neurons is activated.
- The associativity principle states that, in the absence of sensory cues, a retrieved item plays the role of an internal cue that triggers the retrieval of the following item

[‡‡] An Attractor network is a type of recurrent dynamical network that evolves toward a stable pattern over time.

They also introduced the notion that long-term associations *(primarily responsible for the recall process)* between items are determined by overlaps between their neuronal representations in memory networks, rather than short-term associations acquired during the experiment. The model has a single parameter that depends on the sparseness of long-term memory representations, which converges to a constant in the limit of sparse coding, following the findings of Murray [Mur75]. In this limit, the model does not have any parameters left and thus provides a parameter-free analytical estimate for recall performance for an arbitrary list length.

7. Application to different Paradigms

7.1. Recognition

Most current memory models assume that simple recognition decisions are based on a global familiarity value, i.e. the familiarity value is a weighted, additive combination of the activation of all items in memory. This global familiarity value is determined by the match between the probe cues and the memory traces.

7.2. Cued Recall

One of the significant differences among the models discussed here concerns how the retrieval process produces a recalled item. The distributed models involve comparing the entire memory matrix to locate a memory trace with good enough similarity. However, this requires high parallel processing and also, in part, dilutes the composite storage of these models.

Neural Network Models also use a parallel strategy *(this can also be implemented sequentially)* to morph the probe into an old memory using parallel updating of the probe. However, the amount of parallel processing would be comparatively lesser since the weights would theoretically be much lesser than the memory stored.

In SAM and its derived models, separate traces are accessed sequentially, using the probability of the strength matrix. The probability of a successful recall increases with every failed recall process. In these models, an item that was not retrieved on a first retrieval attempt may still be retrieved if an additional attempt at retrieval is made. *(In SAM, it is usually assumed, however, that at least one new cue must be used for a subsequent retrieval to have a chance at success.).* Also, some SAM derived models incorporate learning during the retrieval process, leading to a better probability of the same probe's subsequent iterations.

7.3. Free Recall

Almost all models can easily account for the cued recall process but face difficulty in the free recall due to the absence of a cue. In this regard, the Multi Trace Theory fails adversely due to the absence of a free recall process. Even though surroundings and other parameters may act as a cue, it is not easy to assume it would lead to a successful recall. Neural Network Models also faced the same inability until the Katkov et al. 2017 Model. In this regard, SAM & derived models shine, for SAM was built to incorporate the free recall mechanism.

7.4. Serial Recall

Lastly, serial recall is another primary retrieval process that most models fail to explain and is only explained by TODAM, but even TODAM suffers some setbacks to account for recent experimental data/

7.5. List Effects

Recent research has focused on the effects of other list items on the recall and recognition of target items. There are primarily two such effects: the List Strength Effect, which concerns the effects of strengthening some list items upon memory for other list items in recall and the List Length effect, which concerns the decrease in recall and recognition in longer lists.

This has several consequences, for it poses a structural challenge, i.e. a list must be represented differently compared to a single probe to account for such effects. Thus, the models based on the distributive theory that assume composite storage cannot predict both a positive list-length effect and an absent or negative list-strength effect. Models such as SAM that assume separate storage are in principle better equipped to handle these results, although they too will have to be modified to enable prediction of negative list-strength effects. Some modifications of SAM, i.e. REM, SLiM, can account for most of the list effects and the mirror effect.

7.6. Model Parameters

Current computational models of memory usually incorporate a large number of parameters. These parameters reflect both structural aspects (decay rates, processing times) and task-related aspects (weighting cues, stopping criteria, decision criteria). The parameters are usually estimated from experimental data to ensure the best fit. Although this procedure can be defended on statistical grounds, it is still a cause of concern to date, and models with many free parameters are usually frowned upon with the notable exception of SAM. However, at the same time, we must consider that these parameters provide us with more extensive flexibility to account for more paradigms, especially in modelling damaged memory.

8. Conclusion

There has now been sufficient progress in the past century among models that it is possible to identify the critical modelling assumptions required to account for most memory retrieval paradigms. The cue-dependent nature of memory retrieval, which instantiates the process of recall and recognition, lies at the core of virtually every model of memory and is supported by a plethora of experimental data.

During recall of a given item, subjects tend to recall items with similar temporal, semantic, source, spatial, or affective attributes. Also, various length, strength , recency and latency effects are observed in experimental data, which must be accounted for in the models to come.

The models described above have successfully explained different results and observations of the experiments conducted in memory search. For example, when searching for items in memory, people explore internal representations in much the same way that animals forage in space. Results from several fields support this notion at a deeper level of evolutionary homology, with evidence that goal-directed cognition is an evolutionary descendent of animal foraging behaviour [Hil09]. One of the most successful models of memory retrieval from natural categories is the search for associative memory. Memory foraging is modelled in SAM as being adaptively modulated between local exploitation of patches and global exploration to find new patches when previous ones are depleted.

Other than the models discussed above in the paper, there have been attempts to develop more and more models to justify various paradigms of memory search. One such model is the temporal context model (TCM) [HK02], which uses retrieval of prior contextual states to drive contextual drift. The model can provide a principled explanation of the widespread advantage for forward recalls in free and serial recall. TCM can simultaneously explain both the recency and the contiguity effects across time scales [Kum12]. However, TCM is not a free recall model, and in order to use TCM as a associative engine, we must also account for additional factors such as Immediate Free Recall and Repetitions during the recall process. This will be a vital field of research that will involve tackling several other essential aspects of memory function not yet addressed by TCM.

While several models presented here have tried to provide a means of explanation for several paradigms, they still lack in their ability to provide a uniform and holistic approach to all such effects and to explain many memory defects, which hampers their universal applications. However, the latter would have to go on hand in hand with biological and psychological research since several memory defects are not yet understood biologically as well.

The paradigms and the parameters mentioned here are far from complete. Memory search is a very complex process, and the best model will consist of features that we are still unaware of. Though some core features are necessary, we also cannot comment upon what would "best" mean in the coming future, for our interpretation is highly likely to change with the collection of new experimental data. There might also be a slight need to work upon integrating such widespread theories, and it might even prove to be the best of all worlds. However, we are highly optimistic that we will, with the advent of adequate time, be able to achieve the feat in the coming years.

References

[Ala89] ALANEN L.: Descartes's dualism and the philosophy of mind. *Revue de Métaphysique et de Morale 94*, 3 (1989), 391–413. URL: http://www.jstor.org/stable/40903062. 3

[BHP09] BRUNO D., HIGHAM P. A., PERFECT T. J.: Global subjective memorability and the strength-based mirror effect in recognition memory. *Memory & Cognition 37*, 6 (Sept. 2009), 807–818. URL: https://doi.org/10.3758/mc.37.6.807, doi:10.3758/mc.37.6.807. 7

[BW74] BJORK R. A., WHITTEN W. B.: Recency-sensitive retrieval processes in long-term free recall. *Cognitive Psychology 6*, 2 (1974), 173–189. URL: https://www.sciencedirect.com/science/article/pii/0010028574900097, doi:https://doi.org/10.1016/0010-0285(74)90009-7. 6

[CG96] CLARK S. E., GRONLUND S. D.: Global matching models of recognition memory: How the models match the data. *Psychonomic Bulletin & Review 3*, 1 (Mar. 1996), 37–60. URL: https://doi.org/10.3758/bf03210740, doi:10.3758/bf03210740. 3

[CGW70] CRAIK F. I., GARDINER J. M., WATKINS M. J.: Further evidence for a negative recency effect in free recall. *Journal of Verbal Learning and Verbal Behavior 9*, 5 (Oct. 1970), 554–560. URL: https://doi.org/10.1016/s0022-5371(70)80101-3, doi:10.1016/s0022-5371(70)80101-3. 5

[CM06] CRISS A. H., MCCLELLAND J. L.: Differentiating the differentiation models: A comparison of the retrieving effectively from memory model (rem) and the subjective likelihood model (slim). *Journal of Memory and Language 55*, 4 (2006), 447–460. Special Issue on Memory Models. doi:10.1016/j.jml.2006.06.003. 6

[Den94] DENNIS S.: The null list strength effect in recognition memory: Environmental statistics and connectionist accounts. 7

[FL12] FARRELL S., LEWANDOWSKY S.: Response suppression contributes to recency in serial recall. *Memory & Cognition 40*, 7 (May 2012), 1070–1080. URL: https://doi.org/10.3758/s13421-012-0212-6, doi:10.3758/s13421-012-0212-6. 2

[FSB17] FINNEGAN R., SHAW M., BECKER S.: *Restricted Boltzmann Machine Models of Hippocampal Coding and Neurogenesis*. 12 2017, pp. 443–461. doi:10.1016/B978-0-12-803784-3.00021-4. 8

[GAI91] GLANZER M., ADAMS J. K., IVERSON G.: Forgetting and the mirror effect in recognition memory: Concentering of underlying distributions. *Journal of Experimental Psychology: Learning, Memory, and Cognition 17*, 1 (1991), 81–93. URL: https://doi.org/10.1037/0278-7393.17.1.81, doi:10.1037/0278-7393.17.1.81. 7

[GK04] GREEN C., KITTUR A.: A multiple-trace memory model exhibiting realistic retrieval dynamics, 2004. 4

[GS84] GILLUND G., SHIFFRIN R. M.: A retrieval model for both recognition and recall. *Psychological Review 91*, 1 (1984), 1–67. URL: https://doi.org/10.1037/0033-295x.91.1.1, doi:10.1037/0033-295x.91.1.1. 1, 3

[HH18] HOPPER W. J., HUBER D. E.: Learning to recall: Examining recall latencies to test an intra-item learning theory of testing effects. *Journal of Memory and Language 102* (Oct. 2018), 1–15. URL: https://doi.org/10.1016/j.jml.2018.04.005, doi:10.1016/j.jml.2018.04.005. 6

[HH19] HOPPER W. J., HUBER D. E.: Testing the primary and convergent retrieval model of recall: Recall practice produces faster recall success but also faster recall failure. *Memory & Cognition 47*, 4 (May 2019), 816–841. doi:10.3758/s13421-019-00903-x. 6

[Hil09] HILLS T.: Optimal foraging in semantic memory. 9

[Hin03] HINTZMAN D. L.: Robert hooke's model of memory. *Psychonomic Bulletin Review 10*, 1 (Apr. 2003), 3–14. doi:10.3758/BF03196465. 3

[HK02] HOWARD M. W., KAHANA M. J.: A distributed representation of temporal context. *Journal of Mathematical Psychology 46*, 3 (June 2002), 269–299. URL: https://doi.org/10.1006/jmps.2001.1388, doi:10.1006/jmps.2001.1388. 9

[Hop82] HOPFIELD J.: Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the National Academy of Sciences of the United States of America 79* (05 1982), 2554–8. doi:10.1073/pnas.79.8.2554. 8

[HTJH15] HUBER D. E., TOMLINSON T. D., JANG Y., HOPPER W. J.: The search of associative memory with recovery interference (sam-ri) memory model and its application to retrieval practice paradigms. In *Cognitive modeling in perception and memory: A festschrift for Richard M. Shiffrin*, Raaijmakers J. G. W., Criss A. H., Goldstone R. L., Nosofsky R. M., Steyvers M., (Eds.). Psychology Press., 2015, ch. 5, p. 81–98. 6

[Hub14] HUBER D.: The search of associative memory with recovery interference (samri) memory model and its application to retrieval practice paradigms. 6

[KBG11] KORNELL N., BJORK R. A., GARCIA M. A.: Why tests appear to prevent forgetting: A distribution-based bifurcation model. *Journal of Memory and Language 65*, 2 (Aug. 2011), 85–97. URL: https://doi.org/10.1016/j.jml.2011.04.002, doi:10.1016/j.jml.2011.04.002. 6

[KRT17] KATKOV M., ROMANI S., TSODYKS M.: Memory retrieval from first principles. *Neuron 94*, 5 (June 2017), 1027–1032. URL: https://doi.org/10.1016/j.neuron.2017.03.048, doi:10.1016/j.neuron.2017.03.048. 8

[Kum12] KUMARAN D.: What representations and computations underpin the contribution of the hippocampus to generalization and inference? *Frontiers in Human Neuroscience 6* (2012). URL: https://doi.org/10.3389/fnhum.2012.00157, doi:10.3389/fnhum.2012.00157. 9

[LM89] LEWANDOWSKY S., MURDOCK B. B.: Memory for serial order. *Psychological Review 96*, 1 (Jan. 1989), 25–57. URL: https://doi.org/10.1037/0033-295x.96.1.25, doi:10.1037/0033-295x.96.1.25. 5

[LM12] LEHMAN M., MALMBERG K.: A buffer model of memory encoding and temporal correlations in retrieval. *Psychological review 120* (12 2012). doi:10.1037/a0030851. 7

[LPK11] LOHNAS L. J., POLYN S. M., KAHANA M. J.: Contextual variability in free recall. *Journal of Memory and Language 64*, 3 (2011), 249–255. URL: https://www.sciencedirect.com/science/article/pii/S0749596X10001002, doi:https://doi.org/10.1016/j.jml.2010.11.003. 6

[LW11] LADD G. T., WOODWORTH R. S.: Memory and the process of learning. In *Elements of physiological psychology: A treatise of the activities and nature of the mind from the physical and experimental point of view (thoroughly revised and re-written).* Charles Scribner's Sons, 1911, pp. 542–592. URL: https://doi.org/10.1037/10863-019, doi:10.1037/10863-019. 2

[MC98] MCCLELLAND J. L., CHAPPELL M.: Familiarity breeds differentiation: A subjective-likelihood approach to the effects of experience in recognition memory. *Psychological Review 105*, 4 (1998), 724–760. URL: https://doi.org/10.1037/0033-295x.105.4.734-760, doi:10.1037/0033-295x.105.4.734-760. 6, 7

[McF75] MCFIE J.: Human memory: Theory and data. by bennett b. murdock, jr. new york and london: John wiley amp; sons. 1974. pp. x 312. references and indices 45 pp. price £6.85. *British Journal of Psychiatry 126*, 6 (1975), 584–585. doi:10.1192/bjp.126.6.584-a. 2

[Mor99] MORRIS R.: D.o. hebb: The organization of behavior, wiley: New york 1949. *Brain Research Bulletin 50*, 5-6 (Nov. 1999), 437. URL: https://doi.org/10.1016/s0361-9230(99)00182-3, doi:10.1016/s0361-9230(99)00182-3. 8

[MR88] MENSINK G.-J., RAAIJMAKERS J. G.: A model for interference and forgetting. *Psychological Review 95*, 4 (Oct. 1988), 434–455. URL: https://doi.org/10.1037/0033-295x.95.4.434, doi:10.1037/0033-295x.95.4.434. 6

[Mur75] MURRAY D. J.: Graphemically cued retrieval of words from long-term memory. *Journal of Experimental Psychology: Human Learning and Memory 1*, 1 (Jan. 1975), 65–70. URL: https://doi.org/10.1037/0278-7393.1.1.65, doi:10.1037/0278-7393.1.1.65. 8

[Mur82] MURDOCK B. B.: A theory for the storage and retrieval of item and associative information. *Psychological Review 89*, 6 (1982), 609–626. URL: https://doi.org/10.1037/0033-295x.89.6.609, doi:10.1037/0033-295x.89.6.609. 4

[Mur93] MURDOCK B. B.: Derivations for the chunking model. *Journal of Mathematical Psychology 37*, 3 (1993), 421–445. URL: https://www.sciencedirect.com/science/article/pii/S0022249683710254, doi:https://doi.org/10.1006/jmps.1993.1025. 5

[Mur95] MURDOCK B. B.: Developing TODAM: Three models for serial-order information. *Memory & Cognition 23*, 5 (Sept. 1995), 631–645. URL: https://doi.org/10.3758/bf03197264, doi:10.3758/bf03197264. 5

[NM97] NADEL L., MOSCOVITCH M.: Memory consolidation, retrograde amnesia and the hippocampal complex. *Curr. Opin. Neurobiol. 7*, 2 (Apr. 1997), 217–227. doi:10.1016/s0959-4388(97)80010-4. 3

[NN94] NAIRNE J. S., NEATH I.: Critique of the retrieval/deblurring assumptions of the theory of distributed associative memory. *Psychological Review 101*, 3 (July 1994), 528–533. URL: https://doi.org/10.1037/0033-295x.101.3.528, doi:10.1037/0033-295x.101.3.528. 5

[NSRM00] NADEL L., SAMSONOVICH A., RYAN L., MOSCOVITCH M.: Multiple trace theory of human memory: computational, neuroimaging, and neuropsychological results. *Hippocampus 10* (01 2000), 352–68. doi:10.1002/1098-1063(2000)10:4<352::AID-HIPO2>3.0.CO;2-D. 4

[PZ17] PUNITHAN D., ZHANG B.-T.: Ising model based molecular associative memory for pattern recall. 7

[RCKK12] RACSMÁNY M., CONWAY M. A., KERESZTES A., KRAJCSI A.: Inhibition and interference in the think/no-think task. *Memory & Cognition 40*, 2 (Feb 2012), 168–176. doi:10.3758/s13421-011-0144-6. 6

[RCS90] RATCLIFF R., CLARK S. E., SHIFFRIN R. M.: List-strength effect: I. data and discussion. *Journal of Experimental Psychology: Learning, Memory, and Cognition 16*, 2 (1990), 163–178. URL: https://doi.org/10.1037/0278-7393.16.2.163, doi:10.1037/0278-7393.16.2.163. 2

[RN82] ROEDIGER H., NEELY J. H.: Retrieval blocks in episodic and semantic memory. *Canadian Journal of Psychologyrevue Canadienne De Psychologie 36* (1982), 213–242. 5

[RPRT13] ROMANI S., PINKOVIEZKY I., RUBIN A., TSODYKS M.: Scaling laws of associative memory retrieval. *Neural Computation 25*, 10 (Oct. 2013), 2523–2544. URL: https://doi.org/10.1162/neco_a_00499, doi:10.1162/neco_a_00499. 8

[RS81] RAAIJMAKERS J. G., SHIFFRIN R. M.: Search of associative memory. *Psychological Review 88*, 2 (Mar. 1981), 93–134. URL: https://doi.org/10.1037/0033-295x.88.2.93, doi:10.1037/0033-295x.88.2.93. 5

[SET78] SCHACTER D. L., EICH J. E., TULVING E.: Richard semon's theory of memory. *Journal of Verbal Learning and Verbal Behavior 17*, 6 (1978), 721–743. URL: https://www.sciencedirect.com/science/article/pii/S0022537178904437, doi:https://doi.org/10.1016/S0022-5371(78)90443-7. 3

[Sin76] SINGER B. R.: Robert hooke on memory, association and time perception (i). *Notes and Records of the Royal Society of London 31*, 1 (July 1976), 115–131. doi:10.1098/rsnr.1976.0003. 3

[SRPC21] SHARMA R., RIBEIRO B., PINTO A. M., CARDOSO A.: Emulating cued recall of abstract concepts via regulated activation networks. *Applied Sciences 11*, 5 (Feb. 2021), 2134. URL: https://doi.org/10.3390/app11052134, doi:10.3390/app11052134. 8

[SS97] SHIFFRIN R. M., STEYVERS M.: A model for recognition memory: REM—retrieving effectively from memory. *Psychonomic Bulletin & Review 4*, 2 (June 1997), 145–166. URL: https://doi.org/10.3758/bf03209391, doi:10.3758/bf03209391. 6

[TP66] TULVING E., PEARLSTONE Z.: Availability versus accessibility of information in memory for words. *Journal of Verbal Learning and Verbal Behavior 5*, 4 (1966), 381–391. URL: https://www.sciencedirect.com/science/article/pii/S0022537166800488, doi:https://doi.org/10.1016/S0022-5371(66)80048-8. 2

[WLW03] WANG Y., LIU D., WANG Y.: Discovering the capacity of human memory. *Brain and Mind 4* (01 2003), 189–198. doi:10.1023/A:1025405628479. 4

[You68] YOUNG R. K.: Serial Learning. In *Verbal Behavior and General Behavior Theory*, no. IX. Prentice-Hall, Englewood Cliffs, NJ, 1968, pp. 122–148. 2