Characteristics of Forming Episodic Associations Between Words

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By

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Abstract

The goal of the present study was to explore factors that influence how new episodic associations between words are formed and to characterize the dynamic properties of this process. Of particular interest was the impact of semantic knowledge on such associations. To achieve this goal, I combined psychological experimental methods and computational techniques in a multidisciplinary research approach. First, I tested human participants in a series of psychological experiments and revealed several characteristics of how new associations between words are learned. Second, I developed a computational model based on a neural network constrained by the empirical results, and previously published knowledge in the field. This model was validated by a computer simulation that replicated the human performance. The model was then used to derive testable new predictions about human associative learning. Third, some of these predictions were tested in additional psychological experiments.

The working hypothesis was that the vast majority of the associations formed outside the cognitive laboratory are established incidentally, that is, not as a consequence of intentional learning and without allocating attention to the process of forming association. Therefore, my research focused on how incidental associations are formed. The experimental paradigm in most of the psychological experiments was similar, including an incidental study phase and a test phase. During the incidental study phase, the participants were engaged in an orientation task, which required maintaining word-pairs repeatedly in working memory for nearly a second. Following the study phase, the participants were unexpectedly requested to take different types of memory tests that were aimed at assessing the strength of the association formed between the words paired at study.

In a pilot experiment, fifty semantically unrelated and unassociated word-pairs were presented in an orientation task that directed the participants' attention to the letter-level of the stimuli. Each pair was repeated ten times during this incidental study phase. Surprisingly, in an immediately following cued-recall test, no evidence for incidental learning was found. Several factors that differentiate real-life conditions from the laboratory conditions of the pilot experiment could explain why associations were not formed in these circumstances. These factors were tested in a subsequent series of experiments.

First, assuming that in real life people are not required to form such a large number of associations all at once (50 in the pilot experiment), I tested, in Experiment 1, the influence of memory load. In this experiment, the same design as in the pilot experiment was used, but with only 10 word-pairs, each repeated 20 times. The percentage of cued recall of incidentally formed associations in this experiment was significant and considerably higher than in the pilot experiment. This result indicated that memory overload might have been one of the causes of the pilot participants' failure to learn new associations.

Second, since in real life people attend by default to the meaning of the processed words while the orientation task in the pilot study required letter-level processing, I examined, in Experiment 2, the influence of the level of processing on how new associations are formed. The design of Experiment 1 was replicated, with a single change: the orientation task directed the participants' attention to the meaning of the words rather than to the letters they are comprised of. The increment in cued recall percentage compared with Experiment 1 was dramatic. Consequently, I concluded that the activation of the semantic system during the process of association formation, although not essential to forming episodic associations, significantly contributes to its efficiency.

The influence of semantic factors on the episodic process of forming associations was replicated and extended in a third experiment. In addition to using a semantic-level orientation task, I compared, in Experiment 3, how new associations between semantically related and semantically unrelated pairs are formed. In addition, in the present experiment the strength of the incidental associations formed during the study phase was tested indirectly by assessing how much they facilitate subsequent one-trial intentional associative learning of these pairs. Cued recall following the intentional study phase was significantly better for pairs that were associated during the incidental study phase compared to pairs that were not. In both conditions, cued recall was better for semantically related than unrelated pairs. Hence, this experiment revealed that semantically related words are associated more efficiently both incidentally and intentionally. This outcome indicated that the existence of pre-experimental semantic relations between the to-be-associated words contributes to the episodic associative process.

Two explanations for why semantically related pairs are learned easier, as was observed in Experiment 3, are possible and were examined in additional experiments. According to one explanation, weak associative links exist between semantically related words. By this account, these associations are too weak to be detected in explicit free association questionnaires, but they provide an initial advantage for the semantically related pairs. Hence, according to this account, it is expected that the semantic relatedness advantage should be constant during the learning process. The other possible explanation is that semantic relatedness interacts with the episodic process, facilitating each associative learning episode. If true, the advantage of episodically associating semantically related pairs should increase with the number of co-occurrence episodes. Experiments 4 and 5 were designed to distinguish between the above explanations, by comparing the slopes of associative learning curves of related and unrelated words.

Both experiments demonstrated that pre-existing semantic connections between words boost the incidental formation of associations based on repeated co-occurrence. In Experiment 4 I found that, up to about 10 repetitions of the words' co-occurrence episodes, the advantage of related word-pairs increased linearly with the number of repetitions. This interaction suggests that the structure of the semantic system affects the very process of associative learning. In addition, this experiment established the time course of this effect. A similar interaction between the how much the associations are learned and whether the pairs were semantically related was found in Experiment 5 using a forced-choice cued recognition test. Whereas the outcome of the cued recall test could, in principle, reflect how retrieval strategies used to find semantically related and unrelated associates differ, the forced choice paradigm significantly reduced this possibility. Hence, the outcome of this experiment supported my hypothesis that the semantic boost occurs at study rather than results from differences in retrieval strategies at test. These characteristics of the semantic/episodic interaction in the formation of new associations between words determined and constrained my computational model of forming associations.

Most of the computational models of the semantic system that are relevant to the current study did not address the actual process of forming associations. Rather, they are models of the organization of the semantic system and explain the dynamic aspects of semantic priming, which is the most prominent phenomenon determined by this organization. Generally speaking, two different classes of models have been suggested. One class was based on the localist approach inspired by the theory of semantic networks (Collins & Loftus, 1975). In these models, the semantic system was modeled by a network of nodes where concepts are represented by nodes in the network and relations among the concepts are represented by the connections of the network. The other class of models used distributed representations. Models in this class represent concepts not by single units, but by distinguishable patterns of activity over a large number of units. Each unit participating in the representation accounts for a specific semantic micro-feature, and semantic similarity is thus expressed as an overlap in activity patterns over the set of micro-features.

The model developed in this dissertation, SEMANT (Semantic and Episodic Memory of Associations using Neural neTworks), is a hybrid model in the sense that it takes both a localist and a distributed approach. It assumes a network in which semantically similar concepts are represented by nodes that are close to each other on a two-dimensional semantic map based on high-dimensional representations; episodic associations are represented on this map as direct (lateral) connections between associated nodes. Activation among nodes in this architecture spreads along both semantic and associative connections. Inspired by the notion of Hebbian learning, the strength of an association between two conjointly activated nodes is enhanced when the "wave" of activation spreading from one node overlaps with the activation spreading from the second. Since spreading activation decays with distance from its source, the closer two concepts are on the semantic map, the greater the overlap between their activations is. Consequently, when two semantically related words are conjointly activated, the addition to the strength of the associative connection between them is relatively large. Semantically unrelated words are, by definition, further apart on the semantic map and their activations less overlap. Therefore, a smaller strength is added to the association with each repetition.

In Simulation 1, SEMANT successfully replicated the empirical results, those of Experiment 4 in particular. Following the validation of SEMANT, three testable predictions concerning human behavior were derived by analyzing its underlying mechanisms and by manipulating computational parameters such that they would mimic pathological behavior. The first prediction, "implicit asymmetry" was that it should be easier to form an association from a word with few semantic neighbors to a word with many semantic neighbors than vice versa. The second prediction, "semantic mediation", was based on the principles of the model. This hypothesis predicts that it should be easier to associate words from the semantic neighborhoods of words that are already associated. Note that, for this prediction, it is irrelevant whether the associated words are semantically related or not. The third prediction concerned hypothetical models of schizophrenics thought disorder. In particular, diffuse semantic activation such as that implicated in schizophrenic thought disorder should decrease the advantage of associating semantically related pairs over unrelated pairs.

Within the framework of this dissertation, the first two predictions were tested empirically. Experiment 6 was aimed at revealing the implicit asymmetry predicted by the model. The pairs in the study list were constructed such that in each pair, one of the words had a significantly greater number of associated words than the other word based on free-associations norms. The learning of word-pairs presented with the word with fewer neighbors first was compared to that of word-pairs presented with the word with more neighbors first. As in the previous behavioral experiments, incidental learning and unexpected cued-recall task were employed. The results indicated, again, that semantically related word-pairs were associated significantly better than semantically unrelated pairs. However, I did not find the advantage of pairs in the forward direction over pairs in the backward direction that was predicated by SEMANT. The discrepancy between the results of Experiment 6 and the computational prediction could stem from the fact that the density of the semantic neighborhood was defined differently in the experiment and in the model. In the study list of the behavioral experiment, the density of the semantic neighborhood of a word was defined based on the number of associated words in free association norms (i.e., using episodic measures). In contrast, the semantic neighborhood of a certain word in the model was defined based on the number of words with numerical representation within a fixed high-dimensional distance from the representation of that word (i.e., using purely semantic factors). Consequently, further experimental work is required before the model prediction and its dynamic principles should be modified.

Two experiments (7 and 8) demonstrated, as the model predicted, that strong episodic associations between two semantically unrelated words facilitate the incidental formation of new associative connections between semantic neighbors of the strongly associated words. Experiment 7 demonstrated this effect by showing better cued recall of weak associations when the target pairs represented semantic categories that were already connected via a strong association between other exemplars of these categories. Experiment 8 showed that the establishment of strong episodic associations between exemplars of different semantic categories facilitates the processing of other word-pairs from the same categories, leading to faster decisions on whether the word-pairs are related or not, even if the target pairs had not been presented at study.

Overall, the results of this study enrich our knowledge on the process of forming associations between words. Although this process is episodic by nature, it interacts with the semantic system. These theoretical and empirical findings suggest that although the semantic and associative networks are based on different principles, they are highly intertwined in human memory and interact during learning. On the basis of the strong support that it received from human experimentation, SEMANT can provide a theoretical framework for many additional studies aimed at understanding associate learning in particular and human memory and cognition in general.

1 Background

This chapter describes the theoretical background for the research described in this dissertation. First, the motivation for the research is explained. Second, the basic terminology which is used throughout the dissertation is defined. Third, the classical view on association, from Aristotle to the British empiricist school of philosophers is reviewed. Forth, experimental results based on Behaviorist paradigms and free associations are given. Fifth, the cognitive theories of functional organization of memory are described in details and last, major experimental results based on priming paradigm are outlined.

1.1 Motivation

The fundamental question that this dissertation tries to shed light on is what the organization of the human semantic system is. Numerous studies have addressed this question from many different aspects. My research was focused on one of the most basic abilities that humans have and what seems to be a general principle for storing information in the brain: forming associations. As discussed in the following section, associations are formed on the basis of several grounds. One of these grounds, known from the earliest stages of exploration of human mind, is that stimuli that are perceived in spatial and/or temporal proximity tend to be associated. For example, in free association questionnaires, in which participants are requested to reply with the first association to a given word, many participants would reply the word SUBMARINE to the word YELLOW. This association would have never been formed unless the famous Beatles' song had been written. This dissertation is aimed at unveiling what are the mechanisms that allow humans to do that.

Several cognitive theories which describe the organization of the human semantic system have been suggested, as elaborated in this chapter. Most of them rely on the existence of associations between concepts. Nevertheless, no model has been focused at the actual associating process. In this study, cognitive experiments were run to gain insight on the characteristics of how associations are formed. Constrained by the findings of these experiments, a computational model, SEMANT, was built. SEMANT was validated in computer simulations compared to the empirical findings and then was used to make predictions on human behavior. Finally, these predictions were tested with novel cognitive experiments.

1.2 Basic Terminology

The term "association" does not have a single, precise, definition that could be stated without qualifications (Voss, 1972). In the late '60, the question of what constitutes an association has received considerable attention. Tulving (1968) pointed out that the term association, used descriptively, means merely that one event follows another with some regularity. Although more elaborated definitions have been suggested (e.g., Postman, 1968), the term *association*, following Tulving's approach, has been defined phenomenologically throughout this research. Thus, two words are associated if the presentation of one brings the second to the perceiver's awareness. Commonly held theories ascribe the formation of associations to the co-occurrence of words throughout one's lifespan (e.g., Spence and Owens, 1990). That is, words that co-occur frequently in language will become associated and consequently will activate each other in the lexicon. Such associations, which are based on subjective experience, are labeled *episodic associations* (e.g., Neely, 1991).

Another type of link among words is semantic relationship, which exists when their meanings share common semantic features (for example, if they belong to the same semantic category), or have other types of semantic relation such as "part-whole" (e.g., WHEEL-CAR), a functional relationship (e.g., BROOM-FLOOR), etc. Although associated words do not have to be semantically related, they might be so to various degrees. Conversely, semantically related words may or may not be associated (e.g., CHAIR-TABLE vs. CHAIR-SHELF). Associations between semantically related words are called *semantic associations*. Note, however, that the principle of association between two semantically related words is similar to that described above for unrelated words. That is, frequent co-occurrence is an important factor underlying the formation of association between semantically related words. In the following sections, I will present a synopsis of the relevant research and scientific theories concerning the formation and the manifestation of associations.

1.3 Associations: The Classical View

Associations have been studied since the early days of the endeavor to understand the human mind. The first to question the nature of associations were probably the Greek philosophers. Aristotle, for example, identified three laws for association, in effect, three laws of learning – similarity, contrast and contiguity, where contiguity included both spatial and temporal adjacency (in Crowder, 1976).

The next major step in the journey to understand the principles of forming associations was made only about 2,000 years later, by philosophers in the British empiricist school, who have also examined the laws of associations. A radical point of view of empiricism was presented by David Hume, who essentially reduced knowledge to the correlation of sensation. Hume expressed the view that man is only capable of knowing that occurrence of sensation A is correlated with the subsequent occurrence of sensation B (in Voss, 1972). Hume also proposed three main principles of association: Contiguity (i.e., proximity in time and space), Similarity (or Contrast), and Cause and Effect (e.g., Hume, 1738). Using more modern terminology, we would refer to the first principle as an episodic factor and to the two others as semantic factors. Fulfilling any of these conditions should be sufficient to form an association between concepts. The strength of episodic association is determined by the frequency at which the contiguity condition is fulfilled. An additional important claim of this theory is that intentionality is not a necessary condition for the associative process to occur. Rather, simple exposure to two events fulfilling the episodic condition should be sufficient for an association to be established between them. Another empiricist, James Mill, suggested that there are three criteria for the strength of association: permanence, which we would now term resistance to forgetting; certainty, which we would now call confidence and measure with rating scales; and spontaneity, which might correspond to our own measure of reaction time (in Crowder, 1976).

The first attempt to study memory mechanisms empirically was made by Ebbinghaus (1885) who studied the formation of associations between list items in serial learning. The basic principle of serial learning according to Ebbinghaus was that everything in the list becomes associated with everything else, subject to two qualifications: First, the strength of an association between two list items varies inversely with their degree of remoteness, that is, with how far apart they are in the series. Second, forward associations, for a particular remoteness degree, are stronger than backward associations (in Crowder, 1976). Robinson (1932, in Baddeley, 1997) stated the law of contiguity as follows: "the fact that two psychological processes occur together in time or in immediate succession increases the probability that an associative connection between them will develop – that one process will become the associative instigator of the other". However, Robinson also noted that "It should be kept in mind that mere coincidence in time or more immediacy of temporal succession will not insure the establishment of a demonstrable association between two psychological processes. Thus, even if it could be shown that there cannot be association without contiguity, the presence of the factor of contiguity is not enough to insure association". The current research is aimed at investigating the additional factors that influence the formation of associations in general and the role of semantic information on this episodic process in particular.

Over the past 300 years, empirical and theoretical evidences for the primary role of associations in human thinking and memory have been gathered. My study incorporates to vast research that reveals that the classic principles of associations as have been suggested by the empiricism, although generally true, cannot account for the richness of the phenomena. We now know that other factors such as the saliency of the stimuli, and whether attention is directed at them, for example, affect the formation of associations. Moreover, the classical factors, as well as other factors, interact in a non-trivial manner. Hence, for a deeper understanding of the phenomena, a more systematic way of investigation had to be applied.

1.4 Results of Paired Associate Experiments (Behaviorist Paradigm)

The first to use systematic experimental approach were the behaviorist psychologists in the middle of the 20th century. Current knowledge about factors influencing associative learning relies largely on studies designed within the behaviorist conceptual framework. Such studies emphasize primarily the phenomenological aspects of human behavior rather than exploring their cognitive mechanisms (e.g., Kimble, Mann, & Dufort, 1955). The studies focused, for example, on the number of repetitions required to establish an association, on influences of the list length, on the delay between repetitions, etc. (e.g., Rimm & Biggs, 1967). Characteristic of many of these early studies is the extensive use of meaningless stimuli such as letter trigrams and syllables (e.g., Berry & Cole, 1973) and the fact that the items were presented context free. The paradigmatic name for this phenomenon is *paired associate learning* (Kausler, 1966). Based on such studies, several investigators suggested that meaning and context are not necessary to form associations between perceptual events. Voss (1972) notes: "...it is quite likely that the two dissimilar items do not have similar encoding attributes. Under such conditions, it would seem that associative acquisition would take place via explicit contiguity, that is, by repeated pairings...". In contrast, other studies showed that the degree of meaningfulness of the to-be-associated items positively correlated with pair-associate learning performance (Mandler & Huttenlocher, 1956; Noble, 1952). Note, however, that in these early studies meaningfulness was defined in terms of frequency and fluency of associations, that is, using episodic measures. Moreover, the items used in many of these studies were, indeed, nonsense syllables.

However, evidence that semantic relationship between words facilitate their association comes also from more recent studies. For example, semantically related words were more likely to be associated during an incidental learning procedure, even if the orientation task did not involve semantic processing (Epstein, Phillips, & Johnson, 1975). Furthermore, these authors also found that, if attention is oriented to semantic attributes, incidental paired associate learning is even more effective than intentional learning. A probable cause for this advantage is that during intentional learning the semantic features are mainly activated implicitly.

Although suggestive, these data do not indicate directly on the role of semantic (rather than episodic) links on the incidental formation of new associations because, in Epstein et al.'s study, the strength of possible associative links between related words was not controlled. The absence of such control raises the caveat that the observed advantage for associating semantically related over unrelated words was induced by the existence of pre-experimental associative links rather than by pure semantic relationship. Hence, the question of whether pure semantic relationship interacts with the co-occurrence of previously unassociated items and, if such an interaction exists, how it affects the associative process, requires additional research. The next section describes an alternative common procedure for investigating the structure of associations.

1.5 Results of Free Association Experiments

In a free association task, the participant is given a trigger (for example a word) and requested to produce as fast as possible the first word that "pops-out" in his mind (or, alternatively, a list of such words within a given time) in response to the trigger. It is usually implied that the first, instinctive, response unveils the strongest associate of the trigger. The results of such experiments are statistically analyzed and the outcome of this analysis is called *association norms*. Various attempts have been made to investigate the mechanisms underlying the associative structures that are expressed in free association norms. Even a cursory examination of word-association norms revealed that similarity in meaning plays an important role in determining the associative structure. Indeed, McDonald and Lowe (1998) have found that word-pairs that are both associated and semantically related are more similar (on a corpus-derived measure of semantic similarity) than semantically related pairs that are not associated, though others have not found such relation (Lund, Burgess, & Audet, 1996). Recent explorations of the putative relation between semantic relationship and associative strength have utilized currently available computing power and large language corpora. Co-occurrence rates of words can be calculated from these corpora, and various measures of similarity can be developed. The working hypothesis was that words that are similar in meaning appear in similar contexts (Miller & Charles, 1991). Thus, representations of words based on their co-occurrence with other words can capture the semantic similarity between words.

Using computational measures, several recent studies showed that association strength is positively correlated with the frequency of co-occurrence (Plaut, 1995; Spence & Owens, 1990). Further, words that were both semantically related and normatively associated were found to co-occur more frequently than words that were only semantically related (McDonald & Lowe, 1998). Others, however, have found co-occurrence to predict association strength only for pairs that were semantically similar (Lund et al., 1996). Thus, it seems that the relations between the cognitive factors (namely semantic similarity and association strength) and the linguistic factor (namely textual co-occurrence) call for further investigation. The cause-and-effect directionality between the two types of factors is yet to be clarified and so is the proportion between the two cognitive factors.

1.6 Cognitive Theories of Functional Organization of Memory

1.6.1 Semantic vs. Episodic Memory

The major goal of my study was to explore how semantic relationship interacts with episodic factors affecting the formation of new associations between words. At the basis of this discussion there is a model of memory organization that assumes the existence of two phenomenologically distinct types of informational storage: episodic and semantic. The semantic / episodic memory dissociation was originally proposed by Tulving (1972). According to Tulving's definitions, *episodic memory* is the storage of specific events which occurred in a particular place at a particular time during a person's history (hence including autobiographic elements); in contrast, *semantic memory* is the storage of our conceptual knowledge, stripped of information concerning the time and location of the episode during which this knowledge has been acquired.

In his original essay on the semantic vs. episodic memory dichotomy, Tulving mentioned the difference between the following two possible response-types to memory related tasks: A) "I know (that) the word that was paired with DAX in this list was FRIGID" and B) "I think that the associations between TABLE and CHAIR is stronger than that between the words TABLE and NOSE". Tulving suggested that the first answer results from episodic retrieval and the second is based on information retrieved from the semantic memory. Later, he argued that these different procedures for testing memory actually invoke the operation of functionally distinct memory systems (Tulving, 1983; 1984; in Neely, 1989). However, in addition to distinguishing episodic from semantic memory systems, Tulving also indicated that "In experiments where the to-be-remembered units are meaningful words that refer to concepts stored in semantic memory, the information in semantic memory may be used at the time of the input of the information into the episodic memory store". It appears, indeed, that the formation of episodic associations is dependent on both episodic and semantic memory. Hence, in addition to shedding additional light on how associations are formed, the investigation of the putative influence of semantic relationships among words on the formation of episodic associations should help understanding how episodic and semantic memories interact. Furthermore, since the principles governing the formation of associations are consequential in the formation of episodic traces in memory in general (e.g., Mandler, 1980; Jacobi, Baker & Brooks, 1989), studying how episodic associations are formed can unveil more general memory related processes.

1.6.2 Semantic Networks

Networks were used to model the organization of semantic memory since the days of Aristotle. The Greek philosopher was concerned that words should be properly and logically defined so as to avoid reasoning errors. The system that was introduced by Aristotle is shown in Figure 1.

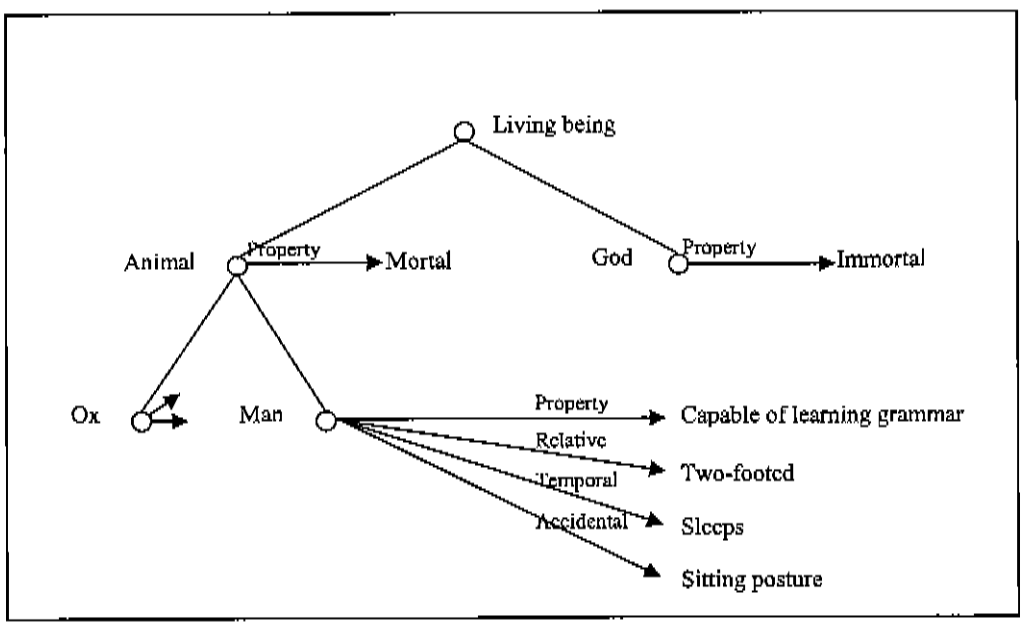

Figure 1: A semantic structure as presented by Aristotle (from Baddeley, 1999). Concepts and properties are linked on the basis of semantic. The notion of networks to illustrate the organization of the semantic system is 2000 years old.

The spotlight on the network approach to modeling semantic memory was rekindled thousands of years later from a different discipline. In 1966, Ross Quillian, a computer scientist, developed as part as his doctoral thesis a computer program to understand text, which he called TLC. As part of the program, he developed a model for semantic memory based on a network of concepts. In collaboration with the psychologist Alan Collins, he suggested his network as a model of the way in which people might actually comprehend text (in Baddeley, 1997) and tested the model's predictions examining human performance (e.g., Collins & Quillian, 1969).

Quillian's model is based on a hierarchically arranged network of links between concepts (Figure 2). The concepts are represented as nodes in the network, with each node being associated with a number of properties. A notable principle of Quillian's model was the assumption of *cognitive economy*. This principle suggested that the properties that apply to a set of concepts are stored at the highest level to which they are generally applicable (in Baddeley, 1997). This model has been criticized on both theoretical and empirical grounds. For example, Rips et al. (1973) and Smith et al. (1974) claimed that network models cannot

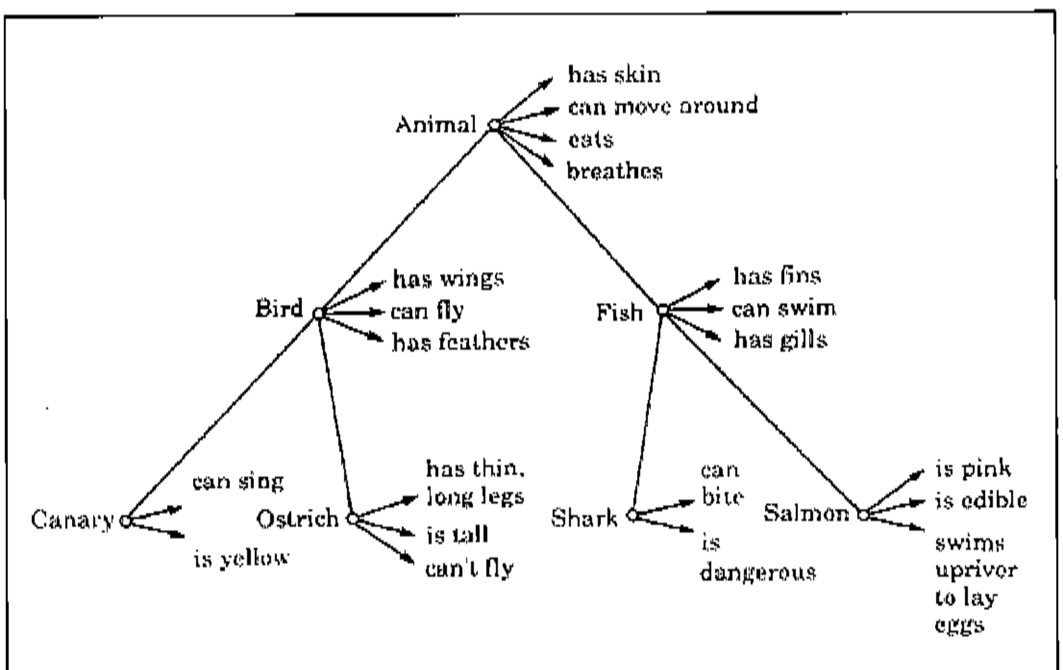

Figure 2: Hierarchical organization of concepts with inherited features as introduced by Quillian (from Baddeley, 1999). Concepts are linked in a network and properties are inherent, based on the hierarchy.

account for data that feature models can. In addition, Conrad (1972) rejected the cognitive economy assumption.

In response to the criticism of the Quillian model, Collins and Loftus (1975) introduced a revised network model. This model differed from Quillian's in a number of respects; most notably, it abandoned the assumption of hierarchically organized semantic nodes, replacing it with a less rigidly structured network. Secondly, in order to account for the many effects of semantic relatedness, Collins and Loftus introduced the concept of *semantic distance*, by which strongly related concepts are located "close" together and unrelated concepts are "far" from one another. Indeed, the distance between two nodes is determined empirically reflecting the ease with which excitation flows from one to the other (i.e., using the notion of a *weighted graph* in computer science). A third major change in this network comprised the introduction of a range of different types of links such as super-ordinate and subordinate (chess *is a* game), modifier (a dog *has a* tail, a kangaroo *can* jump), and so on. (in Baddeley, 1997; Figure 3). In addition to

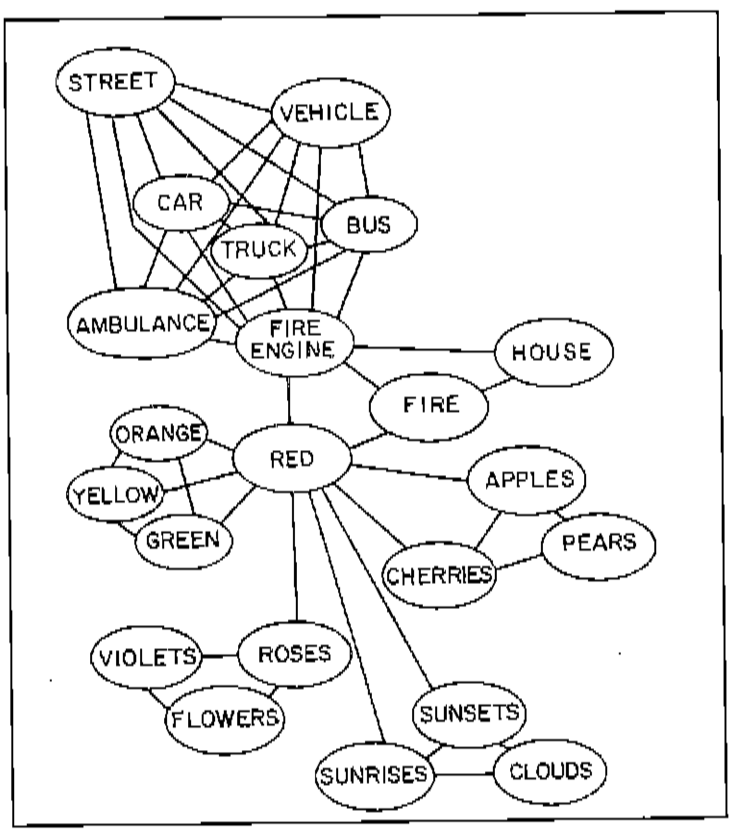

Figure 3: A schematic representation of concept relatedness in a stereotypical fragment of human memory, where a shorter line represents greater relatedness (from Collins & Loftus, 1975). The semantic system can be represented as a weighted graph.

revising the architecture of the network, Collins and Loftus also introduced the term *spreading activation*. The basic assumption of this term is that at each moment in time, each node in the network is at some level of activation and that activation spreads among nodes along the links. If the level of activation reaches a high enough value in some portion of the network, that portion of the network is accessible to conscious awareness (Collins & Loftus, 1975; Gröbler, Marton, & Erdi, 1991).

Most theories of semantic (or cognitive) activation that were based on this approach assume two different activation processes (Posner & Snyder, 1975; Shiffrin & Schneider, 1977). Activation of the first type propagates automatically from the node that is activated by an external input to (semantically) adjacent nodes. Within each node the activation raises and decays as a wave. This mechanism is spontaneous, is not related to any search strategy and does not require processing resources. In other words this process is automatic and thus, by definition, it acts fast and can occur without intention or conscious awareness.

The second activation process reflects strategies for retrieving information from semantic memory. It does require processing resources and intention. Thus, by definition, it acts slow and requires attention. Due to the limited-capacity of the attention system and the limited computational resources, this activation, as opposed to the automatic process, inhibits activation in (semantically) unrelated nodes. As described above, spreading activation over semantic networks can account for various semantic relatedness and semantic priming effects. The next section will review priming results that are specifically relevant for this research.

1.7 Results of Priming Experiments (Cognitive Paradigm)

A well-known interaction between semantic relationships and episodic associations is demonstrated in the *semantic priming effect* (Meyer & Schvaneveldt, 1971). The semantic priming effect is evident when the presentation of a "prime" word that is semantically related to a "target" word, (presented simultaneously with the prime, or immediately after it), facilitates the processing of the target word, as is evident in tasks such as lexical decision or naming. The facilitation is expressed both in enhanced performance accuracy and in a reduction of the reaction time (RT) (for comprehensive review, see Neely, 1991). The interaction between the semantic and episodic/associative systems is examined by comparing the semantic priming effect for prime and targets that are semantically related but not associated, semantically related and associated, or associated without a clear semantic relationship. An increasing number of studies have been aimed at isolating the types of word relations that mediate this phenomenon (e.g., Carroll & Kirsner, 1982; Durgunoglu & Neely, 1987; Fischler, 1977; McKoon & Ratcliff, 1979, 1986; Moss et al., 1995; Neely & Durgunoglu, 1985; Shelton & Martin, 1992). Fischler (1977) was the first to unconfound semantic and associative relationships, by looking at priming for both associative pairs and pairs that were semantically related but not associated. An overview of the results does not present a consistent pattern (Lucas, 2000). Fischler (1977) found that semantically related pairs that were not also associated did exhibit priming. Shelton and Martin (1992), however, argued that automatic priming comes about for associated words and not for words that have a semantic relation but no association. Mckoon and Ratcliff (1979, 1986) found priming for episodically studied, semantically unrelated pairs, but other attempts to find evidence for co-occurrence priming have failed (Carroll & Kirsner, 1982; Durgunoglu & Neely, 1987; Neely & Durgunoglu, 1985). Although the debate still continues, it is safe to say that both classes of relations may result in priming and that their combination may have an additive effect (Lucas, 2000).

1.8 Conclusion

Associating concepts is a fundamental property of human cognition and understanding the mechanisms by which it occurs may shed light on human thinking and memory in general. Concepts may be semantically related or associatively linked. The classical laws of associations assume that concepts would become associated if they are semantically related or if they are perceived in temporal or spatial proximity. However, modern research shows that other cognitive factors may be involved in the process of forming associations. Most theories on the organization of the semantic system use the notion of networks where related concepts are linked using weighted connections, which represent the strength of the connection between the concepts. Nevertheless, no model has been suggested to describe how concepts are being associated and how the organization of the semantic system interacts with this process. This dissertation is aimed at suggesting such a model.

1.9 Dissertation Outline

Chapter 2 describes a series of behavioral experiments aimed at gaining insights on the process of associations. In Chapter 3, the details of SEMANT, the computational model for word associations which I developed and the predictions on human behavior which were derived from it are detailed. Chapter 4 describes additional novel behavioral experiments, aimed at testing the predictions of the computational model. In Chapter 5, both the computational and experimental aspects of this dissertation are discussed and further research directions are suggested. Last, in chapter 6, the conclusions and summary are given.

2 Behavioral Experiments

In this chapter, a review on incidental learning is given. Then, a series of behavioral experiments aimed at examining the characteristics of association formation process and at setting constraints for a computational model, are detailed.

2.1 Incidental Learning

Although incidental learning of associations between words has been the investigated in many studies, the necessary and sufficient conditions for learning without intention and the parameters that modulate the efficiency of this process are not fully understood. However, the fact that participants are able, under certain conditions, to associate words, even if they are not explicitly instructed to learn the pairing is clear (Underwood & Lund, 1980; Mayes & McIvor, 1980; Clark, 1995).

For example, in an attempt to reveal the conditions for incidentally forming new associations, Nairne (1983) investigated whether associations are formed between items rehearsed together, without explicit associative learning instructions. The results showed that the word-pairing was substantially remembered during rehearsal. However, the number of repetitions of rehearsal did not affect the strength of the associations. Note, however, that in this experiment, each word-pair was presented to the participants only in the first two rehearsals, while the participant was instructed to read the words aloud, regardless of the overall number of rehearsals (4, 8, or 16). This result suggests that although substantial associative learning may occur during the two perceived rehearsals, little additional associative processing seems to occur once the presentation of the stimuli during rehearsal has stopped.

Most of the studies have found intentional learning to be stronger than incidental learning. Nevertheless, Yarmey and Ure (1971) found that when the instructions guided the participants to use imagery during the orientation task, the performance for incidental learning was similar to that of intentional learning. In the same study, Yarmey and Ure also addressed the question of association symmetry and found that directionality, i.e., presentation of the left or the right item as the cue in the recall test had no effect. This finding was supported by Epstein et al. (1977) who found that asymmetry favoring forward associations resulted from intentional learning instructions, while incidental learning instructions resulted in symmetry.

In other studies of incidental learning, concrete items have been found to associate more effectively than abstract items (Gumenik, 1976; Yarmey & Ure, 1971). Weingartner, Walker, Eich, and Murphy (1976) used both incidental and intentional learning tasks to train to associate pairs of highly imageable stimuli, presented either as words or pictures. In later testing, when the stimulus presentation mode (pictures or words) was congruent to the training, associate pairs of items were reconstructed more accurately than in disparate recall conditions. They have found the effect particularly marked for incidentally learned pairs of items.

Guttentag (1995) investigated such learning with 10-11-year old children who were shown semantically related and unrelated words under deliberate memorization and incidental learning conditions. In this study, cued recall performance with related pairs was superior to performance with unrelated pairs in both conditions.

To conclude, several studies have shown a substantial level of incidental learning of word-pairs associations and this learning was found to be sensitive to several factors. A few studies express the importance of perception in the associative process (Gumenik, 1976; Nairne, 1983; Yarmey & Ure, 1971). Based on the evidence for incidental learning, it was used in the series of experiments described in this chapter as well. However, the design of all of the above-mentioned experiments, however, was different from the present experiments in several aspects. First, the exposure time to the stimuli was much longer (in the early studies, even seconds). Second, although the orientation task was different in each experiment, the task that has been used in most of the experiments in this study, namely letter search, was not used. Third, in most of the experiments the words were presented simultaneously as opposed to one after the other. One of the goals of the pilot experiment, detailed below, was to explore incidental learning of associations between words using a paradigm that served us in the following research.

2.2 General Paradigm and Rationale

2.2.1 Participants

In all the experiments the participants were undergraduate students who were paid a nominal fee or received course credit for their participation. They were all native Hebrew speakers with normal or corrected to normal vision. Gender and dominant hand were not controlled. In each experiment, a new group of students participated such that no participant took part in more that one experiment.

2.2.2 Association Questionnaires

In most of the experiments, word-pairs were required to be unassociated prior to the experiment. In such cases, a pilot study minimized the possibility that the pairs included words associated a priori. In this pilot study, 50 participants were asked to write the first 3 associates to each of the 20 words that formed the 10 related pairs. In half of the questionnaires, the first word in each pair was listed first and in the other questionnaires the second word in each pair was listed first. Each questionnaire was presented to different 25 participants. The nouns paired in all the experiments did not elicit one another among the first three associates in any of the pilot survey participants.

2.2.3 General Procedure

Unless otherwise specified, each experiment consisted of an incidental study phase and one or two subsequent test phases, one explicit (cued recall) and one implicit (free association).

In most of the experiments, a letter search task was adopted for the incidental study phase. In each trial, two nouns were presented sequentially followed by a letter, about which the participant had to decide whether it was comprised by either of the two words or not. A "shallow" orientation task was chosen in order to minimize semantic activity and the activation of "natural" semantic associates. A right-hand button was used for “yes” responses, and a left-hand button for “no” responses. The accuracy of the responses in this phase was monitored. Each trial in the study phase started with a rectangle frame appearing at the center of the screen. 700 ms after the onset of the frame, the two words were presented sequentially at the center of the rectangle frame for 150 ms each, and with an SOA of 700 ms between them. The target letter was presented 650 ms after the offset of the second word and remained on the screen for 1500 ms, during which time a response was expected. Hence, because the participant could not know in advance which letter would be probed, both words had to be conjointly kept active in working memory for at least 800 ms (Figure 4). Each pair was randomly repeated during the study phase. The number of repetitions was assumed to determine the strength of the episodic association formed between the two words. Thus, it was a major factor manipulated across and within experiments.

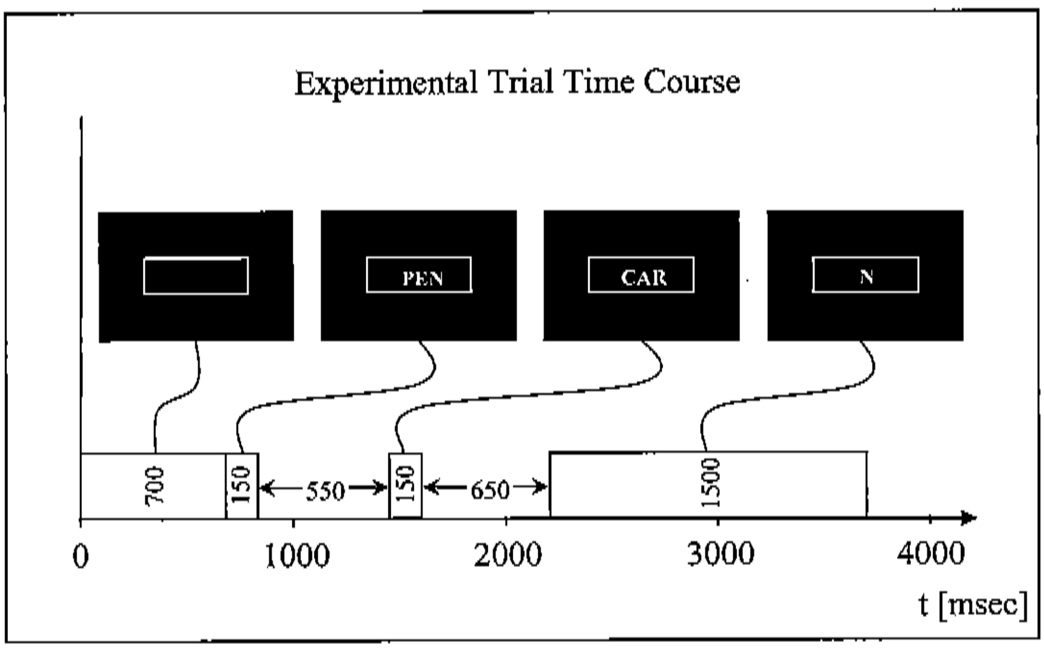

Figure 4: The time course of each trial in the study phase. Each trial started with a rectangle frame appearing at the center of the screen. 700 ms after the onset of the frame, the two words were presented sequentially at the center of the rectangle frame for 150 ms each, and with an SOA of 700 ms between them. The target letter was presented 650 ms after the offset of the second word and remained on the screen for 1500 ms, during which time a response was expected. Both words had to be conjointly kept active in working memory for at least 800 ms.

The test phase immediately and unexpectedly followed the study phase, starting with a cued recall test. In this test, the first nouns that occurred in half of the pairs were presented consecutively and the participants were instructed to respond by providing the second member of each pair. Following cued recall, a free association test was administered. The participants were presented with the first nouns from the other half of the studied pairs and were asked to respond as quickly as possible with the first word that comes to mind. They were explicitly instructed to ignore the study phase during the free association test. Within the context of the present study, responding with a studied paired word in the free association test was labeled "correct" in our reports. No time constraints were imposed on either test.

2.2.4 Experimental Set-Up

All the psychological experiments were run in the Cognitive Electrophysiology Laboratory at the Department of Psychology, the Hebrew University of Jerusalem. The participants were tested in secluded, dedicated experimental rooms, keeping exterior noise to minimum. The experiments were controlled by PCs using dedicated software packages, MEL 2.1 and E-Prime, on Microsoft Windows 98 and Windows 2000 workstations. Statistical analysis of the results was performed with SYSTAT 10, under Windows 2000.

2.3 Pilot Experiment

This experiment was run as part of a parallel series of studies at the Cognitive Electrophysiology Laboratory at the Department of Psychology with a goal of exploring the effects of attention on forming associations. It included collection of ERPs as well as performance data. Here I will report only those aspects of the pilot experiment that were directly relevant to this dissertation and limit myself only to the description and analysis of performance measures.

The participants acquired new associations between unrelated words in an incidental or an intentional learning condition. The working hypothesis was that frequent episodic proximity between words should result in their association even if learning was not intended. To this end, the aim of the pilot experiment was to assess the formation of incidental associations and compare this performance with the result of intentional learning. A cued recall test was used as a measure of associative learning.

2.3.1 Methods

Participants

Thirteen different participants were tested in the intentional and incidental study condition.

Stimuli

The stimuli were 50 pairs of three-letter unrelated nouns[1] each repeated 10 times. Repetitions were randomly scattered in the list. See Appendix A – Stimuli, below for stimuli list.

Procedure

In the incidental learning condition, a letter search task was employed, followed unexpectedly by a cued recall test and a free association test (for details, see section 2.2.3). In the intentional learning condition, identical study and test procedures were applied, except that the participants were informed about the forthcoming memory test and encouraged to learn the associations.

2.3.2 Results

As evident in Table 1, 10 repetitions of unrelated words in proximity were insufficient for episodic associations to be formed incidentally between them. Indeed, across participants, only one pair out of the 50 was recalled. This outcome suggests that, at least under the circumstances of this experiment, participants had to allocate attention to the study process. These observations were corroborated by a mixed-model ANOVA with type of study as the "between groups" factor and type of study as the "within subjects" factor. This analysis showed that associative memory was better in the intentional than in the incidental condition and better in the cued recall than in the free association test.

[1] Notice that because Hebrew is usually written without vowels, a three-letter printed word in Hebrew is equivalent to a 4-5-letter word in English.

Table 1
Percentages of correct response in cued recall and free associates tests, by study condition. Negligible incidental learning was achieved.

	Incidental	Intentional
Cued recall	2.2%	27.4%
Free association	0.3%	5.7%

2.3.3 Discussion

The absence of incidental learning was unexpected. Several reasons can account for this result. One obvious reason is that, whereas associations are usually formed individually in real life, in the pilot experiment the participants were required to form 50 different associations during a relative short period of time. It is conceivable that the excessive memory load prevented the incidental formation of reliable associations, hence reducing the cued recall performance. A related reason could have been that the relatively small number of repetitions may also have contributed to the poor incidental learning. As reviewed in the general introduction, episodic associations result from frequent repetition of conjoint processing episodes. Admittedly, we have no real account of the number of repeated episodes needed to form an association in real life. Indeed, it is possible that real-life associations might result from only a few conjoint encounters of two events, provided that other factors such as semantic and episodic context, which will be discussed below, are active. However, in the artificial experimental circumstances, it would not be surprising to find that a considerable number of repetitions need to occur before a psychologically real association is established.

Another reason that could have accounted for the poor cued recall performance was that outside the psychological laboratory, the episode during which an association is formed is rich in information. That is, words that become associated are usually not encountered as an isolated pair out-of-context but within sentences, discourse, text – in other words, within a meaningful context. Furthermore, unless prevented by the task, the meaning of encountered words is processed by default (Smith, Bentin, & Spalek, 2001). In contrast, the letter search paradigm which was used as orientation task during the incidental study phase directed the participants' attention to the letter-level instead of the word level. In fact, this task could have been successfully performed without even processing the stimulus words meaning.

To conclude, several factors differentiate real life scenario from the lab setting of the pilot experiment and these factors could have lead to the negligible incidental learning of new associations. In the following experiments, I have investigated the contribution of each of these factors and determined the constraints of the computational model.

2.4 Experiment 1: The Effect of Memory Load

The poor recall performance in the incidental study condition of the pilot experiment was unexpected because mere observation would reveal that in real life, most associations are, indeed, formed incidentally. In an attempt to analyze how the experimental circumstances differed from real life, I isolated several factors. In this experiment, I examined the role of memory load and the number of repetitions by reducing the number of pairs presented at study and increasing the number of repetitions of each pair.

2.4.1 Methods

Participants

Thirty-two undergraduates participated in this experiment. They were all native Hebrew speakers and did not participate in the pilot experiment.

Stimuli

The stimuli were 10 out of the 50 pairs that were used in the pilot experiment. Note that the number of pairs used in this experiment is not outstandingly small compared to paired associates experiments (cf. Murdock, 1970; See Appendix A – Stimuli).

Procedure

Since the study focused on the processes that take place during incidental learning and, indeed, the problems raised by the pilot experiment centered around the incidental learning condition, in this and the forthcoming experiments only the incidental condition is explored. A second change from the procedure of the pilot experiment was that the number of repetitions of each pair was increased to 20 (i.e., doubled). Repetitions were scattered randomly in the list. Performance in this condition was compared to the performance in the incidental condition in the pilot experiment in order to assess the affect of significantly reducing the number of pairs and doubling the number of repetitions in the study phase.

2.4.2 Results and Discussion

The percentage of cued recall of incidentally formed associations in Experiment 1 was considerably higher than in the Pilot Experiment (Figure 5). Implicit evidence for experimentally induced new associations emerged also in the free association test. Although the free associations performance was lower than the explicit cued recall (1.3% vs. 17.5%, respectively), any influence on free associations is remarkable, because not only such influence must overcome life-long associations, but (as described in section 2.2) none of the paired words elicited the other within the first three free associations.

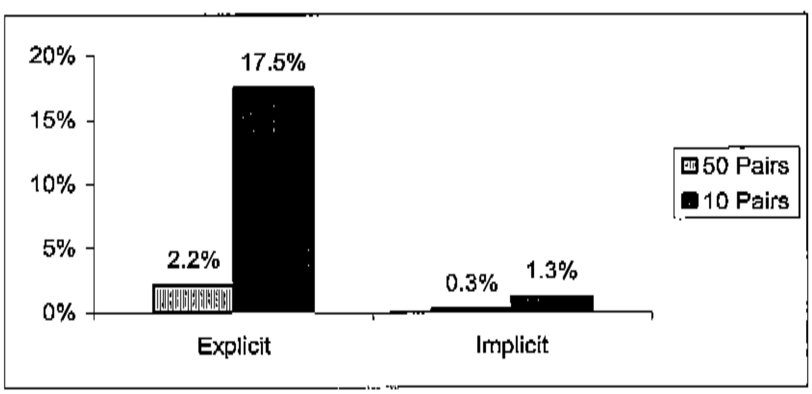

Figure 5: Cued recall (Explicit) and free association (Implicit) performance after incidental learning of 10 pairs compared to 50 pairs. Reducing the number of pairs and increasing the number of repetitions improved both explicit and implicit performance.

The results of Experiment 1 demonstrated that reducing the number of pairs and doubling the number of repetitions led to incidental learning of associations. Whereas the absolute percentage of accuracy was still small, it was significant and considerably higher than in the pilot experiment. This pattern indicates that memory overload might have been a (non-interesting) cause of the initial failure to learn new associations. This factor, however, could not be the only one determining the low cued recall performance in the pilot experiment. The main reason is that despite the improvement, the performance in Experiment 1 was still lower than expected. Furthermore, because in most cases participants used words from the set, but not the correct pairing, the probability for a random correct pairing was higher in the 10 than in the 50-pairs conditions. Hence, some of the observed improvement could be accounted for by chance. Therefore, in the next experiment, I examined the relevance of the second factor mentioned in the discussion of the pilot experiment, namely, the depth of processing the words requested by the orientation task.

2.5 Experiment 2: The Effect of the Level Of Processing

The effect of *Level Of Processing* (LOP; Craik & Lockhart, 1972) is well documented. Since the first demonstration, many studies have showed that both recognition and recall are better if the orientation task is *deep* (i.e., directs the participant's attention to the meaning of the word) than if it is *shallow* (i.e., directs the participant's attention to the physical aspects of the word).[2] Within this context, the letter search task could have, in fact, prevented the processing of the meaning because directing the attention to the letter-level might have impaired the processing of the word as a whole. This factor that clearly affects memory for single items, might, as well, affect memory for pairing. In Experiment 2, I examined the contribution of the shallow level of processing to the low performance in the pilot experiment by comparing cued recall following incidental study using a shallow and a deep level orientation task.

[2] Other authors have emphasized how important is the transfer of appropriate processing from study to test (e.g., Morris, Bransford, & Franks, 1977), but this caveat does not reduce the robustness of the level of processing effect on recall and recognition.

2.5.1 Methods

Participants

Sixteen undergraduates, none of whom was tested in the previous experiments, participated in this experiment.

Stimuli

A new list of pairs was prepared. The stimuli consisted of 10 pairs of three-letter unrelated nouns. Occasionally, relatively big object such as CAMEL was paired with an even bigger object such as RIVER to prevent the participants from performing a size judgment based only on the first word. (Appendix A – Stimuli, for stimuli list).

Procedure

The design of this experiment was identical to Experiment 1, except that the orientation task directed attention to a deeper level of processing. This task was to make a decision of whether the object denoted by the first word was bigger (in size) or smaller than that denoted by the second word. As in the previous experiments, the question determining the response-type (Bigger? Smaller?) was presented only 800 ms after the offset of the second word. The major difference between this task and the one used in the previous experiments was that in Experiment 2, the participants' attention was directed to the word level rather than to the letter-level.

2.5.2 Results and Discussion

The results showed a dramatic effect. Both the cued recall accuracy and the use of incidental studied words as free associations after deep incidental study was high, almost 4 times higher than in Experiment 1, which was based on letter search (Figure 6). The reliability of the LOP effect was established by t-tests comparing performance between the participants tested in Experiment 1 and those tested in Experiment 2. These analyses showed that in both the explicit cued recall and the implicit free association tests, the level of processing effect was significant.

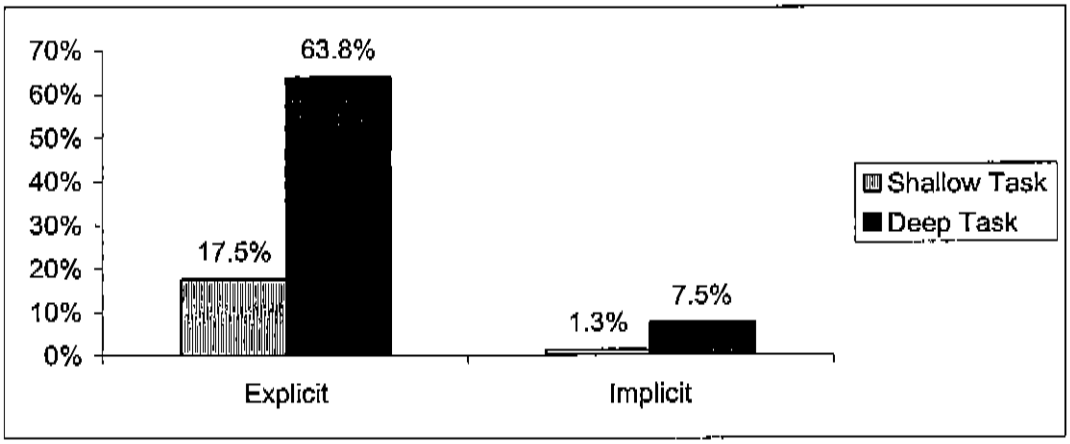

Figure 6: Cued recall (Explicit) and free association (Implicit) performance after incidental learning during a letter search task (Shallow) compared to incidental learning during a size comparison task (Deep). Deep processing improved both explicit and implicit performance.

Performing the deep task, all participants reached a very high level of association recall. Finding a LOP effect in the cued recall test extends, indeed, the well known effect of level of processing on item memory that was cited in the introduction. The present data suggest that the level of processing during incidental study of pairs affects memory for association as well as item memory. Note that, although cued recall might have been, in principle, affected by item memory, recently published data from our laboratory demonstrate that manipulations of the incidental study circumstances affect cued recall independently of item memory (Prior & Bentin, 2003).

The LOP effect on free associations is also not self-evident. Note that in some studies, no such effect was found in other implicit tasks such as stem completion (Graf & Schacter, 1985; 1987). This result is, however, in agreement with at least one other study in which LOP effects were found in an implicit test (Bentin, Moscovitch, & Nirhod, 1999).

Another important difference between the orientation tasks used in Experiment 1 and Experiment 2 was that in the deep level orientation task the participants were asked to perform a comparison between the two words while in the letter search task no such comparison was needed. This relational processing of the two words may have caused greater interaction between the two active representations in working memory during the period in which the participants waited for the question and therefore may have been a factor that contributed to the enhanced associative performance, which is not related to the LOP itself.

To conclude, Experiment 2 suggests that although intentional learning might not be necessary for forming episodic associations, semantic factors may facilitate this process. This hypothesis was directly tested in the next Experiment.

2.6 Experiment 3: The Effect of Semantic Relatedness

In the previous experiment, I found that orienting the participants to a semantic level of processing during the incidental study phase significantly enhanced the cued recall performance. This outcome suggests that conjoint activation of two nodes in the semantic network may facilitate forming associations. Another approach to investigate possible interactions between the semantic and the episodic systems is taken in Experiment 3. In this experiment, I compared how associations are formed between words that are semantically related but not associated (e.g., CHAIR-SHELF or COW-CAMEL) and words that are not semantically related (e.g., CHAIR-CAMEL and COW-SHELF). Based on the assumption that the formation of episodic associations is based on conjoint activation of the two events in memory and on the indication that the semantic factors contribute to the efficiency of this process, it is conceivable that conjoint activation of semantically related nodes would be more consequential for the associative process than the conjoint activation of unrelated nodes.

2.6.1 Methods

Participants

Twenty-nine undergraduates, none of whom was tested in the previous experiments, participated in this experiment.

Stimuli and Design

The experimental list was based on 144 pairs of nouns formed such that the words in each pair belonged to the same semantic category and were not the most typical exemplars of that category. The words in each pair were not associated to each other, as established empirically using questionnaires (section 2.2.2). These pairs were used to form four stimulus-types conditions:

A. Related – Repeated: Thirty-six semantically related (but not associated) pairs were included in this condition. Words in each pair belonged to the same semantic category, and each pair was repeated 5 times at study.

B. Unrelated – Repeated: Thirty-six semantically unrelated and not associated words (formed by re-matching related pairs) were included in this condition.

C. Unrelated – Non-Repeated: This condition consisted of 36 target words, each paired with 5 different prime words. All the resulting 180 pairs in this condition included semantically unrelated and not associated words.

D. Related – Non-Repeated: A different group of 36 semantically related (but not associated) pairs were included. In this condition, pairs did not repeat.
The list is presented in Appendix A – Stimuli.

Procedure

The experimental procedure was modified to include three phases:

1. Incidental learning: Two words forming a pair were presented one after the other in a trial. At 800 ms after the onset of the second word, one of two deep level questions randomly appeared: "Bigger?" or "Prefer?" If the question was "Bigger?" the participant's task was to press one button if the object denoted by the first word is bigger (in size) than the object denoted by the second word, and another button if the object denoted by the second word is bigger. If the question was "Prefer?" the participant's task was to press one button if he/she prefers the object denoted by the first word (based on subjective judgment) compared with the object denoted by the second word, and another button if he/she prefers the object denoted by the second word. As in the previous experiments, episodic proximity was achieved by having the participants store the two words together in working memory for 800 ms. Total number of trials in this phase was (5 repetitions × 36 different pairs) × 3 conditions + 36 different pairs in condition D = 576.

2. Intentional learning: Each different word-pair of conditions A, B and D, and one word-pair for each target word from condition C was presented once, and the participant was explicitly asked to learn the pairing, expecting a cued recall test. The total number of trials in the phase was 36 different pairs × 4 conditions = 144.

3. **Test phase** – As in the previous experiments, associative memory was tested by cued recall. The prime word in each of the 144 pairs that were memorized in phase 2 was presented and the participant was asked to provide the target word. Total number of trials was 36 different pairs × 4 conditions = 144.

Note that although in this experiment an intentional learning phase was included, pairs from each condition in this phase appeared only once, regardless of the condition which they belonged to in the incidental learning phase. Hence, by comparing the participants' performance in the explicit test between pairs from the 4 different conditions, it was possible to assess (implicitly) the contributing of the incidental learning that occurred in phase 1. In particular, the comparison of the performance between pairs from conditions A and B, which differed only in the semantic relatedness of the pairs, enabled to evaluate the contribution of the semantic relationship factor to the incidental learning. The same is true for pairs from conditions C and D. Furthermore, conditions A and B differed from conditions C and D by the fact that in the former, each pair was repeated five times during the incidental learning phase while in the latter each pair appeared only once. Hence, if a significant interaction between the relatedness factor and the repetition factor is to be found, it would suggest that the contribution of the semantic knowledge is on-going even in latter repetitions.

2.6.2 Results and Discussion

Both main effects, that is, that of prior semantic relationship (relatedness) and that of number of repetitions in the incidental learning phase (repetition) were statistically significant ($F(1,28)=297.3$, $P<0.001$, and $F(1,28)=199.9$, $P<0.001$, respectively; Figure 7). The interaction between the relatedness and repetition conditions was also significant ($F(1,28)=4.5$, $P<0.05$), suggesting that the contribution of the semantic knowledge is on-going even beyond the first presentation.

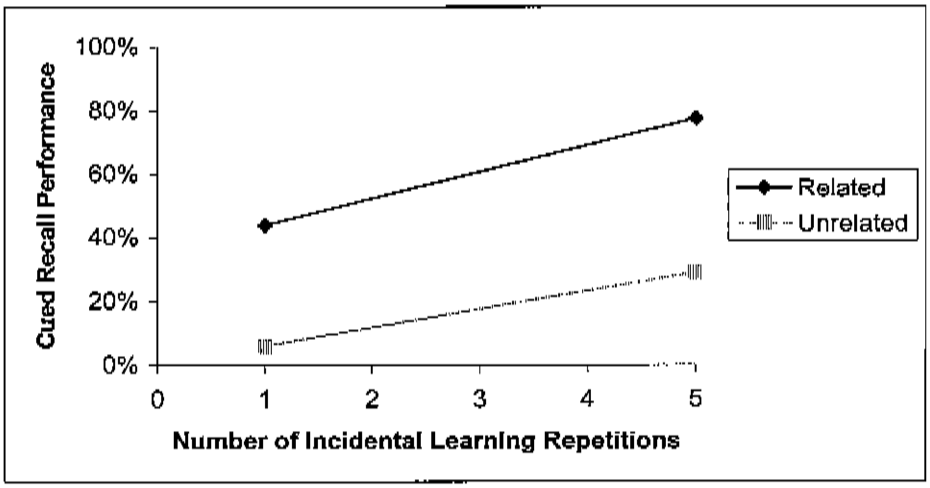

Figure 7: Cued recall performance after 1 and 5 incidental learning repetitions for pairs with and without prior semantic relationship. Performance is higher for semantically related pairs and the number of repetitions interacts with the relatedness condition, suggesting a contribution of semantic knowledge to forming associations, which lasts even beyond the first presentation.

2.7 Experiment 4: A Semantic Boost for Episodic Association[3]

The major goal of the present experiment was to explore possible mechanisms for the influence of semantic relatedness on the formation of associative links between words. A possible account for the semantic relatedness effect is that this advantage is caused by pre-existent, weak, associative links between semantically related words. Another possible mechanism is that the formation of the new episodic links is facilitated by semantic information recurrently, at each episode. According to the latter account, common semantic attributes interact with, and facilitate the associative process at each episode of co-occurrence.

The above two accounts imply different predictions regarding the dynamics of associative learning. As mentioned above, it is possible that semantic information is irrelevant to the process of learning a new association, and that the relative advantage of related pairs reflects primarily an initially higher level of association between semantically related words. If so, the learning curve for the semantically related pairs (as reflected by cued-recall performance) should start at a higher level of memory, but progress in parallel with the learning curve of the unrelated

[3] Experiments 4 and 5 were submitted to the *Quarterly Journal of Experimental Psychology* titled "A Semantic Boost for Episodic Association between Words: A Search for the Mechanism".

pairs. Alternatively, if semantic knowledge interacts with the on-line learning process, each presentation should yield more strength to the associations formed between semantically related pairs compared to those formed between unrelated pairs. Consequently, the slope of the learning curve should be steeper for semantically related than for unrelated words reflecting this cumulative influence (Figure 8). In order to examine which of these two predictions is valid, I compared cued recall of semantically related and unrelated pairs, following 1, 5, 10, or 20 presentations of each pair during incidental study.

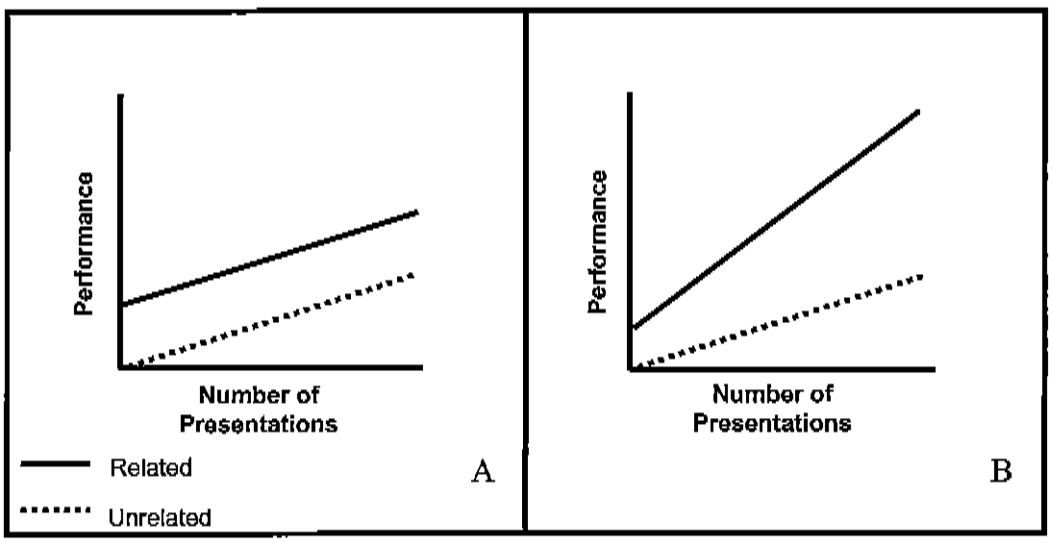

Figure 8: Performance in the cued recall test predicted by two possible accounts for the semantic relatedness advantage: A) Prediction based on the hypothesis that the semantic relatedness advantage is solely based on pre-existent associations between semantically related words. B) Prediction based on the hypothesis that semantic relatedness facilitates associative learning at each episode of co-occurrence.

2.7.1 Methods

Participants

The participants were 96 undergraduates who were paid a nominal fee or received course credit for their participation. They were all native Hebrew speakers with normal or corrected to normal vision. None had participated in the previous experiments.

Stimuli

Twenty-four pairs of Hebrew nouns were selected such that the two words belonged to the same semantic category but were not associated (Appendix A – Stimuli). Two lists of 24 pairs each were assembled. Each list was comprised of 12 semantically related word-pairs and 12 unrelated pairs. The unrelated pairs were created by shuffling the words of the 12 pairs that were not presented in the related condition. The semantically related pairs in one list were unrelated in the second list and vice versa.

Design and Procedure

In order to avoid overloading the participants' memory, the effect of the number of presentations had to be tested between-subjects, with a different group of 24 participants examined at each level (1, 5, 10 and 20 presentations). In each group, 12 participants were assigned to each of the two lists. Consequently, the main effect of semantic relatedness was tested within-subject with different pairs, but across participants the same words were used in the related and unrelated conditions. The experiment consisted of an incidental study and a test phase. A letter search task was again adopted for the incidental study phase. Immediately after the study phase, associative learning was tested by a cued recall test, which was administered unexpectedly.

2.7.2 Results and Discussion

Cued recall was better for semantically related than for unrelated pairs. Furthermore, the size of the relatedness effect increased with the number of presentations (Table 2 and Figure 9).

Table 2
Mean percentage of the improvement in cued recall induced per repetition during incidental study of semantically related and unrelated pairs of words. The curve of the semantically related pairs is nearly linear until 10 repetitions and the curve of the semantically unrelated pairs is nearly linear from the second repetition.

Number of presentations (from – to)	1	2-5	6-10	11-20
Related	6.3%	4.3%	4.2%	1.4%
Unrelated	0.0%	1.1%	0.8%	0.7%

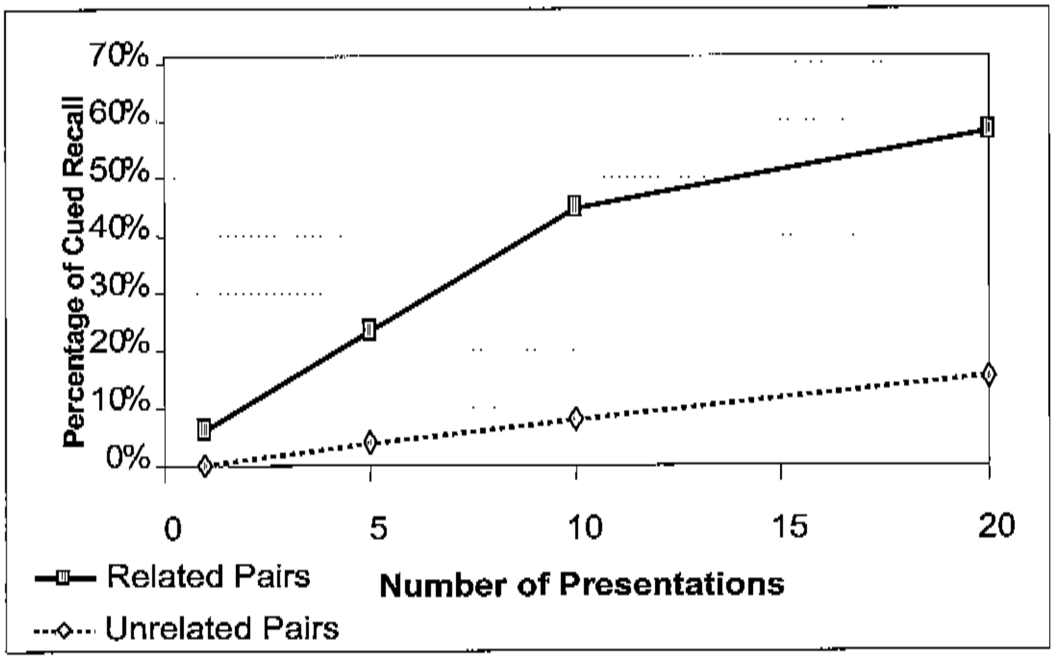

Figure 9: Percentage of correct cued recall for semantically related and unrelated pairs of words following various numbers of incidental co-occurrences at study. Semantically related pairs are learned faster in each of the first 10 iterations.

The statistical reliability of these observations was tested by a mixed-model, two-way ANOVA. The between-subjects factor was the number of presentations (1, 5, 10, 20) and the within-subjects factor was semantic relatedness (related, unrelated). The ANOVA[4] showed that both main effects were significant ($F(1,92)=204$, $P<0.0001$ and $F(3,92)=25$, $P<0.0001$, for semantic relatedness and number of presentations, respectively). More importantly, however, the interaction between the two factors was highly significant ($F(3,92)=19$, $P<0.0001$), suggesting that each repetition contributed more to related pairs than it contributed to unrelated pairs. Furthermore, calculating the percentage of cued recall that was added by each presentation revealed that the study rate remained relatively stable for both relatedness conditions up to 10 presentations. For unrelated pairs, performance improved at a steady rate of 1% per repetition, across the entire range examined. In contrast, for related pairs, a slope of about 4% was steady up to 10 presentations, following which it was reduced to 1.6%, similar to the slope of unrelated pairs (Table 2). Post hoc analyses showed that the

[4] Here and in all the following statistical analyses, the p-value is based on the Greenhouse-Geisser correction for sphericity due to multiple levels within factor.

interaction between the semantic relatedness and number of presentations factors held until 10 presentations; from 10 to 20 presentations the interaction between the two factors was insignificant (i.e., above 9 presentations, increasing the number of presentations is equally effective for related and unrelated pairs).

The results of Experiment 4 showed that even with one presentation, cued recall was better for semantically related than unrelated pairs. This difference suggests that some initial weak association could have, indeed, existed between semantically related nouns. Such associative links might have been too weak to be revealed in our pilot survey, but still exerted consequential influence implicitly (Nelson, McEvoy, & Dennis, 2000). However, although memory improved with the number of repetitions for unrelated as well as for related pairs, the significantly steeper slope of cued recall for related pairs up to 10 presentations reveals that, at least during that dynamic range, semantic relations between pairs facilitated the incidental formation of episodic associations cumulatively. With more than 10 presentations learning continued to improve, but the additional episodic learning was equal for related and unrelated pairs. This change was caused by a significant decrease of the cued-recall slope for related pairs, suggesting that semantic relatedness helps associating events only as long as the association is relatively weak.

The main effect of semantic relatedness in this experiment provides additional support to the hypothesis that semantic relatedness per se facilitates the formation of episodic associations. Such a conclusion, however, is qualified by the possibility that the better recall of the related words may have resulted from a more constrained retrieval process at test, rather than from more efficient formation of associations at study. According to this interpretation, participants became aware during the study phase that half of the pairs on the list were semantically related and, therefore, adopted a strategy to search first for a semantically related associate to the cue within a limited-size semantic neighborhood (cf. Baddeley, 1972). This strategy was obviously efficient for related but not for unrelated pairs. Moreover, the likelihood of noticing the semantic relatedness of some pairs might have increased with the absolute number of presentations of related pairs in the study list. Since in the present experiment I aimed at exploring the time course of the semantic relatedness effect at four levels, different participants had to be tested at each level of the number of presentations factor. Consequently, it is possible that participants tested with many presentations were more prone to use the semantic search strategy than participants tested with only a few presentations. Hence, cued recall strategies could not only explain the advantage of related over unrelated pairs, but also the interaction between this advantage and the number of presentations.

These caveats, however, were less relevant in the next experiment, in which I used a complete within-subject design and a forced-choice recognition task to assess associative learning.

2.8 Experiment 5: A Semantic Boost – Forced Choice Paradigm

This experiment was aimed at expanding the exploration of the semantic relatedness influence on the formation of new associations and, at the same time, reduce to some extent some of the caveats regarding the interpretation of Experiment 4. Thus, Experiment 5 was different from Experiment 4 in several important aspects. First, associative memory was tested using forced-choice recognition rather than cued recall. Second, in the design of Experiment 5, I excluded the 20 presentations condition, which enabled us to manipulate both the number of presentations and the semantic relatedness factors within-subject.

Using a forced-choice recognition paradigm, I ensured that the search and selection of the correct answer for related and unrelated pairs was based on equal sets of potential candidates, namely those presented as options to the participant. Furthermore, in order to discourage using semantic relatedness as a cue for selecting the correct answer even further, all alternative choices were members of the same semantic category as the correct answer, that is, they were all related among themselves. In addition, the forced choice design enabled us to perform an error analysis by which the strategic tendencies in the participants' performance could be assessed (albeit post hoc).

The within-subject manipulation of the number of presentations ensured that all participants were exposed to the same number of trials and were equally likely to notice the fact that the study list included both related and unrelated word-pairs.

Therefore, any retrieval or search-based strategies should have had an equal effect across the number of presentations.

Additionally, in the Experiment 5, I substituted a deep processing level (semantic) task for the shallow letter search task used in the previous experiment. This was done since relative to cued recall, recognition involves data driven processing to a larger extent (Roediger, Weldon, & Challis, 1989). Therefore, I was concerned that by using a data driven task at test combined with a shallow level task at study, I might eradicate any possible influence of semantic factors.

Finally, in Experiment 4, we learned that semantic relatedness is consequential particularly at low levels of associative memory. It was expected that the combination of a deep-level orientation task at study and a recognition (rather than cued recall) task at test would lead to high levels of memory performance. In order to ensure our ability to observe the semantic effects of interest, a delay of 24 hours was introduced between the incidental associative learning phase and the assessment of associative memory.

Hence, while the present experiment expanded the exploration of semantic factors on the formation of new associations using a different level of incidental learning and a different method of assessing associative memory, it was also instrumental in addressing the major caveats that constrained interpreting the outcome of Experiment 4.

2.8.1 Methods

Participants

The participants were 36 undergraduates who were sampled from the same population as the participants in Experiment 4. They were paid a nominal fee or received course credit for participation. None had participated in the previous experiments.

Stimuli

Ninety-six pairs of concrete Hebrew nouns were selected such that they would belong to 24 different semantic categories (4 pairs per category). I ensured that the words of each pair were not associated to each other prior to the experiment, by using Hebrew free association norms (Henik, Rubinstein, & Anaki, unpublished). According to these norms (which were unavailable when the previous experiments were run), the two words did not elicit one another while testing free associations in 100 students either as a first response or as one of the responses elicited during a minute following the presentation of the cue. Two lists of 96 pairs were assembled, each comprising of 48 semantically related pairs and 48 unrelated pairs, in which the related words were shuffled. The semantically related pairs in one list were unrelated in the second list and vice versa (Appendix A).

Design and Procedure

The effect of semantic relatedness and the effect of number of presentations were tested within-subject. In each of the two study-lists, 32 pairs, 16 related and 16 unrelated, were assigned to each of the three levels of number of presentations (1, 5, and 10). These levels cover the dynamic range of the learning curve observed in Experiment 4. Across participants, the pairs assigned within each list to each number of presentations were rotated. Half of the participants were tested with List A and the other half with List B. Consequently, across participants, the same words were used in all six relatedness by repetition conditions.

As in the prior experiment, the present experiment consisted of an incidental study phase and a test phase. Participants were exposed to 512 study trials (32 pairs × 10 presentations + 32 pairs × 5 presentations + 32 pairs × 1 presentation). Each study trial started with a fixation mark exposed for 200 ms. The paired words were simultaneously presented for 500 ms immediately following the offset of the fixation mark, centered to the right and left of its location. Following the presentation of the pair, one of four single word questions of a subjective nature was presented (Impressive?; Beautiful?; Preferred?; Familiar?). The question was randomly selected on each trial. Participants were told that in a previous survey, a different group of participants compared the two nouns presented on the screen and selected the one better fitting the feature denoted by the probe word. In effect, no such previous survey was conducted. The orientation task required the participants to guess how the previous fictitious participants replied to these same probe words. I chose this indirect semantic task to ensure that participants remained engaged in the task throughout the study phase, notwithstanding the lack of an objective criterion by which their performance could be assessed. To enhance their motivation even further, a monetary bonus was promised to participants who guessed within one SD from the "true" mean. In reality, all participants received this bonus. The question word was presented 300 ms following the offset of the pair, and remained on the screen for 1500 ms, during which time a response was expected. Since the participants could not know in advance which question would be asked, they had to keep both words conjointly active in working memory for at least 800 ms.

Following the study phase, the participants were requested to return the following day, at which time they completed the test phase. They received no information that the second part would include any form of memory test. In the test phase, forced choice recognition memory test was administered. The first word of each of the 96 pairs was presented as a cue, and the participants were instructed to select its pair as it appeared in the study list, out of five possible answers exposed underneath.

As described above, in the study phase, half of the pairs were related and half were unrelated. When the cue word had been studied in the related condition, all five alternative responses belonged to the same category as the cue, and consequently were all related to each other. When the cue word had been studied in the unrelated condition, once again all five possible responses belonged to the category of the correct answer, and therefore none of them were related to the cue word. In both cases, of the five alternative responses, one was the correct answer, two were new items, not previously encountered during the incidental study phase (New), and two were words that had appeared in the study list paired with different items. These latter two studied words had always appeared on the left in the study display[5], and both belonged to the same number of presentations level as the pair probed. Of these two studied distracters, one had appeared at study in the

[5] Since Hebrew is written from right to left, the left-hand word is the second word of the pair, the so-called "target".

same relatedness condition (SRC) as the probed pair, that is, if the probed pair was related, the SRC distracter had also been studied in a related pair. The second studied distracter had appeared at study in the opposite relatedness condition (ORC), i.e., if the probed pair, once again, was related, the ORC distracter had been studied in an unrelated pair.

The five possible responses were presented in two lines beneath the cue, and their positions were fully randomized. No time limits were imposed during the test phase. Hence, as in the previous experiment, accuracy was the only dependent variable.

2.8.2 Results and Discussion

As in Experiment 4, performance was better for semantically related than for unrelated pairs, across all three presentation conditions. Furthermore, the effect of semantic relatedness was different across different presentation numbers, replicating the interaction found in Experiment 4 (Figure 10).

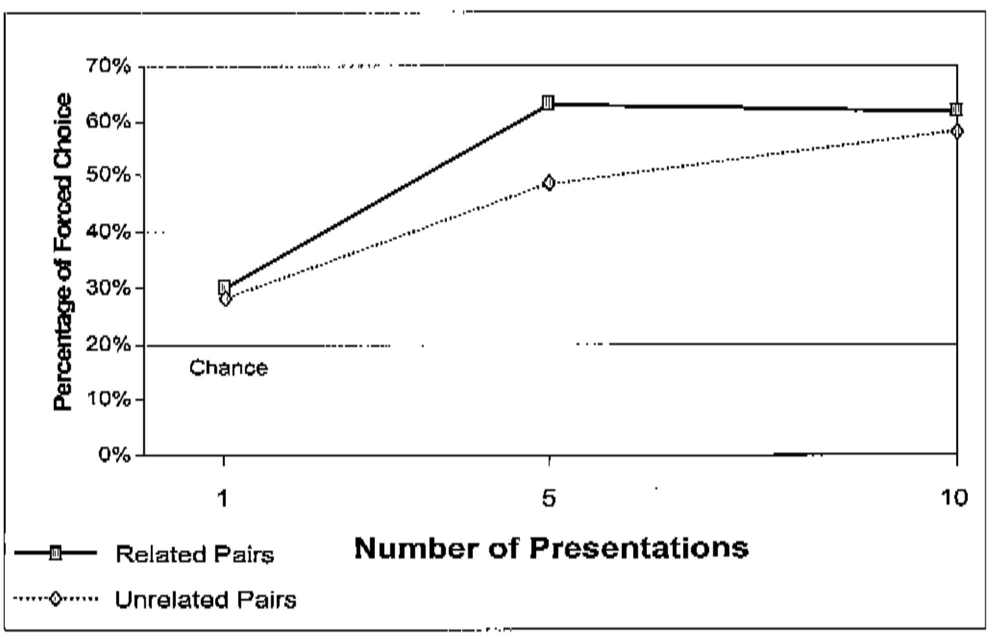

Figure 10: Percentage of correct forced choice cued recognition for semantically related and unrelated pairs of words following various numbers incidental co-occurrences at study. Semantically related pairs are learned faster in each of the first 5 iterations.

The statistical reliability of these observations was tested by a within-subject ANOVA. The two factors were the number of presentations (1, 5, 10) and semantic relatedness (related, unrelated). This analysis showed that both main effects were significant ($F(2,70)=121.0$, $P<0.001$; $F(1,35)=18.5$, $P<0.001$ for number of presentations and semantic relatedness, respectively). More importantly, however, the interaction was significant as well ($F(2,70)=6.3$, $P<0.005$). In other words, the number of presentations influenced the semantic relatedness effect.

Since the total percentage of errors mirrored, in fact, the percentage of correct responses, in the error analysis, I was interested only in the main effect of error type and its possible interactions with semantic relatedness and number of presentation factors. As evident in Figure 11, there were more SRC than ORC and New errors.

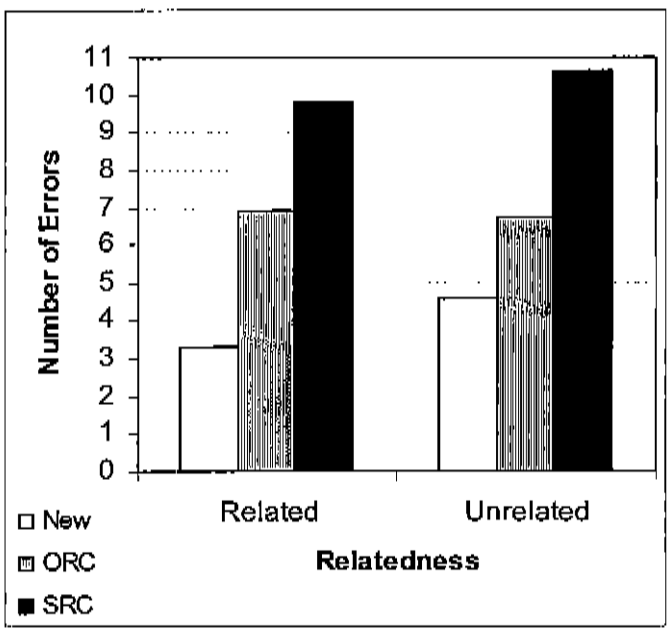

Figure 11: Number of false recognitions of distracters that were not presented at study (New), of distracters that were presented at study in the same relatedness condition as the target (SRC), and of distracters that were presented at study in the opposite relatedness condition (SRC). The errors are presented separately for the related and unrelated study conditions. There were more SRC than ORC and New errors.

The statistical evaluation of the pattern of errors was based on a within-subject, three-way ANOVA. The independent variables were error type (SRC, ORC, New), number of presentations (1, 5, 10), and semantic relatedness (related, unrelated). All three main effects were significant ($F(2,70)=77.2$, $P<.0001$, $F(2,70)$ 72.5, $P<.0001$, and $F(1,35)=7.4$, $P<.01$, for the error type, number of presentations and relatedness effect, respectively). Post hoc Univariate contrasts showed that fewer false alarms were made for New distracters (1.3) than for ORC distracters (2.3; $F(1,35)=39.4$), while the SRC distracters elicited most false alarms (3.4; $F(1,35)=56.4$). More errors were made following 1 study presentation (3.1) than following 5 presentations (2.1; $F(1,35)=69.8$), least errors were made following 10 presentations (1.8; $F(1,35)=9.8$). The interaction between Relatedness and number of presentations was significant ($F(2,70)=7.0$, $P<.01$), as was the interaction between error type and number of presentations ($F(4,140)=4.6$, $P<.01$). Both interactions were qualified, however, by a significant second order interaction between the three factors ($F(4,140)=2.9$, $P<.025$).

The source of the second order interaction was examined by separate number of presentations × Relatedness ANOVAs for each error type, and by error type × number of presentations for each relatedness condition. These analyses showed that, whereas the first order interactions were slightly different at each level of the third factor, they all pointed in the same direction: The difference between error types was more conspicuous with 5 and 10 presentations (particularly for unrelated pairs) than with 1 presentation, and the relatedness effect was less pronounced for New distracters.

Despite the 24 hours delay between study and test for both related and unrelated pairs, associative memory was well above chance even for pairs presented only once during the study phase. Compared to Experiment 4, the elevated level of performance and an increased slope of the learning curve were conspicuous primarily for unrelated pairs. However, notwithstanding the level of performance, the present findings also showed the semantic relatedness advantage, namely, associations formed between related words were better remembered than those formed between unrelated words. Moreover, relative to cued recall, retrieval strategies could hardly account for the relatedness effect in the present design. In the forced-choice recognition paradigm, the search set was explicitly defined, and was of equal size for related and unrelated pairs. Further, since all alternative choices were semantically related among themselves for both pair types, the response could not have been guided by semantic relatedness.

The overall recognition memory performance in Experiment 5 was high. Thus, compared with cued recall, fewer presentations were required to reach a plateau. This finding is not surprising, given that in Experiment 4 the study task was shallow (letter search) and the memory task was conceptually driven (cued recall), while the present experiment made use of a deep study task (semantic decision) and a more data-driven memory task (forced choice recognition). Deep processing is known to lead to better memory performance than shallow processing (Craik & Lockhart, 1972), at least if the transfer of appropriate processes between study and test are comparable across processing levels (cf. Morris, Bransford, & Franks, 1977).

The analysis of errors revealed a complex, but informative pattern. The basic findings were that, regardless of whether the tested association was between two related or between two unrelated words, participants selected New words considerably less often than words that were presented at study. Moreover, they were more inclined to make SRC errors, that is, to choose alternatives that were studied in the same relatedness condition as the tested pair. Hence, it is evident that, at least when the participants had no explicit recollection of the paired associate to a cue, they chose alternatives that were episodically familiar. Furthermore, since the correct responses and the four distracters were semantically related among themselves, the relatedness condition was evident in each trial. Hence, the significantly higher frequency of SRC errors indicates that participants had (at least implicit) knowledge about the relatedness condition in which the familiar alternatives were studied. This knowledge was obviously acquired at study and, as revealed by the reduced effect of error type following one repetition, its consequence on the forced-choice performance depended on the strength of the studied association. Finally, the absence of an interaction between error type and semantic relatedness suggests that similar selection strategies were used at test for related and unrelated pairs.

2.9 Conclusion

The experiments described in this chapter showed that associations can be formed incidentally between unrelated words. Occasionally, these newly learned associations can be sufficiently strong to (temporarily) replace the natural associations. More importantly, this first series of experiments showed that semantic relatedness facilitates association formation. Moreover, the semantic contribution continues through learning implying that the semantic system influences the episodic process. These conclusions may serve as guidelines for developing a computational model to describe the process of forming association which can explain the interaction with the existent knowledge in the semantic system. Once such a model would be verified, it may lead to extracting further predictions on human behavior. The computational model is described in the next chapter.

3 Computational Model – SEMANT

Constrained by the results of the behavioral experiments (chapter 2) and based on common theories of semantic and episodic memory (section 1.6), I developed a biologically-motivated artificial neural network model to suggest a computational mechanism for the formation of episodic associations between words. In this chapter, this model, called SEMANT (Semantic and Episodic Memory of Associations using Neural neTworks) is presented. The network architecture, the semantic word representations and the simulations aimed at validating the model are described in detail.

3.1 Background

The following section describes the computational background for SEMANT. Following an overview of related models, Self Organizing Maps and Semantic Maps are described in detail and motivation for their use is given.

3.1.1 Related Models

As was reviewed in section 1.6.2, Ross Quillian (1966) first developed a computer program with the goal of understanding text. As part of the program, he developed what could be considered the first computational model for semantic memory. Quillian's model is based on a hierarchically arranged network of links between concepts. In response to the criticism of the Quillian model, Collins and Loftus (1975) introduced their *Semantic Network* model and the notion of *Spreading Activation.* As described in section 1.6.2, spreading activation over semantic network models can account for various semantic relatedness and semantic priming effects.

Recently, an alternative modeling approach has been proposed to explain semantic priming. Models in this class represent concepts not by single units, but by distinguishable patterns of activity over a large number of units (Hinton, 1990; Masson, 1995; Moss et al., 1994; Plaut, 1995). Each unit participating in the representation accounts for a specific semantic microfeature. Thus, semantic similarity is expressed as an overlap in activity patterns over the set of microfeatures. Activity propagates through recurrent connections until the network settles to a stable state (*an attractor*). Semantic priming is explained by the fact that after settling to the priming concept, fewer modifications in the nodes' state should take place when settling to the target concept, thereby making the response faster.

Although several computational models of semantic priming have been proposed, all have focused on the processes based on already established associations (Masson, 1995; Moss et al., 1994; Plaut, 1995). Plaut's (1995) model, however, suggests a distinction between the way by which semantic and episodic relations could be formed. As in other distributed models, similar representations represent semantic relations. However, according to his model, episodic relations between word-pairs are formed based on co-occurrence information throughout the learning history. Nonetheless, there is no computational understanding theory of the process of forming associations and of how the strength of existing semantic connections among other factors affects this process.

3.1.2 Self-Organizing Maps

The architecture of SEMANT is based on a laterally connected self-organizing map. The Self-Organizing Topographic Feature Maps (SOM) learning algorithm (Kohonen, 1982, 1990) is an Artificial Neural Network (ANN) model for generation of spatial maps (most commonly: two-dimensional layers), which classify data and represent features of the input as topographic qualities on the map. The algorithm has two different manners of implementation. One version is biologically motivated and, therefore, includes computations that are biologically plausible. The other version is more abstract in nature, i.e., less biologically plausible, and the equations that govern it are abstractions of the computations in the biological version. In both versions the architecture of the model is a two-layered neural network, where the input is presented on the first layer and the map is organized on the second. In addition, in the biologically motivated version, the neurons of the output layer are interconnected with all-to-all lateral connections that are used to implement a *winner-takes-all* computation. According to the SOM algorithm, inputs that are significantly different in their features are mapped onto distinct locations in the output space and vice versa. The learning of the inputs, by an iterative process, is *unsupervised* and the map is organized according to the statistics of the input's features, without any direct instructions or prior knowledge coded in the algorithm.

In both versions of the algorithm, each iterative step consists of two stages:

1. Selecting the most responsive node in the output layer to the input vector.
2. Modifying the weight vectors of the most responsive node and neighboring nodes to become more similar to the input vector.

In the abstract version, the selection of the most responsive node is done simply by selecting the node with the minimal distance (usually by a Euclidean metric function) between its weight vector and the input vector. The neighborhood in which weight vectors will be modified is then defined around the most responsive node, with a radius that decreases with the iterations, from nearly the size of the entire map down to zero. The weight vectors of nodes in the neighborhood are changed to become closer to the input vector according to the following equation:

$$w_{ij}(t+1) = w_{ij}(t) + \varepsilon(t)\left[i(t) - w_{ij}(t)\right] \,, \qquad (1)$$

where $w_{ij}(t)$ is the map's weight vector for neuron (i,j) at time t, $i(t)$ is the input vector at time t, and $\varepsilon(t)$ is the adaptation rate, which decreases to zero with t.

In the biologically motivated version, the map's response to the input vector is determined by calculating the scalar product of the weight vectors of each node and the input vector:

$$s_{ij} = \sum_k w_{ij,k} i_k \quad , \qquad (2)$$

where s_{ij} is the response of node (i,j) at time t (in a two-dimensional map).

Once the map's response is calculated, the selection of the most responsive node is done by an iterative process of a *winner-takes-all* computation, according to the following equation:

$$\eta_{ij}(t'+1) = \sigma\left(s_{ij} + \sum_{u,v} \gamma_{uv,ij} \eta_{uv}(t') \right) \,, \qquad (3)$$

where $\eta_{ij}(t')$ is the response of node (i,j) at time t', $\gamma_{kv,ij}$ are the lateral connections which, for the purpose of implementing the winner-takes-all, have the form of a *Mexican Hat* or a difference of Gaussians, and

$$\sigma(x) = \frac{1}{\left(1+e^{-x}\right)} \quad , \qquad (4)$$

is the sigmoid function (for a comprehensive review of both versions of the algorithm, see Miikkulainen, 1993, chapter 7).

3.1.3 Semantic Maps

A common use of the SOM algorithm is mapping inputs with inherent metric properties (Kohonen 1990; 2000). Such inputs are typical in lower-level perception. However, when dealing with high-level processing such as language and memory, the input is often discrete and does not necessarily convey obvious metric features.

In order to cope with mapping of symbols, Ritter and Kohonen (1989) implemented the SOM algorithm on words that were represented in two alternative ways. In the first, the representation of the word was a *feature vector*, where bits represented a set of fixed properties (big/small, has 2 legs/4 legs, etc.). In the other, the context of the word, i.e., the representation of the word and the predecessor and successor words, were used as the input. In both cases, meaningful maps were created and expressed grammatical and semantic relationships between the words. Figure 12 shows the semantic map that was formed based on the latter representation method. They coined the term Semantic Maps for these structures. As a follow-up, the latter methodology was implemented on a larger corpus, the entire text of the Grimm fairytales, with significant success (Honkela, Pulkki, & Kohonen, 1995).

It is important to mention that in the 'context' approach, the coding of the words themselves was random. Hence, the organization of the maps was enabled by information that was implicit in the context. This approach has been used in several other studies as well, in which meaningful representations for words were generated based on the context in which they appear in a large corpora, suggesting that the meaning of a word can be extracted from the various contexts in which it appears (e.g., Miikkulainen, 1993; Lund, Burgess, & Atchley, 1995; Landauer, & Dumais, 1997; Wettler & Rapp, 1991).

.	Water	.	Meat	.	.	.	.	Dog	Horse
Beer	.	.	.	.	Bread	.	.	.	.
.	.	.	.	.	.	.	.	.	Cat
.	.	.	Little	.	.	.	.	.	.
Fast	.	.	.	.	.	Seldom	.	.	Bob
.	.	.	.	Much	.	.	.	Jim	.
Slowly	.	Often	.	.	.	.	.	.	.
.	.	.	.	.	.	Eats	.	.	Mary
Well	.	.	.	Works	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
Poorly	.	.	Speaks	.	.	.	.	.	Phones
.	.	.	.	.	Buys	.	.	Visit	.
.	.	.	.	.	.	Sells	.	.	.
.	.	Runs	.	.	.	.	.	.	.
Drinks	.	.	.	Walks	.	.	Hates	.	Likes

Figure 12 (from Ritter and Kohonen, 1989): Example of a map organized in the 'context' approach. Words with similar meanings are represented by nearby locations over the map.

3.1.4 Use of Semantic Maps in Related Models

Miikkulainen (1997) suggested a model of the human lexicon as part of DISCERN, a sub-symbolic Natural Language Processing (NLP) integrated model of Scripts, Lexicon and Memory (Miikkulainen, 1993). This model is based on two Kohonen maps, one that represents semantic features of concepts and one that represents orthographic properties of words, which are linked together in a many-to-many fashion by across-maps connections. The model explains human reading errors as well as other phenomena and demonstrates how useful it is to use such maps with regard to words and concepts.

Semantic maps have been successfully used in various other studies of the semantic system as well such as language acquisition (Li, 1999, 2000), sentence processing (Mayberry & Miikkulainen, 2002), semantic priming (Lowe, 1997), and document representation and retrieval (Kohonen et al., 2000; Scholtes, 1991).

3.1.5 Motivation for Using Semantic Maps

Since self-organizing maps are based on biologically plausible unsupervised Hebbian learning, and maps in general are common in many parts of the cortex (Knudsen, Lac, & Esterly, 1987), self-organizing maps are most appealing as a biologically plausible analogue of classic semantic networks (Spitzer, 1997).

A strong motivation for using maps for modeling associations between words comes from several observations that may indicate the actual existence of physical maps of concepts in the human brain. There are reports about patients with brain damage that have lost only a portion of the semantic memory (Farah & Wallace, 1992; Caramazza et al., 1994). These patients show deficit in the use of sub-sets of words such as inanimate versus animate, or even more category-specific such as body parts or fruits and vegetables.

Moreover, semantic category specificity in the brain is supported also by non-invasive research using Functional Magnetic Resonance Imaging (fMRI). These studies revealed separate areas of activation while naming animals versus furniture (Spitzer, 1997; Pulvermüller, Assadollahi, & Elbert, 2001). Lowe et al. (2003) have also found evidence for semantic categorization in the brain and a map-like organization of magnetic brain waves using Magnetoencephalograph (MEG). Spitzer also found supporting evidence for the idea of spreading activation over semantic maps in his research with schizophrenic patients. Both their type of mistakes and their performance in semantic priming tests could be interpreted along this view.

The computational model of episodic association formation that is suggested in this research is based on a semantic map, namely, a map of concepts map, as a computational, biologically plausible model of the semantic system.

3.1.6 Laterally Connected Semantic Maps

Recall that in the more biologically plausible version of the SOM algorithm (section 3.1.2) the winner-takes-all section of the algorithm is implemented using lateral inhibitory connections between each of the nodes in the map, in addition to the feed-forward connection from the input layer. These lateral connections are used in another part of DISCERN, where the SOM is used as a base for episodic memory. In order to enable fast (single-presentation) imprinting of memory traces, as opposed to the gradual iterative process of maps' organization, the lateral inhibitory connections are changed towards excitation, to direct the convergence process towards nodes that have been presented in the past (Miikkulainen, 1992; 1993). In SEMANT these lateral connections within the map are used to represent episodic associations between words that are represented on the nodes of the map.

3.2 Model Description

In this section, the technical details of the computational model will be described. The numerical representations for the words, the semantic map organization procedure and its correspondence to simulating different computational participants, the network architecture and dynamics are explained in detail.

3.2.1 Word Representations

In order to organize the semantic map, I used numeric representations based on the lexical co-occurrence analysis in the Hyperspace Analogue to Language (HAL) model of Burgess and Lund (1997). In this model, high-dimensional numeric representations for words are formed based on the context in which they occur in large text corpora. A moving window of several words is placed around each word in the text. A co-occurrence matrix is calculated according to how often each word occurs in the different positions in the window. The rows and columns of this matrix are high-dimensional vector representations for each word. To make them practical, the 100 dimensions with the highest variance are used for the final representations. HAL vectors have been shown to capture the semantics of words well (Burgess & Lund, 1997; Lund, Burgess, & Atchley, 1995; Lund, Burgess, & Audet, 1996) and have been successfully used in creating sensible Self-Organized Semantic Maps (Li, Burgess, & Lund, 2000; Li, 1999, 2000).

In this dissertation, HAL representations were based on the 3.8-million-word CHILDES database, a corpus with particularly clearly defined word semantics. Out of the 4,300 words with numerical representations that are available in CHILDES, the semantic map of SEMANT consisted of 250 nouns, selected randomly and organized on a 40 by 40 grid. I selected 48 nouns that formed 24 pairs of words such that the words in each pair belonged to the same semantic category. The words were English translations of the 48 Hebrew words used in Experiment 4 (Appendix A – Stimuli). In some cases, where a direct translation did not exist or the translated word did not appear in our set of HAL representations, a similar English word was selected. Another 202 nouns were selected randomly from the set of representations as fillers in the map in order to create a richer semantic neighborhood in which the 48 words of interest could organize.

3.2.2 Map Organization

The model is based on a SOM with lateral connections as described in section 3.1.6 (Miikkulainen, 1992; Ritter, & Kohonen, 1989). The map is formed in an unsupervised learning process where words that are close in their meaning become represented by nearby nodes in the map. Hence, distance on the map represents how closely related words are. For a pseudo-code description of the algorithm, see Appendix B – MatLab Code.

3.2.3 Simulated Participants

In the experiments, 12 different participants were generated by self-organizing the semantic map from different random initial starting points. In each case, a random sequence of input words was used. The maps learned to represent the similarities of the data, but differed in the details of how they were organized. For example, in the map of Figure 13, foods are clustered in the bottom and body parts on top. These clusters were prominent on other maps as well, but were shaped slightly differently and located in different regions of the map. In this sense, they can be seen as different individuals with roughly equivalent representations of semantic relatedness. Simulated psychological experiments were then conducted in this group of computational participants in order to explain the behavior observed in human behavioral studies.

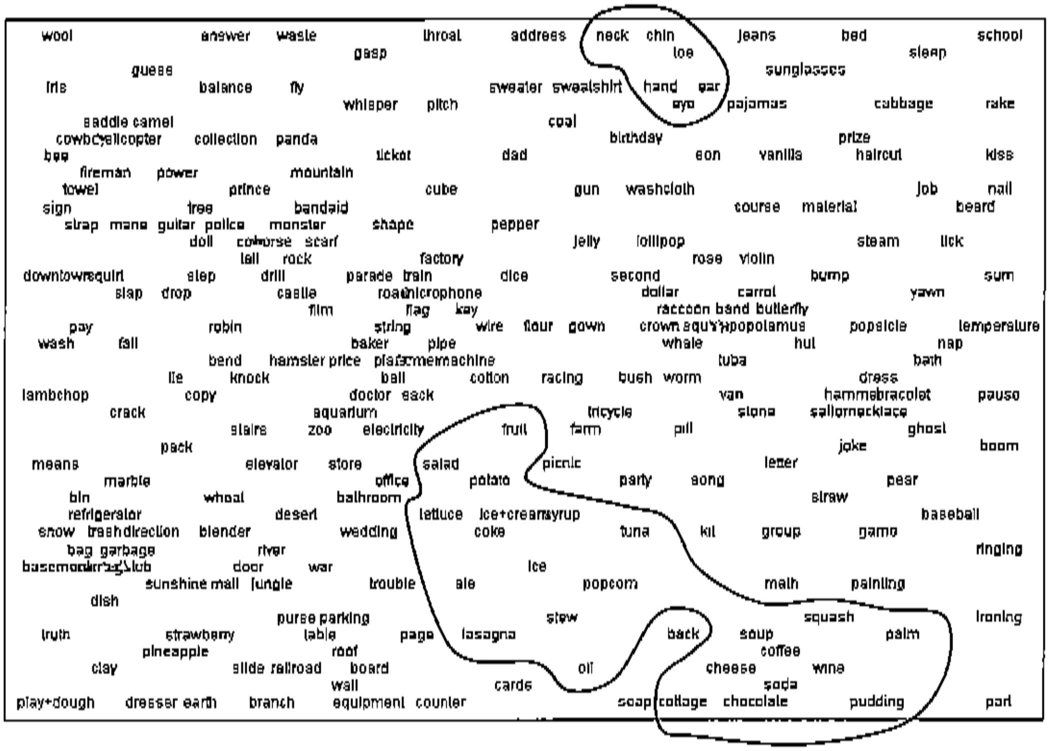

Figure 13: The self-organized semantic map. Semantically related words such as those denoting body parts and foods are mapped to adjacent nodes.

3.2.4 Network Architecture

Building on a semantic map, I included all-to-all unidirectional lateral connections to represent the potential associations between two words. The strength of each such connection is composed of semantic and episodic components:

$$L_{ij,uv} = S_{ij,uv} + E_{ij,uv}, \qquad (5)$$

where $L_{ij,uv}$ is the connection weight from node (i,j) to node (u,v). The semantic component represents the distance on the map and is given by the equation:

$$S_{ij,uv} = \frac{1}{\left(1+e^{\left|\vec{w}_{ij}-\vec{w}_{uv}\right|}\right)}, \qquad (6)$$

where $\vec{w}_{ij}$ is the map's weight vector for neuron (i,j). Therefore, the strength of each lateral connection is inversely proportional to the 100-dimensional distance between the two corresponding weight vectors of the map. Initially, the episodic part of all the lateral connections was set to zero. Hence, prior to any learning of associations, the lateral links only capture the topographic organization of the map, i.e., the semantic relatedness of words.

3.2.5 Dynamics

When a word is presented to the model, an activity bubble is generated surrounding the node representing it, by calculating the map's response to the stimulus word:

$$A_{ij}^{0} = \sigma\left(\bar{w}_{ij} \cdot \bar{x}\right) , \tag{7}$$

where A^{t}_{ij} is the activity of neuron (i,j) at time t, $\vec{x}$ is the HAL numerical representation vector of the stimulus word, and

$$\sigma(\xi) = \frac{1}{\left(1+e^{-\xi}\right)} , \tag{8}$$

is a sigmoid function, which is used to sharpen the activity bubble around winning node (Figure 14). The activity wave then spreads through lateral connections

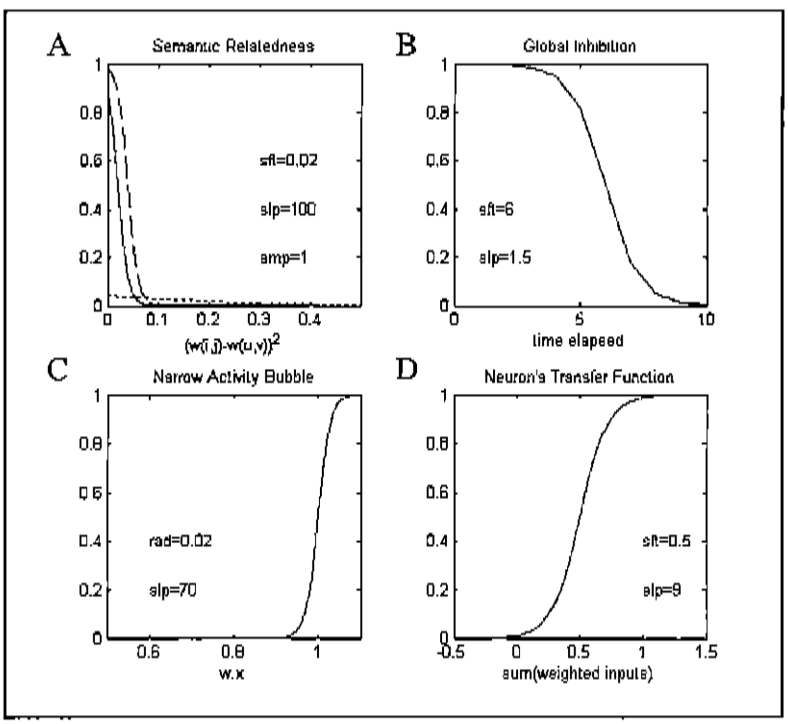

Figure 14: The four sigmoid functions that are used in the model. A) Semantic relatedness values as a function of the distance between the nodes' weight vectors (normal condition in solid line, pathological conditions in dashed lines – see sections 3.4.3 and 3.4.4). B) Global inhibition as a function of time-steps in the trial. C) Narrowing the initial activity bubble over the map as a function of the map's response to the external input. D) The neuron's transfer function: The neuron output as a function of the sum of the weighted inputs. The sigmoids that describe different aspects of the model are different.

according to synchronized recurrent dynamics. At each time-step, the input to each neuron is the sum of the activities of all neurons in the previous time-step, weighted by the lateral connections. Then, the neuron's activity is limited between the values 0 and 1 and is set according to a sigmoid function

$$A_{ij}^{t} = \sigma\left(\sum_{u,v} L_{ij,uv} A_{uv}^{t-1}\right). \quad (9)$$

When two words are presented to the model (as in the study phase of Simulation 1), both activities spread independently over the map. The intersection, namely the smaller value between these two activations, is summed over all the map's neurons and over all time-steps and added to the episodic component of the lateral connection between these two words. When the distance between the two words is smaller (indicating stronger semantic relatedness), the resulting activity waves overlap more, amplifying the connection between them. Thus, it is easier for the model to associate related words than unrelated words. Conceptually, this method is an abstraction of Hebbian learning of episodic links, since the resulting connection strength depends on the intersection of both words' activation waves. Figure 15 shows two snapshots of the simulation, demonstrating activations spreading from two different word-pairs.

3.3 Validating the Model

In order to use the computational model to derive predictions on human behavior and to suggest further psychological experiments, it needs to be validated by matching it with human performance. In this section, the first simulation, aimed at replicating the empirical results of Experiment 4 and 5 which demonstrated semantic facilitation on forming associations, is described in detail. Comparing the simulated performance of the model to those of human participants allows validating the model's assumptions and calibrating its parameters. Furthermore, the model's resistance to noise, applied at different levels can be estimated. Once the model replicates human behavior satisfactorily, we can enrich our understanding of related phenomena by modifying it and examining its emerging predictions, as elaborated in section 3.4.

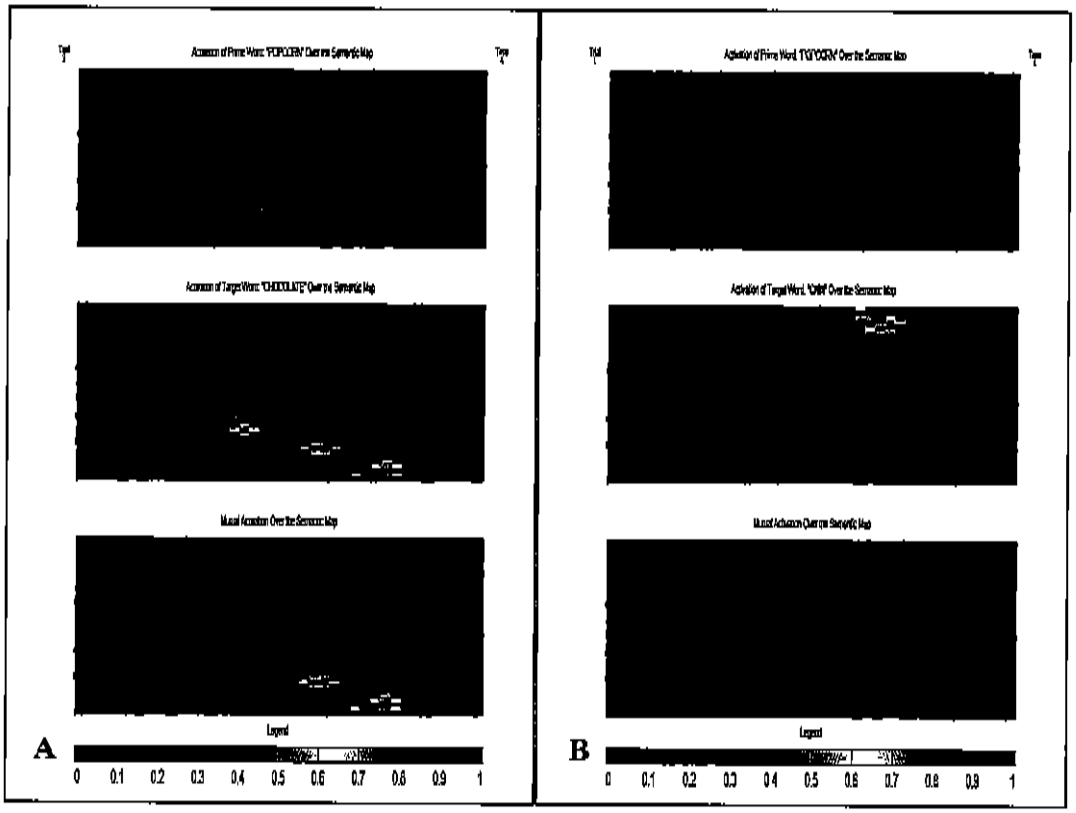

Figure 15: Two simulation snapshots. A) Semantically related but not associated word-pair trial (<POPCORN>-<CHOCOLATE>). B) Unrelated word-pair trial (<POPCORN>-<CHIN>). Each figure displays three snapshots of the semantic map. On the upper map, the activation wave generated by the first word is presented, shown in color scale. The middle map represents the activation wave generated by the second word. The lower map shows the intersection of the two activity waves. A stronger intersection of activity waves results from the semantically related pair.

3.3.1 Simulation 1: Replicating the Semantic Boost Effect

Recall that in the behavioral experiments, even the words within the semantically related pairs were not associated prior to the experiment even though they belonged to the same semantic category. That is, the presentation of the first word did not elicit a significant activation of the second word. The reason for it is that the activation from the first word probably spread to closer, i.e., more strongly semantically related, words within the category than the second word I chose. However, the computational model's lexicon has only 250 words compared to tens of thousands in the average human lexicon. Therefore, there are usually no more than two words within a semantic category. Thus, selecting the second word of the semantically related pairs from the same semantic category of the first word would necessarily mean that it would also be the closest word to it among the entire lexicon and therefore would be its first associate.

In order to avoid this problem, out of the 24 semantically related pairs that were embedded in the semantic map (section 3.2.1 - Word Representations, above), 12 pairs with a Euclidean distance between HAL representations shorter than the average distance over the map (0.88) but larger than a threshold (0.35) were selected. This way I made sure that the words were semantically related, but not strongly enough to be always recalled, regardless of any episodic associations.

To create the semantically unrelated pairs, the other 12 semantically related pairs were randomly re-matched to form 12 semantically unrelated pairs (the average Euclidean distance between HAL representations is 0.91) as was done with the stimuli of the behavioral experiments. The simulation procedure was replicated 12 times, each time using a different map, and statistical analysis was performed on the data.

Procedure

During the study phase, two words were presented to the model with an appropriate temporal delay (SOA) in each trial. The absolute time scale of the network is arbitrary and was adjusted to fit the data. Consequently, the temporal delay was determined experimentally such that the second word would be presented shortly after the activation wave of the first word had significantly spread (3 time-steps). Each of the 24 pairs (12 related and 12 unrelated) was presented once. Because the episodic information does not affect the spreading activation process during the study phase, the episodic association resulting from multiple presentations was calculated by multiplying the result of a single presentation by the number of repetitions which was varied from 1 to 30. During the testing phase, only one word was presented to the model. The resulting activation wave spread based on the same dynamics, except that in this phase, both the semantic and the episodic components of the lateral connections were taken into account. The activity continued to spread until the first neuron reached an activity threshold (0.98). The word represented by this node was then taken as the output of the model. In case a fixed number of time-steps (chosen to be 8, when the activation wave had usually decayed to a negligible level) had elapsed and no such neuron had been found, SEMANT was programmed to output the word represented by the neuron with the highest activation level. This scenario simulated the situation in which the subject could not recall any word and would answer with the word that first comes to mind. In practice, this scenario never occurred.

Results and Discussion

In Figure 16, the model results that correspond to the number of repetitions in the behavioral experiment (1, 5, 10 and 20) are presented. The percentages of correct recall for the related and unrelated pairs, averaged over 12 simulations each, are shown for each case. SEMANT successfully replicates the results from the behavioral experiment. In the early stages, the slope of the learning curve of the related pairs is steeper than the slope of the learning curve of the unrelated pairs. At about 10 repetitions, a ceiling effect reduces the slope of the learning curve of the related pairs such that the advantage of these pairs over the unrelated pairs is abolished. In addition, the slope of the learning curve of the unrelated pairs is relatively constant, as was found in human participants. Statistical analysis of the data revealed that both main effects, i.e., the effect of semantic relatedness and of number of repetitions, as well as the interaction between them, were reliable ($F(1,11)=104.4$, $P<0.001$, $F(3,33)=352.4$, $P<0.001$ and $F(3,33)=35.2$, $P<0.001$, respectively). It is important to note that although each repetition in the study phase contributes an equal amount to the episodic component of the lateral connections between the words, the recurrent dynamics of the model introduce

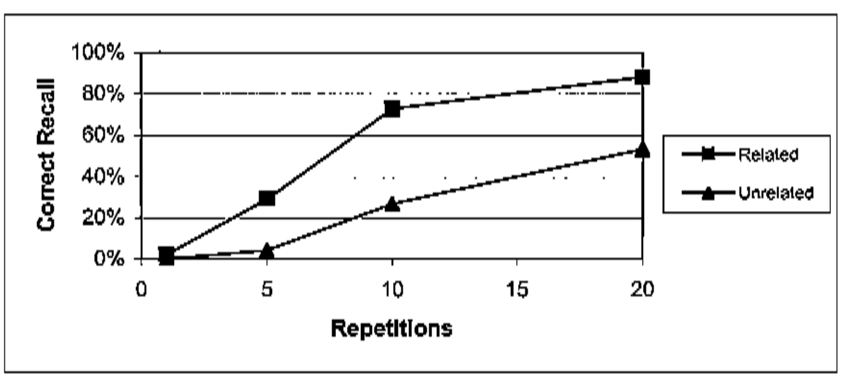

Figure 16: Average percentages of correct recall demonstrated by the model, after 1, 5, 10 and 20 repetitions at the study phase, for semantically related and unrelated pairs. A steeper learning curve is demonstrated for the semantically related pairs in the first 10 repetitions. This effect is diminished after 10 repetitions. The pattern of the simulation's results is similar to the one obtained in the behavioral experiments (Experiment 4).

non-linearity to the testing phase (section 3.2.5). Hence, the linear way in which multiple repetitions were modeled does not impose a linear learning curve. Instead, it emerges as a result of the timing in which the accumulative activation levels in the neuron, representing the target word, cross the threshold.

3.3.2 Resistance to Noise

After validating the performance of SEMANT in comparison with results of human participants using deterministic dynamic equations, its resistance to noise had to be tested. That is, I needed to verify that the success of the model in replicating human data is not related to a particular set of parameters and that it can resist a certain level of statistical noise in its equations. Therefore, I introduced noise to the equations in two different ways. In both cases, a Gaussian noise with varying amplitude was added. In one case, the noise was added to the neuron's transfer function, i.e., to the output of the neuron as a function of the weighted inputs. In the other case, the noise was added to the value of the lateral connections. In both cases, no dramatic changes in the model behavior were observed. The learning curve of both semantically related and unrelated pairs became slightly steeper as the noise's amplitude was gradually incremented and the difference between the learning curves of related and unrelated pairs bleared. However, the general pattern of the results remained as in the deterministic care until large noise amplitudes.

3.4 Predictions of the Model

After validating the model by accurately simulating the empirically observed human performance (Simulation 1) further simulations were run in order to explore predictions regarding principles in human associative learning. In the following sections, I describe three such simulations. The behavioral trends predicted by these simulations were explored in new psychological experiments that will conclude the dissertation.

The prediction explored in each of the three simulations is based on different conceptualizations. First, the Implicitly Mediated Associations prediction (section 3.4.1), stems from theoretical analysis of the concept behind the model. Therefore, it was not based on the results of a simulation. Second, the Implicit Asymmetry prediction (section 3.4.2) arises from observation in a non-trivial behavior of the model. In order to explore this behavior, a dedicated simulation was designed, which yielded a testable prediction on human behavior. Third, the prediction on modeling STD (sections 3.4.3 and 3.4.4) was derived by implementing a theoretical hypothesis regarding human pathological memory processes in the model. The parameters of the model were modified to reflect pathological spreading activation, which was suggested to cause STD, and simulations were run in order to yield testable predictions on the behavior of human patients. Each prediction will be described in detail below.

3.4.1 Implicitly Mediated Associations

The main principle that governs the model dynamics is that activation spreads over the semantic map, based on the weights of the lateral connections between the nodes. These lateral connections are comprised of semantic and episodic components (Equation 5). However, the proportional contribution of the two components, semantic and episodic, to the strength of the lateral connection, is irrelevant to the activation dynamics. Hence, already existing semantic and episodic information may interchangeably influence how new episodic association are formed. The first prediction of SEMANT is about the combined influence of prior semantic and episodic information on the formation of new episodic links.

According to the model, episodic associations are formed based on how the activation waves spreading from the activated words over the map are intersecting. This mechanism predicts that conjoint activation of two unrelated words (e.g., DOG-TABLE) can implicitly facilitate the formation of episodic connections between other words, if these other words are semantically related to the presented words (e.g., CAT-CHAIR). When the first word (CAT) is presented, activation automatically spreads to nearby, semantically related, nodes. One of these nodes (DOG) is associatively connected, due to a prior co-activation, to a node (TABLE) in the semantic neighborhood of the second word (CHAIR). Consequently, activation spreads from the first semantic neighborhood to the second, and there, it intersects with the activation elicited by the second word. According to the model, a stronger new episodic association is formed, due to the greater intersection surrounding the second semantic neighborhood (Figure 17). This effect is a novel prediction and will be tested in human participants for the first time in section 4.2.

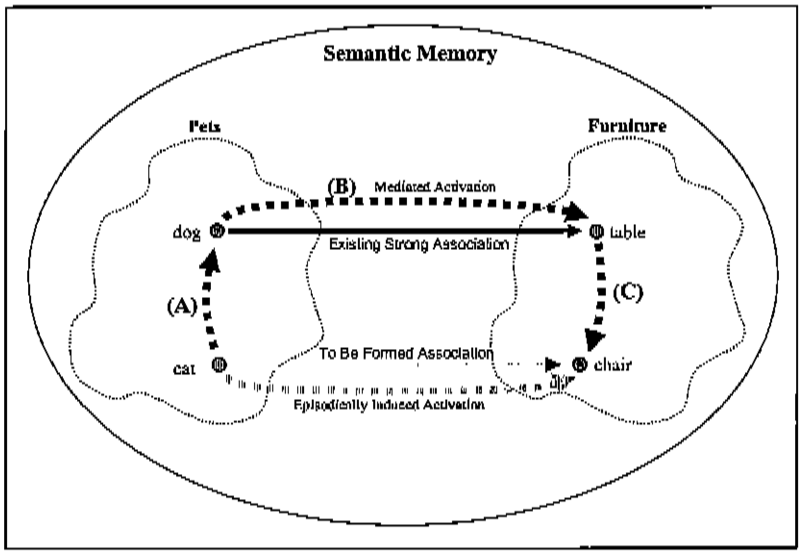

Figure 17: An illustration of the mechanism underlying implicitly mediated associations: (A) The activation spreading from CAT to its semantic neighbors reaches DOG. (B) Since a strong episodic association between DOG and TABLE exists, activation spreads efficiently to TABLE. (C) Activation spreads from TABLE to its semantic neighbors, thus increasing the amount of overlapping activation surrounding CHAIR. The model assumes that the strength of the formed association is proportional to the amount of overlapping activation spreading from the two words. Thus, it explains the mechanism by which an existing strong association between DOG and TABLE reinforces forming a new association from CAT to CHAIR.

3.4.2 Simulation 2: Implicit Asymmetry

Associations between word-pairs are directional. In free association questionnaires, participants reply, for most pairs, with word B after A with a different probability than with word A after B (Koriat, 1981). In SEMANT, such an explicit asymmetry results from the unidirectional lateral connections, which represent the association between two words in the map. However, SEMANT predicts an additional asymmetry, which I call implicit asymmetry: it should be easier to form an association between two words in one direction than in the opposite direction even before episodic information is taken into account. Before any episodic co-occurrence, all the lateral connections are equal in strength and hence symmetric (equations 5 and 6). Thus, the only possible source for such an implicit asymmetry is the non-homogeneous distribution of words and unassigned nodes of the semantic map, within the multidimensional semantic space, and the local densities surrounding the words to be associated. Simulation 2 was aimed at validating this hypothesis and quantifying the phenomenon.

Simulation Setup

First, the density of the semantic neighborhoods of the words that were used in section 3.3.1 was calculated as follows: For each of the 48 words of interest, I counted how many of the 250 total words in the model's semantic system were within a fixed 100-dimensional distance (0.4) in their HAL representations. The number of such words defined the semantic neighborhood density. For each of the previously used 24 pairs (12 semantically related and 12 unrelated), I calculated the difference in the densities of the semantic neighborhoods of the two constituent words and selected 3 related and 3 unrelated pairs with the greatest difference between them.

Procedure

The procedure of Simulation 1 was then replicated with the six selected pairs. First, the pairs were presented in the forward direction, from sparse semantic neighborhood to dense. Then, the network was reset to its original state and the entire procedure repeated with the pairs presented in the opposite order. The cued recall performance in the two simulations was then compared. The simulation procedure was replicated 12 times using a different map each time and statistical analysis was performed on the data.

Results and Discussion

Figure 18 shows the percentages of correct recall, averaged over 12 simulations each, as demonstrated by the model for related and unrelated pairs in the forward and backward direction in each presentation condition. Word-pairs in the forward direction (sparse neighborhood $\rightarrow$ dense neighborhood) were learned faster. ANOVA showed that the advantage is statistically reliable ($F(1,11)=24.8$, $P<0.001$). However, the entire direction effect stemmed from the related pairs: The related word-pairs in the forward direction were learned faster ($F(1,11)=46.6$, $P<0.001$), while no significant direction effect was found for the unrelated word-pairs ($F(1,11)=0.05$, $P>0.8$).

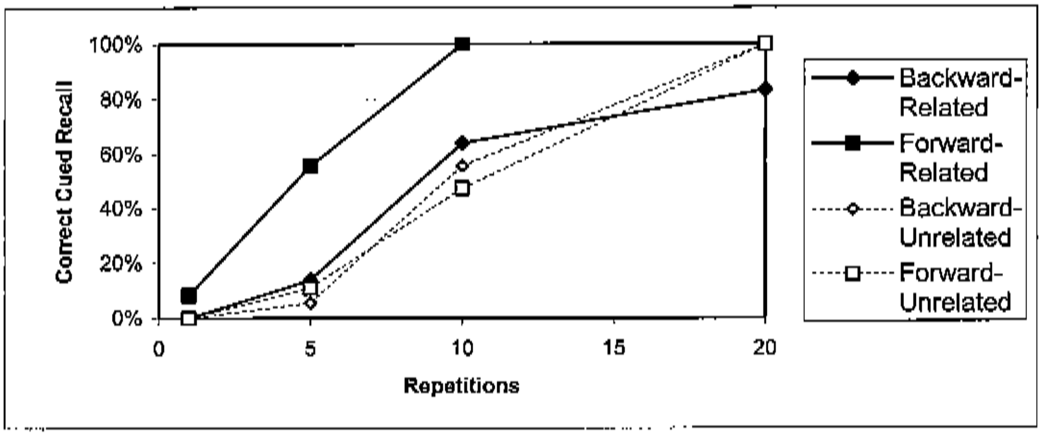

Figure 18: Average percentages over 12 simulations each of correct recall demonstrated by the model for related and unrelated word pairs in forward (spare to dense) and backward directions. The model predicts that learning is easier from sparse to dense neighborhoods. This prediction will be verified experimentally in section 4.1.

The reason for this implicit asymmetry is that activation spreads over a non-uniformly distributed high-dimensional space (as elaborated in chapter 5). Consequently, each word has a unique pattern of activation over the map as a function of time. Recall that the episodic component of the lateral connection is strengthened on the basis of the intersection of the two activations. Due to the unique pattern of activation caused by each word and since the word-pair is not presented simultaneously, the intersection pattern of the two activation waves is different when the word presentation order is reversed, favoring the presentation of the word with sparse neighborhood first. This difference in intersection patterns yields a difference in the amount added to the weight of the relevant lateral connection. For unrelated word-pairs, the difference in the intersection patterns is inconsequential due to the negligible overlapping activation. Prior to SEMANT, such an implicit asymmetry has not yet been demonstrated in humans. A behavioral experiment that was aimed directly at verifying this prediction is presented in section 4.1.

3.4.3 Simulation 3A: Modeling STD by Elevated Activation

Disrupted thought processes have long been described in terms of association psychology terms and studied by using free associations and semantic priming. Schizophrenia patients have been found to produce fewer close associates in word association tests than normals, generating more indirect, or mediated associations (e.g., BULL – MILK is a mediated association via COW; Kent & Rosanoff, 1910). Increased semantic priming effect was discovered in schizophrenia patients who suffered from formal thought disorder (STD), as compared with non-thought-disordered schizophrenia patients and normal control participants (Maher et al., 1995; Manschreck et al., 1988, Spitzer, 1997). In general, schizophrenic thinking is characterized by loose, mediated, indirect or oblique associations, that is, by dysfunctional associative processes.

To account for this pattern of results, a model of STD, based on the Collins and Loftus's (1975) theory of spreading activation, was suggested by Spitzer (1997). The model suggests that the activity wave over the semantic network of STD patients spreads faster and farther than that of normal participants. This unfocused activation can explain experimental results in STD patients, who show stronger direct (e.g., between the words COW and MILK) and indirect, mediated semantic priming (e.g., between the words BULL and MILK, which is mediated by the word COW) compared to normal participants. It may also explain the clinical phenomenon of loose, oblique and derailed associations. My hypothesis is that if, indeed, one cause for STD is a broader and farther-spreading activation wave, it would reflect in their ability to form episodic associations. Recall that according to the assumptions of SEMANT, associations are formed when the spreading activation waves of the two words intersect. Thus, according to the model, it should be easier for STD patients to form episodic associations compared to normal participants.

In simulation 3, this hypothesis is tested computationally. The shape of the activation wave of STD patients is modeled in two different ways. In the first, the farther spreading activation was assumed to be the result of elevated activation wave, representing stronger semantic activity. In the second, the farther spreading activation was assumed to be the result of a broader activation wave, representing an unfocused and diffused semantic activity (Figure 19). Based on the results of the simulations, predictions regarding the behavior of STD patients are derived.

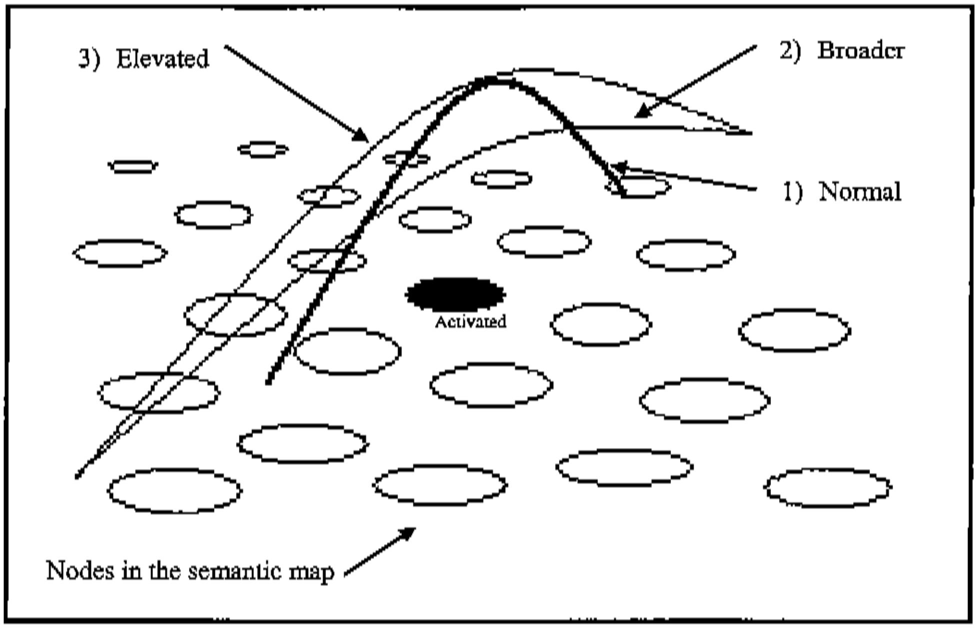

Figure 19: Illustration of three different activation waves over the semantic map. The curves represent the shape of the activation waves in: 1) Normal participants, STD patients (modeled by broader activation) and 3) STD patients (modeled by elevated activation). Different activation waves yield different performance.

Simulation Setup and Procedure

The simulation setup and procedure of Simulation 1 were again used here, with only one change. Recall that the distance between the word representations contributes to the strength of the lateral connection between them according to a reversed sigmoid function (Equation 6, section 3.2.4). To establish a less focused, farther spreading activation wave, this sigmoid was elevated by shifting the offset of the sigmoid by a factor of 2 (Figure 20). As a result, the area

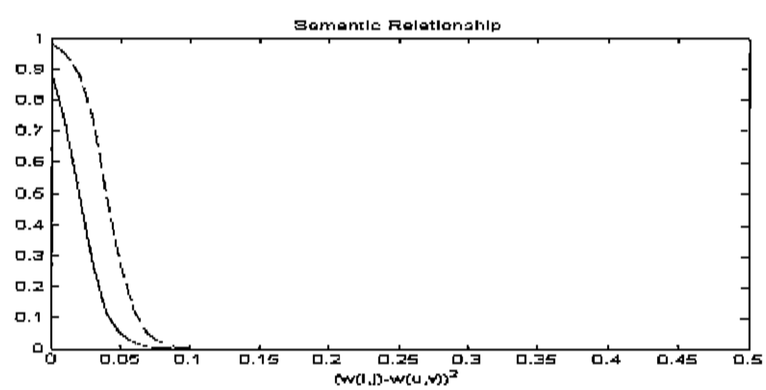

Figure 20: Semantic relationship value as a function of the distance between word representations in normal (continuous line) and in STD (dashed line) simulations. An elevated curve is used for modeling the semantic connections in STD patients, representing higher energy in activation wave.

underneath the curve also increased, but the overall shape of the sigmoid remained as in the normal condition. The psychological interpretation of this change is that the unfocused activation wave results from a higher "energy" in the system or, in other words, a higher overall activation in the semantic system. The simulation procedure was replicated 12 times using a different map each time and statistical analysis was performed on the data.

Results and Discussion

Figure 21 shows the percentages of correct cued recall demonstrated by the model for normal participants and STD patients, averaged over 12 simulations each. The association recall performance of STD patients in both related and unrelated conditions is better than of normal participants, up to a relatively large number of repetitions ($F(1,11)=58.9$, $P<0.001$). Because cued-recall and priming paradigms, despite clear distinction between them, are both used as indicators for memory organization, this pattern is in agreement with the findings of increased semantic priming in schizophrenic patients. Computationally, this increment is caused by the elevated sigmoid, which generates an overall greater activity. In addition, it is clear that the relatedness advantage in the slope of the learning curve is diminished (significant three-way interaction $F(3,33)=13.4$, $P<0.001$). This result corresponds to the finding that STD patients show more mediated associations in the sense that in both cases they associate distinct words more easily than normals

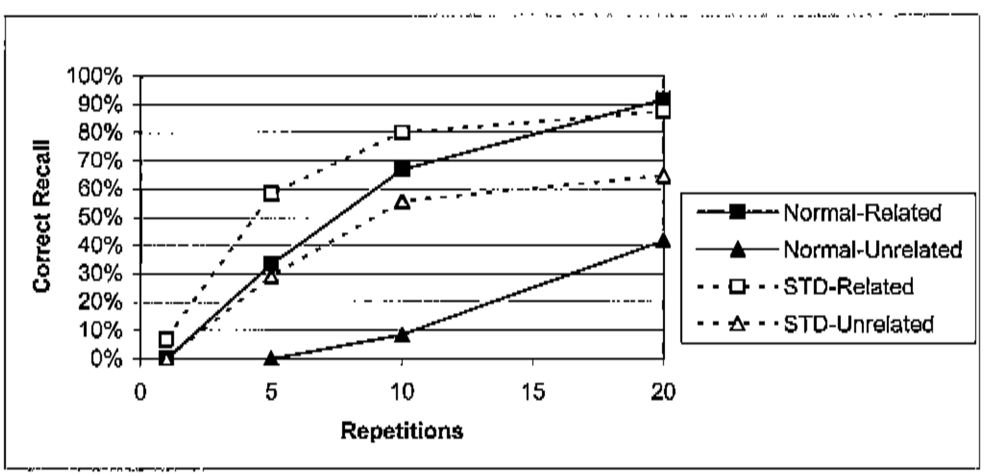

Figure 21: Average percentages (over 12 simulations) of correct recall demonstrated by the model for normal and STD participants with elevated activity. Performance in the STD condition is elevated for both related and unrelated pairs and the difference between the two conditions is diminished.

do. Nevertheless, such an elevated performance is intriguing. Despite the fact that STD patients show stronger semantic priming, they would be unlikely to perform better in memory tests, especially those measuring learned associations. Hence, an alternative way to model the unfocused activation wave should be found. The alternative suggestion is described and implemented in Simulation 3B.

3.4.4 Simulation 3B: Modeling STD by Broader Activation

In the previous simulation, the loose associations resulted from a stronger activation wave, caused by the elevated graph that defines the semantic lateral connections. A similar effect can also be achieved with a more diffuse and broader wave, that is, with a graph that is shallower rather than elevated. Thus, although the activation wave is broader, the total amount of semantic connection weights in the system is the same as in the normal case.

Simulation Setup and Procedure

The setup and procedure was similar to that of Simulation 3A, except that the sigmoid was normalized such that the sum of the semantic components of all the lateral connections over each of the semantic maps was identical to that in the Simulation 1 (Figure 22). Hence, the energy of the activation wave was not stronger due to enhanced semantic connections. The simulation procedure was replicated 12 times using a different map and a slightly different sigmoid each time, due to the slightly different normalization factors, and statistical analysis was performed on the data.

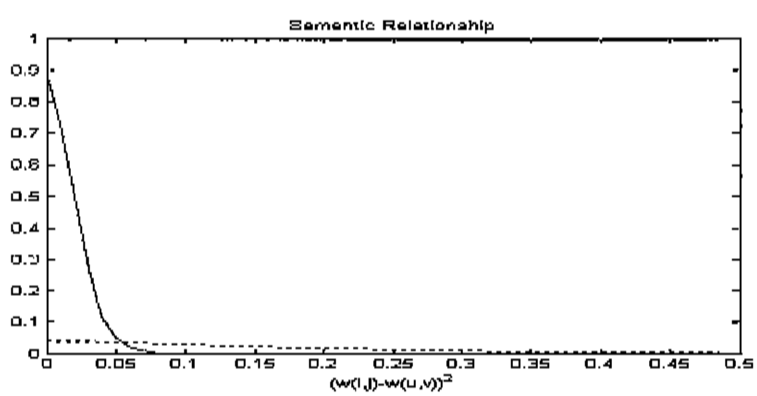

Figure 22: Semantic relationship value as a function of the distance between word representations in normal (continuous line) and in STD (dashed line) simulations. A shallower curve is used for modeling the semantic connections in STD patients, representing a shallower activation wave with identical energy.

Results and Discussion

Figure 23 shows the percentages of correct cued recall in the model for normal and STD simulations, assuming equal total semantic weights in both cases, but more diffusely distributed in the latter. The simulations showed reduced performance with related pairs while the performance with unrelated pairs was better than in the normal condition. ANOVA did not indicate that there was a reliable difference between normal and STD participants ($F(1,11)=0.09$, $P>0.75$). The effect between related and unrelated pairs was significant ($F(1,11)=193.893$, $P<0.001$) as was the interaction between the relatedness and pathology conditions ($F(1,11)=26.6$, $P<0.001$), which indicates that the semantic relatedness has a different effect in the normal and in the STD conditions. Moreover, as in Simulation 3A (section 3.4.3), the qualitative difference in the rate of learning is decreased (significant three-way interaction $F(3,33)=15.6$, $P<0.001$).

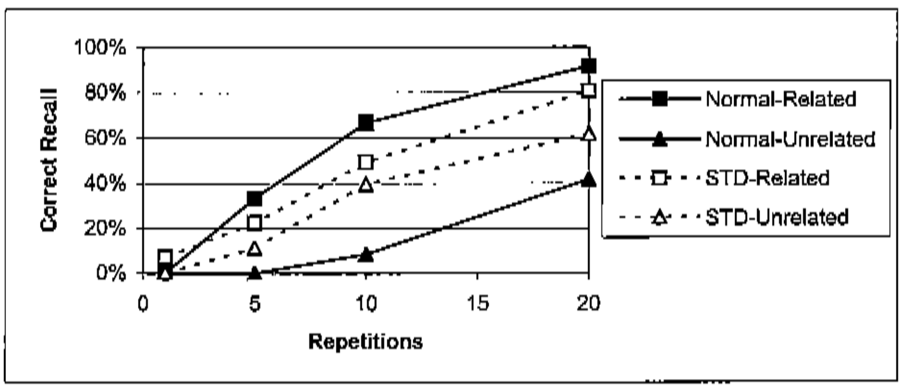

Figure 23: Average percentages over 12 simulations each of correct recall in the model for normal and STD participants with normalized semantic connections. Compared to normals, performance under STD is degraded for related pairs, elevated for unrelated pairs, and the difference between the two conditions is diminished.

In sum, the different versions of the model lead to different testable hypotheses about associative impairments in STD patients. The model's parameters were modified so that they would reflect a farther spreading activation wave in two different ways: through elevated and through shallower activation. The cognitive interpretation of these two ways of implementation are different and may lead to different assumptions regarding the physiological causes for STD. Should one of the predictions be validated experimentally in human participants, it would enrich our understanding of the cognitive and physiological mechanisms of STD.

3.5 Conclusion

This chapter described the computational model, SEMANT, and simulations carried out as part of this study. Based on empirical results suggesting that semantic information facilitates (up to a ceiling) the process of forming new episodic associations throughout learning, an artificial neural network model was developed. This model was based on spreading activation along laterally connected nodes in a self-organizing map. Simulating associative learning with this model replicated the empirical results and lead to further predictions into how such associations can be asymmetric, why it is easier to learn some associations than others, and how the associative process can be impaired in STD patients. In the next chapter, cognitive experiments aimed at validating two of the predictions are described.

4 Model Derived Experiments

In this chapter, a series of behavioral experiments aimed at validating two of SEMANT's prediction on human behavior are described. First, an experiment that tested the Implicit Asymmetry prediction in humans is presented. Second, two experiments that validated the implicit asymmetry prediction are detailed. In the following chapter, the implications of this validation on our understanding of the structure of the human semantic system are discussed.

4.1 Experiment 6: Implicit Asymmetry

Experiment 6 was intended to test the prediction that it is easier to associate a word with only a few lexical neighbors to a semantically related word with many lexical neighbors, than vice versa (3.4.2, above). Based on the analysis of SEMANT's behavior, a possible source for such an implicit asymmetry was found: when there is a large difference in the "local densities" of the semantic neighborhoods of the two words, semantic activation would not flow in both directions in an equal efficiency. Consequently, when the two words are semantically related and their activations interact substantially, it would not be equally easy to form both directions of the associations between the two words. Hence, in the following experiment, both semantically related and semantically unrelated pairs in which the two words significantly differ in their lexical neighborhood were used. The incidental learning of these pairs in both presentation directions was compared.

4.1.1 Methods

Participants

Forty-eight students, none of whom was tested in the previous experiments, participated in this experiment for nominal payment or for course credit. They were all native Hebrew speakers with normal or corrected to normal eyesight.

Stimuli

Twenty-four semantically related but unassociated word-pairs were selected from the Beer-Sheva norms of word association (Rubenstein et al., in preparation). In each pair one word had a rich lexical neighborhood and the other had a poor one. The neighborhood of each word in that corpus was determined empirically by testing free associations to it in a group of 100 participants. Based on the free associations, three parameters have been calculated. The first, *m*, was defined as the total number of different associates produced within one minute by all participants. The second, *n*, was defined as the number of the different first free associates produced by the participants. In addition, from the same corpus, I used the *mean_RT* (that is, the average reaction time until the first association was given by each participant) in order to determine the efficiency of exploring a neighborhood.

The pairs were selected such that in each pair one word had a higher *m* (by at least 25 associations), and a higher *n* than the other word. Across the 24 pairs, this difference in the two parameters was statistically significant. While the semantic neighborhoods of the two words in each pair differed in size, their ranked familiarity, ranked concreteness, and *mean_RT* were similar (statistically controlled across the 24 pairs). Forward direction was defined from words with small neighborhoods to words with large neighborhoods; backward direction was defined in the opposite direction. (Appendix A – Stimuli for the list of pairs).

Design and Procedure

As in the general paradigm, the experiment consisted of an incidental study phase and an unexpected, explicit, cued recall test. In the study phase, the 24 pairs appeared once in random order, presented one word after the other. The orientation task at study required "deep" processing. After each pair, one of five questions: "which was bigger?", "which one do you prefer?", "which is more expensive?", "which is softer?", or "which is more useful?" appeared randomly[6]. Each trial in the study phase started with a 500 ms blank screen with a rectangle

[6] In Hebrew, these are all one-word questions.

frame at the center of the screen. After 200 ms, the first word was presented at the center of the frame for 150 ms. Following an SOA of 700 ms, the second word was presented for 150 ms. The question word was presented 650 ms after the offset of the second word and remained on the screen for 1500 ms, during which time a response was expected.

Two stimulus lists were prepared. In each list, 12 pairs were presented in the forward direction and the other twelve in the backward direction. Across lists, the pairs were counterbalanced so that each pair appeared in both forward and backward order. Half of the participants studied one list and the other half the other list.

After the study phase, an unexpected cued recall test was done. The participants were presented with the first word of each pair and were asked to respond with the second.

4.1.2 Results and Discussion

As described in section 3.4.2, associations in SEMANT are easier to form in the forward than in the backward direction. Consequently, I predicted that cued recall would be more accurate for pairs presented in the forward than for pairs presented in the backward direction. The actual performance of human participants in the cued recall test on pairs is presented in Figure 24.

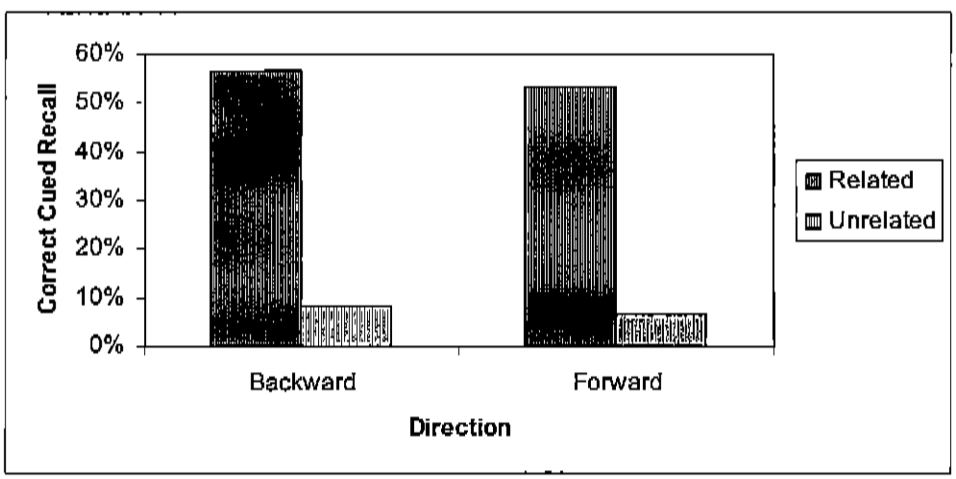

Figure 24: Cued recall performance after incidental learning of 24 semantically related pairs and 24 semantically unrelated pairs in the forward and backward conditions. No statistically reliable difference between the conditions was found. Experiment 6 did not support the model's prediction that associations are easier to form from words with low density neighborhoods to related words with high density neighborhoods, than vice versa.

As was in all the behavioral experiments in chapter 2, there was again a statistically reliable advantage in cued recall for related pairs (55%) over unrelated pairs (7%; $F(1,46) = 87.3$, $P < 0.001$). However, as can be seen in Figure 24, the predicted difference in the backward or forward direction was not statistically significant ($F(1,23)=0.9$, $P>0.3$ and $F(1,23)=0.6$, $P>0.4$ for related pairs and unrelated pairs, respectively). Nor was the interaction between the relatedness and the direction factors significant ($F(1,46)=0.1$, $P>0.7$).

The most straightforward interpretation of these results is that the model does not accurately represent human performance. However, before rushing to change the basic principles of the model, other accounts should be considered.

For example, in the behavioral experiment, I may not have controlled the parameters that determine the "density of the SEMANTIC neighborhood". In fact, the n and m parameters that were used in the Rubenstein et al's corpus were based on free associations rather than on pure semantic criteria. It is possible that, if the participants had been asked to respond with "semantic associates" rather than "first associates", different values for these variables had been obtained.

To conclude, Experiment 6 did not support the model's prediction that associations are easier to form from words with low density neighborhoods to related words with high density neighborhoods, than vice versa. However, caveats regarding the validity of these data were raised, suggesting that additional work is necessary before rejecting (or accepting) this dynamic principle of the model.

4.2 Experiment 7: Implicitly Mediated Associations – Cued Recall[7]

The prediction of the computational model concerning implicitly mediated associations (section 3.4.1) was validated in two experiments with human participants. Both experiments included a study phase in which pairs of unrelated words were repeatedly presented while an orientation task required to compare the meaning of the words in each pair along different dimensions. The repeated conjoint activation instigated the formation of associations between the words in

[7] Experiments 7 and 8 will appear in *Psychological Science* titled "associating unseen events: semantically mediated formation of episodic associations".

each pair, as evidenced by cued recall. In an immediately following test phase, the impact of these incidentally formed associations on associating their semantic neighbors was tested explicitly by cued recall (Experiment 7) or implicitly, using a semantic decision task (Experiment 8).

4.2.1 Methods

Participants

The participants consisted of 33 undergraduates who were paid a nominal fee or who received course credit for their participation. They were all native Hebrew speakers with normal or corrected to normal vision.

Stimuli and Design

The stimuli in the first experiment consisted of 48 Hebrew nouns, exemplars of 24 well-defined base-level semantic categories (2 words per category). These nouns were used to form a study list of 24 semantically unrelated and unassociated word-pairs. Twelve of the 24 pairs were randomly repeated 30 times during the study phase in order to establish strong episodic associations between the words in each pair. The other 12 pairs were randomly repeated only 3 times in order to establish weak episodic associations between the words in each pair. All 24 semantic categories were represented by one exemplar in the strongly associated pairs and one exemplar in the weakly associated pairs. Thus, each word included in a weakly associated pair had a semantically related correspondent included in a strongly associated pair. Based on this semantic relationship, the weakly associated pairs were equally distributed between two conditions: In the "same" condition, the words of each weakly associated pair were exemplars of the same semantic categories that were represented by one of the strongly associated pairs, and in the same order of presentation. For example, on the basis of the strongly associated pair DOG-TABLE, a corresponding weakly associated pair in the "same" condition would be CAT-CHAIR. In the "different" condition, the weakly associated pairs were formed by recombining the semantic categories represented by the words in strongly associated pairs. For example, for the weakly associated pair CAT-CHAIR, the corresponding strongly associated pairs were DOG-SUN and

DAISY-TABLE. The pairs tested in the "same" and "different" conditions were counterbalanced across two lists, so that, with half of the participants assigned to each list, all 12 pairs were presented an equal number of times in each condition.

Procedure

As in the general paradigm, the experiment consisted of an incidental study phase and an unexpected, explicit, cued recall test. The 36 trials, in which the 12 weakly associated pairs were repeated, followed immediately the presentation of the 360 trials during which the 12 strong associations were formed. There was no marked distinction between the two types of trials.

Each trial in the study phase started with a fixation mark exposed for 200 ms. The paired words were simultaneously presented for 500 ms immediately following the offset of the fixation mark, centered to the right and left of its location. A question word was presented 300 ms following the words' offset, and remained on the screen for 1500 ms, during which time a response was expected. Six single-word questions (e.g., "Bigger?"; "Softer?") were randomly presented across trials and the participants had to answer relating the right word to the left word[8]. Since the participants could not know in advance which question would be asked, they had to keep both words conjointly active in working memory for at least 800 ms.

Immediately following the study phase, a cued recall test was unexpectedly administered. Note that, according to the model, an advantage in associative learning of "same" over "different" pairs should occur only if a strong association exists between the other exemplars of the same semantic categories. Therefore, we analyzed separately the performance of 18 participants who successfully recalled at least 80% of the strongly associated pairs and distinguished it from the analysis of the entire group.

4.2.2 Results and Discussion

As expected, cued recall was considerably more accurate for strongly than for weakly associated pairs. Furthermore, cued recall of strongly associated words,

[8] Hebrew is read from right-to-left.

that their respective weakly associated pairs belonged to the same condition, was practically identical to that of strongly associated words that their respective weakly associated pairs belonged to the different condition (Figure 25). However, the most important result was that cued-recall accuracy for weakly associated pairs was significantly higher in the same than in the different condition ($t(32)=1.7$, $P<0.05$). Moreover, as the computational model predicted, this effect was more conspicuous when the 18 participants who passed the a priori criterion for strong associations were analyzed separately ($t(17)=2.1$, $P<0.025$).

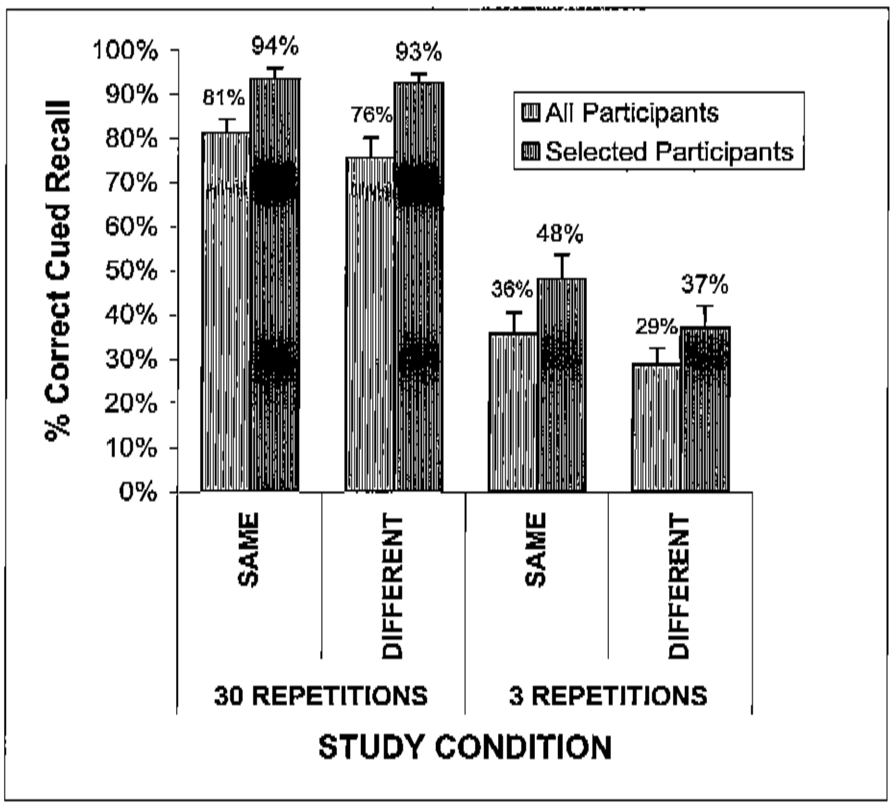

Figure 25: Percentage of correct cued recall for strongly and weakly formed associations (SEM). As predicted by the computational model, cued recall is better in the *SAME* than in the *DIFFERENT* target-pair condition.

The high cued recall accuracy for pairs that were repeated 30 times (79% for the entire sample and 93.5% for the selected participants) and the considerably lower accuracy for pairs that were repeated only 3 times (32% for the entire sample and 42.5% for the selected participants), indicated that, indeed, strong and weak associations were formed during 30 and 3 repetitions, respectively. This pattern conforms to the associative learning mechanism implemented in SEMANT (Chapter 3). Recall that, according to SEMANT, the strength of an association is determined by the sum of overlapping activity spreading from each node across time. The significantly higher cued recall accuracy for weakly associated pairs in the same than in the different condition, which occurred despite an equal number of repetitions, suggests that the amount of overlapping activation during conjoint processing of the two words was larger in the former than in the latter condition. The spreading of activation between the conjointly activated unrelated words was probably facilitated in the same condition, by the pre-existent lateral connections between other words in the respective semantic neighborhoods. In the different condition, no such associations pre-existed, hence, many more episodes of conjoint activation were necessary to establish an association (Figure 25).

Although the outcome of this experiment was predicted by SEMANT, there are alternative accounts that should be considered. One is that the pre-existing associations influence cued recall performance at the retrieval rather than at the incidental study stage. When a weakly associated cue is presented, the corresponding semantically close neighbor is activated, pointing to its strongly associated pair, which then hints the correct response. Another alternative account is that when weakly associated pairs were presented during the study phase, the participants noted the resemblance of the same pairs to the previously (strongly) associated corresponding pairs. This extra attentional boost might have given those pairs the cued recall advantage over the different pairs. Whereas the latter account is similar to our account in assuming that the source of the effect is a more efficient process of forming new associations (rather than affecting the retrieval stage), a different mechanism produces the two accounts.

Note that the retrieval-based alternative account is valid only as long as associative learning is tested by cued recall, and the attention-based account requires that the weakly associated pairs be presented at study. If performance differences between "same" and "different" weakly associated pairs persist when these pairs are not studied and no explicit retrieval is required, both alternative accounts can be discarded. To this end, in Experiment 8, I used a semantic decision task, instead of cued recall, to test whether forming strong associations between words could implicitly induce associative connections between their semantic neighbors that were not presented at all during the study phase.

4.3 Experiment 8: Implicitly Mediated Associations – Reaction Time

Experiment 8 differed from Experiment 7 in two important aspects. First, the target pairs (formally coined "weakly associated pairs") were not presented during the incidental study phase. Thus, evidence for an incidentally formed association between the unrelated words composing a target-pair could only result from the association formed between the other two exemplars of their semantic categories. Second, the "same/different" effect was assessed by requesting the participants to determine as quickly as possible whether two words presented in a trial were semantically related. Hence, whereas conjoint processing of the target-pair at test was necessary, the task did not require retrieving one word when cued by the other.

4.3.1 Methods

Participants

The participants were 20 undergraduates, all native Hebrew speakers with normal or corrected to normal vision[9]. Neither of them participated in the previous experiments. They were either paid or received course credit for participation.

Stimuli and Design

The relevant stimuli consisted of 96 Hebrew nouns from 32 base-level categories (3 words per category). Thirty-two words (one per category) were used to form a study list of 16 unrelated word-pairs (one word from each category). Those pairs were randomly repeated 30 times during the incidental study phase. The remaining 64 words were used to form a test list of 32 semantically unrelated target-pairs, equally sub-divided between a "same" and a "different" condition. Each of the studied categories was represented once in each of the test conditions (by different exemplars). In the "same" condition, the pairing of the categories represented by the studied pairs was preserved at test. For example, following the study pair DOG-TABLE, the "same" target pair was CAT-CHAIR. In the "different" condition the categories were recombined. For example, following the study pairs

[9] One participant was discarded due to chance performance in the semantic relatedness decision.

DOG-TABLE and SUN-TULIP, the "different" target pairs were HAMSTER-DAISY and MOON-BED. The pairs used to induce each test condition were counterbalanced between two study lists, so that over all participants, each pair appeared an equal number of times in both experimental conditions. Note that regardless of condition, all the relevant pairs were comprised of semantically unrelated words. Therefore, 32 additional semantic categories were used to compose filler pairs of semantically related words, making each choice equally likely.

Procedure

The incidental study phase was similar to that described in the previous experiment. The test phase followed the study unexpectedly and immediately. A pair of words was presented in each trial and the participants were instructed to respond by pressing a button indicating whether the words were semantically related or not. Speed and accuracy were equally emphasized by the instructions. The instructions made no reference to the previously presented pairs and, indeed, post-experimental debriefing revealed that all participants considered the two phases to be independent.

A test trial began with a fixation mark followed 200 ms later by the pair of words presented simultaneously, centered right and left of fixation, until a response was given. An inter-trial interval of 1500 ms separated the response from the onset of the next trial. Reaction times (RT) were measured at 1 ms accuracy. Following the semantic decision test, the associations formed between the words presented as pairs in the study phase were tested by cued recall.

4.3.2 Results and Discussion

The discrimination between related and unrelated pairs was almost perfect, and equal for the same and different pairs (95%). However, the participants' mean RT to pairs in the same condition was significantly shorter than the RT to pairs in the different condition [958 ms (sd = 33) and 937 (sd = 31), respectively; $t(18) = 1.9$, $P < 0.05$)]. The mean cued recall performance for the presented pairs was 86%, suggesting that reliable associations were formed between the words in each pair during the incidental study phase.

The significant difference between the RT in the two conditions confirmed that processing a pair of unrelated words is facilitated by the existence of a strong association between other exemplars of their respective semantic neighborhoods. Furthermore, the design of this experiment helped reject the retrieval-based and attentional-based accounts for this effect, thus supporting the mechanism for forming associations implemented in SEMANT. Recall that the target pairs were not presented during the study phase. Furthermore, the semantic decision did not require explicit retrieval of cued words from memory. Hence, the obtained difference between the "same" and "different" pairs cannot be explained by either attention modulation at study or by retrieval-dependent processes. Finally, since the studied categories were represented equally in both conditions, single-item category repetition effects (cf. semantic priming) cannot account for the observed effect either. Therefore, SEMANT's account for the semantic-mediation of associative learning, based on conjoint processing of exemplars of the same semantic categories during a previous study phase, is the most reasonable explanation.

4.4 Conclusion

In conclusion, Experiment 6 failed to validate the computational prediction that in some cases it would be easier to form associations between to words in one direction than in the other. However, the results of Experiments 7 and 8 validate an a priori prediction of SEMANT. Thus, they provide a strong empirical evidence for the mechanism, suggested by SEMANT, of formation of semantically mediated association.

5 General Discussion and Future Work

5.1 Experimental Contributions and Limitations

The goal of the present study was to explore the impact of semantic knowledge on the episodic formation of new associations between words and to reveal the dynamic characteristics of the episodic associative learning mechanism and its interaction with the semantic system. In a series of experiments, I have demonstrated that previous semantic links between words boost the formation of new associative connections based on frequent co-occurrence. Furthermore, newly formed associations between semantically related words might be strong enough to supersede, at least temporarily, free associations that were established naturally during life experience. Associative learning was assessed by cued recall in Experiments 1-4 and by forced-choice recognition in Experiment 5. While controlling for pre-experimental associative connections between related (as well as unrelated) words, all experiments support previous suggestions that pure semantic links between words boost the incidental formation of associations during frequent co-occurrence. More importantly, the results shed light on the mechanism of the pure semantic facilitation of forming new associations between words and revealed some of its constraints. Experiment 1 showed that the number of simultaneously learned associations is limited. Experiment 2 showed that semantic elaboration of the stimuli facilitates forming associations between them. Experiment 3 showed that previous semantic relations between the to-be-associated words contribute to forming associations between them. Together, Experiments 2 and 3 showed that the semantic system is involved in the episodic process of forming associations.

Two alternative mechanisms were suggested for the contribution of the semantic system to the association formation process (section 2.7), and Experiments 4 and 5 were aimed at distinguishing between them. In Experiment 4, I found that, in the early stages of association formation, the advantage of the related pairs increased with the number of presentations. This interaction suggests that the structure of the semantic system affects the very process of associative learning and established the time course of this effect. In Experiment 5, retrieval strategies used by the participants were better controlled by using a forced-choice cued-recognition test. Although the procedural difference between Experiments 4 and 5 do not allow a direct straightforward comparison, the outcome of Experiment 5 supported my hypothesis that the semantic boost occurs at study and is not the result of differences in retrieval strategies for related and unrelated pairs. In concert, the results of these two experiments demonstrate that semantic relatedness boosts the incidental formation of episodic associations between words by facilitating associative learning at each co-occurrence. Although in Experiments 4 and 5 this trend was sampled at only a few points, a similar trend was found in Simulation 1, in which the effect of the semantic relationship was examined consecutively between 1 and 30 presentations (section 3.3.1).

The pattern of the results of Experiments 4 and 5 was observed using both shallow and deep processing during the incidental learning phase and testing memory by both cued recall and forced-choice cued-recognition. Furthermore, the priming effects in Experiment 8 were obtained without exposing the target-pairs at study at all. Thus, I showed that the dynamic effects reported in Chapter 2 are not peculiar to a particular level of processing at study or to a particular form of testing memory. Note that, using a shallow task, Goshen-Gottstein and Moscovitch (1995) found no explicit evidence for associative learning. Yet, their methods are too different from mine (determined by different goals) to allow direct comparison. For example, they tested associative learning using the priming paradigm, which is a perceptual, data driven task. In this dissertation, associative learning was tested mostly using cued recall, which is a more conceptual task. Overall, the results in this dissertation suggest that their conclusion, namely, that associative learning is perceptual based only, is inaccurate.

A close examination of the time course of the semantic boost of associative learning in Experiments 4 and 5 reveals that this effect is limited to weak association. Although the upper limit of the interaction effect shifted from 10 to 5 co-occurrences of the paired words when using forced-choice delayed recognition, once this limit was reached, the interaction ceased in both experiments. The limit on the semantic boost can be explained assuming that the amount of semantic activation elicited by a word decreases and sharpens with repetition, and consequently the advantage of concurrent activation of closely related words is reduced. Evidence for the plausibility of this assumption is provided by functional neurophysiological and neuroimaging studies, where a repetitive activation of stimuli yields less activation (e.g., Baylis & Rolls, 1987; Schacter & Buckner, 1998; Ringo, 1996; for a review, see Wiggs & Martin, 1998).

Note, however, that the percentage of cued recall continued to increase at a relatively steady rate even when semantic knowledge ceased to make a significant contribution to learning. This residual learning can be attributed primarily to episodic co-occurrence. This trend is, of course, congruent with ample evidence provided by the paired-associate paradigm used extensively in the late fifties and early sixties (see, for example Crowder, 1976, Chapter 9). Interestingly, cued recall continued to improve for both related and unrelated pairs with additional training, while delayed recognition continued to improve only for unrelated pairs. This pattern suggests that, at least in laboratory experimental conditions, associative learning is limited by various factors that prevent it from reaching the ceiling. In real life, the semantic context in which incidental associations are formed is richer and more complex than simple categorical relatedness and, therefore, more conducive to forming strong associations. The dissociation between the attenuating effect of repetition on semantic activation and its facilitatory effect on associative learning suggests that semantic and episodic processes, although interactive, are separate.

The goal of Experiments 7 and 8 was to provide empirical evidence for semantically mediated contributions of existing associations to the formation of new episodic associations, as predicted by SEMANT. The two experiments have demonstrated that strong episodic associations between two unrelated words facilitate the incidental formation of new associative connections between semantic neighbors of the strongly associated words. Experiment 7 suggested this effect by showing better cued recall of weak associations when these pairs represented semantic categories that were already connected via a strong association between other exemplars. Experiment 8 showed that the establishment of strong episodic associations between exemplars of different semantic categories facilitates the conjoint processing of other word-pairs from the same categories, leading to faster semantic decisions even if the target pairs had not been presented at study. Hence, Experiment 8 demonstrated that the semantic mediation effect on forming new episodic associations is not confined to retrieval processes and does not result from differential allocation of attention between the two pair-types. Rather, SEMANT accounts for these effects assuming that an existent episodic connection between exemplars of two (unrelated) semantic categories provides an efficient channel via which activation can spread from one category to the other. Hence, when the two previously associated words are activated (by within-category spreading of activation among semantic neighbors), the amount of overlapping activity during conjoint activation generated by a new pair of unrelated words is larger than if no such channels exist (Figure 17).

The unexpected direction of the observed difference in Experiment 8 provides an additional interesting insight into the associative process and, at the same time, points to a more general functional organization of semantic and associative (episodic) connections in memory. Counter-intuitively, the existence of an episodic association between unrelated exemplars of two semantic categories facilitated (rather than inhibited) subsequent decisions that exemplars of these two categories are not related. This result indicates that the formation of episodic connections linking two specific words does not directly influence the organization of the semantic map, at least in short time scales. Nevertheless, it is not unreasonable to hypothesize that the organization of the semantic system is affected, or even determined by solid episodic information, which is established over long period during one's life span. Such issues are very difficult to address through experimental by laboratory experimental setups and hence are appropriate for computational-model-based research. Such reciprocal influence between episodic information and the organization of the semantic system is further discussed below (section 5.4.8).

Two possible mechanisms could account for the pattern observed in Experiment 8, both based on the model's assumption that the repeated conjoint activation of the two semantic neighborhoods during the learning phase facilitated the conjoint processing of their target exemplars. One of these accounts is that although the target-pair had not been presented at study, pairs of words in the same condition were implicitly activated together and this implicit conjoint activation facilitated the conjoint perception of the two words. As explained above, the implicit conjoint activation could have been mediated by automatic spreading of activation among semantic neighbors while the strong association between other exemplars was formed. Note that it is the conjoint (rather than individual) activation that matters, because, indeed, words forming pairs in the different condition had also been activated by spreading of activation, but not together.

The second account is similar in essence but focuses more on decision processes. According to this account, when a target pair was presented and the participant had to make a decision regarding its semantic relatedness, the respective semantic neighborhoods were activated and compared. For pairs which their neighborhoods were already conjointly activated during the intensive learning, a decision that they are different was easier and resulted in a shorter RT. The observed facilitation in RT is similar in nature to association-specific repetition priming (Goshen-Gottstein & Moscovitch, 1995), but in Experiment 8, it is the repetition of the specific semantic categories (rather than specific pair of words) that facilitates the performance of the task at test.

5.2 Experimental Future Work

Following the experimental work completed in this dissertation and based on the results of the computational model that was built and simulated, several possible directions for expanding the experimental work can be proposed in order to gain a broader experimental basis for the relevant phenomena and to determine additional and more accurate constraints for the computational model. There are three major directions for potential experimental work. The first consists of re-addressing experiments and methodologies whose results were difficult to interpret and hence did not lead to clear theoretical insights such as the Implicit Asymmetry experiment. The second direction of future work consists of further theoretical study of issues such as how other parts of speech are organized in the semantic system in relation to nouns. The third direction consists of experimentally testing these predictions of SEMANT that were not validated within this study, such as the diffuse activation as the cause of Schizophrenic Thought Disorder.

5.2.1 Implicit Asymmetry

One of the predictions of SEMANT was that sometimes it would be easier to form an association between two semantically and associatively unrelated words in one direction than in the opposite direction (section 3.4.2). This prediction, termed as *implicit asymmetry*, emerged from the simulation and was not based on prior theory. An examination of the results suggested that this asymmetry stems from the inhomogeneous distribution of the concepts in the high-dimensional metric space. According to the results, I predicted that it should be easier to form an association from a word with a spare semantic neighborhood to a word with a dense semantic neighborhood. In an experiment aimed at testing this prediction directly (section 4.1), the density of the semantic neighborhood was defined according to several parameters based on free association questionnaires, and the existence of an association at the end of the study phase was tested in a cued recall test, as in most of the other experiments in this research. The results did not support the prediction.

Despite the fact that the experiment did not support the model prediction, it would be premature to conclude that the prediction is invalid. One possible reason may be that the density of the semantic neighborhood was determined based on averaged results of free association questionnaires. According to SEMANT, free associations are influenced by episodic factors in addition to semantic organization. Hence, the parameters obtained from free associations do not accurately reflect the density of the semantic neighborhood as required by the prediction.

A second difference from the conditions of the prediction emerges from the fact that the organization of the semantic memory varies between participants. This factor is especially important if the assumption that it reflects also episodic factors is correct. The parameters' values were averaged across participants and, more importantly, the group of participants that took part in the experiment was different from the group of participants that answered the free association questionnaires. Hence, it could very well be that delicate effect such as the implicit asymmetry would be lost due to between-subjects variance.

The analysis that was performed on the computational model is a third potential factor. Recall that the effect that was first detected was the asymmetry in the strength of the formed associations between two words. A significant correlation was later found between the difference of densities of the two to-be-associated words on one hand and the association strength differences between the two directions on the other. The difference of densities was therefore suggested as a potential cause for the implicit asymmetry. Nonetheless, other factors, possibly more significant, such as word familiarity cannot be ruled out as potential cause of this asymmetry. Joint computational and experimental work is required in order to evaluate these factors.

If these factors will be modified in future experiments, empirical evidence to support the model prediction may be found. Such result would be very interesting for two reasons. First, it would tell us what are the factors dominating the propagation of semantic activation. Second, it would prove the usefulness of computational studies for studying cognitive phenomena: without the model, there is very little chance that this effect would have been found.

5.2.2 Other Parts of Speech

In the series of behavioral experiments that were performed so far, as well as in the computational model, all the words were nouns. Obviously, our semantic memory contains other linguistic categories such as verbs, adjectives, etc. The semantic links between words from different linguistic categories are apparently more diverse in real life. For example, it is reasonable to assume that nouns (e.g., CAR) have primarily functional semantic links to verbs (e.g., DRIVE). In addition, it is far less likely to find semantic relatedness based on belonging to semantic categories between words from different linguistic categories. Recall that in the work throughout this dissertation, both experimental and computational semantic relatedness was defined as belonging to the same semantic category. Hence, paradigmatically, involving other linguistic categories would force us to modify the definition of semantic relatedness and harden the control on the strength of the pre-experimental links. Nonetheless, the information that could be gained by including other linguistic categories and additional types of semantic links is valuable since it would enable us to analyze the process of sentence comprehension and generation. Doing so would also be likely to raise new theoretical and computational issues that would challenge the computational model.

5.2.3 Schizophrenic Thought Disorder

As was described in detail in sections 3.4.3 and 3.4.4, a possible cause for STD, namely a faster and farther-spreading activation wave was implemented in SEMANT in two alternative manners. The two different implementations yielded two different predictions about performance of STD patients in experiments similar to Experiment 4. Performing a similar experiment on STD population and comparing the results to those of the normal population may allow us to distinguish between the two optional implementations and consequently converge on one of the two potential theoretical explanations for STD.

Due to the involvement of an abnormal population, a special attention should be paid while designing the experiment to fitting the experimental paradigm to the disabilities of the patients. First, the number of available participants would probably be much smaller than in the normal population. Second, since the ages and I.Q. of some of the patients that will participate will probably be different from those in the normal population that participated in Experiment 4 (20-30-year old), a different control group will have to be run. Third, memory performance in general is lower in STD patients (Aleman et al., 1999). Hence, an index to assess the degraded performance of STD patients, to allow comparing their performance to those of the normal population, would have to be developed.

Nevertheless, since the two predictions of the computational model differ mainly in the pattern of interaction between the performance in the related and unrelated conditions, a general degradation in performance should not prevent determining which one of them reflects the actual results more accurately. Fourth, due to limited concentration and other physical disabilities of the patients, the overall duration of the experiment should be rather limited. Despite these expected difficulties, running such an experiment would be worthwhile and evidence to support one of the possible theoretical variations regarding the nature of the pathology would certainly be beneficial in the endeavor for finding a cure for the disease.

5.2.4 Conclusion of Experimental Future Work

As elaborated in this section, many further behavioral questions arise directly from the experiments in this study and from the computational model that was developed based on it. The suggested experimental work may allow us to better understand the basic process of human associations, to provide further constraints for computational simulations of related phenomena, and to enrich our grasp of the human memory and thinking in general.

5.3 Computational Contributions and Limitations

Following the first series of psychological experiments, which investigated how semantic factors affect the process of forming associations between words, as was described in Chapter 2, my goal was to develop and evaluate a computational model that could account for these results, and to produce further predictions on how words are associated. The model described in Chapter 3, SEMANT, shows how both semantic relatedness and episodic associations can be implemented in a single structure using two types of representations. Semantic relatedness was expressed as proximity in a high-dimensional feature space, spanned by the 100-dimensional numerical representations of the concepts. Episodic associations, in contrast, were represented by arbitrary "physical" connections between the units that represent the words. Both types of relations were implemented simultaneously in a self-organizing semantic map with lateral connections.

Like human participants, SEMANT showed that semantic information facilitates learning new associations. This facilitation emerged in a natural, mechanistic manner, without involving top-down intentional processes. It was achieved by Hebbian link-strengthening, based on intersections of spreading activation waves over a semantic map. Based on SEMANT's success in replicating certain aspects of human behavior, it was used to examine other aspects of it as well.

One such known aspect of human behavior is the asymmetric nature of word associations, which is difficult to explain with computational models that rely on distances between high-dimensional numeric representations. One atypical example is Plaut's (1995) model, which can potentially capture asymmetrical associations between word-pairs based on the relative frequency of the two directions of presentation, termed *explicit asymmetry* in section 3.4.2. Similarly, SEMANT is based on perfectly symmetric foundations such as high-dimensional vectors and the self-organization algorithm that establishes the semantic map. Nonetheless, SEMANT demonstrates two kinds of asymmetries. The first, explicit asymmetry, is achieved by unidirectional lateral connections that are implemented on top of the symmetric organization of the semantic map. These connections enable asymmetric associations between two words, based on different episodic experiences in the two directions. The second, implicit asymmetry, emerges from the non-uniform distribution of concepts in the high-dimensional space. This distribution makes spreading activation asymmetric between two points in the semantic space that would otherwise be equidistant.

The model suggests that the unassigned units in the high-dimensional space are significant, since they serve as a mediating substrate for spreading activation. Any system organized in an unsupervised fashion to accommodate an unknown number of items, such as our semantic system, would be expected to have a much larger capacity than is usually needed. In semantic maps, this property is expressed by the number of nodes in the grid, which is much larger than the number of represented words (in the case of the current model, which includes 40^2 nodes in which only 250 words are embedded, there are 6.4 nodes per word on average). However, due to the self-organization algorithm, these unassigned units are not distributed uniformly in the high-dimensional space, but rather represent the densest areas of the input space. Consequently, they help magnify the effects that are due to the statistical properties of the input. An example of such an effect is the asymmetry in the learning efficiency between two directions of word-pairs.

In the current version of SEMANT, the episodic information is added, as learning continues. The model does not forget anything (see section 5.4.7 for suggestions on how a forgetting mechanism could be implemented in the future).

Consequently, the lateral connections keep getting stronger without limit. Such an unconstrained process may lead to two undesired results. First, the episodic components of the lateral connections may become much stronger than the semantic component. Thus, the semantic information would be practically eliminated and the activation would spread, based only on the episodic connections. Second, if the lateral connections become too strong, the dynamic process would "explode", namely, the activation values would reach ceiling very quickly in large areas of the semantic map. Not only are these two consequences computationally undesirable, they also have no possible equivalence in human behavior. Thus, the conclusion from these computational and cognitive considerations is that a forgetting mechanism is important for stabilizing the dynamic system and keeping it functioning efficiently for long time (human's life time). Another suggestion on how episodic connections may eventually assimilate into the semantic map is discussed in section 5.4.8.

In sections 3.4.3 and 3.4.4, SEMANT was used to gain insight into one of the theories of Schizophrenic Thought Disorder (STD) as suggested by Spitzer (1997). According to this theory, the activation over the semantic network of STD patients spreads faster and farther than that of normal subjects. The results of STD simulations (sections 3.4.3 and 3.4.4) show that if a stronger wave were the cause for this difference, STD patients would perform better in both the related and unrelated conditions. On the other hand, if the organization of the semantic system of STD patients is less focused but the sum of the weights is not greater than that of normal participants, they would perform better only in the unrelated condition; in the related condition, their performance should be impaired. Consequently, by replicating Experiment 4 on STD patients and comparing the results to those predicted by the model, it would be possible to determine which version of the model is likely to be correct, thereby gaining insight into the causes of the impaired performance of STD patients.

5.4 Computational Future Work

Based on the computational model that was developed in this dissertation, several possible directions for future work can be undertaken to achieve a more accurate and comprehensive simulation of human behavior. There are three major such directions: The first consists of extending SEMANT to extract additional and more accurate predictions based on more plausible computations. Possible such extensions include: improving semantic representations, scaling up the lexicon, and modeling interaction between the activation waves. The second direction of future work consists of expanding the model to cover further aspects of human behavior, including modeling: semantic and phonetic maps, the effect of attention, episodic vs. semantic recall, and forgetting. The third direction involves developing an additional version to the model, based on an alternative assumption, namely, that episodic associations assimilate into semantic information over time. This direction is discussed in section 5.4.8.

5.4.1 Improved Semantic Representations

As detailed in section 3.2.1, the numerical representations used in the current version of SEMANT are based on the HAL algorithm, which was implemented on the CHILDES data base. During this research, I attempted to use HAL representations that were derived based on larger and more general databases (USENET, REUTERS) but they did not yield semantic maps where semantically related words, according to my subjective judgment, were clustered properly on the map. A closer examination at those HAL representations revealed a rather puzzling phenomenon. The high-dimensional distance between semantically related words was in some cases much larger than that between completely unrelated words. Such discrepancies are problematic to SEMANT since the semantic maps are organized based on these representations, and the performance of the entire model depends on them. This phenomenon raises doubts concerning whether HAL representations in general are capable of capturing semantic properties of words. Hence, using alternative numerical representations might improve the performance of SEMANT. Such representations could be based on already existing algorithms such as LSI (Landauer & Dumais, 1997) or FGREP (Miikkulainen, 1993; Miikkulainen & Dyer, 1991), or on completely new algorithms. Furthermore, since the current version of SEMANT was successful in replicating human performance, the use of numerical representation based on various sources while running identical simulations may serve as a benchmark task, allowing us to compare and quantify the success of the various representations in capturing the semantic of words.

5.4.2 Scaling Up the Lexicon

Recall that the lexicon of SEMANT consists of only 250 nouns (section 3.2.1). Using alternative representations, as discussed in the previous section, which might better capture the semantic content of the words, should allow scaling up SEMANT more easily. Note, however, that the ratio between nodes in the map that are assigned to words and "empty" nodes that do not represent any word should remain approximately as it is in the current version of SEMANT (6.4 nodes per word on average, section 5.3). Therefore, larger maps should be used.

5.4.3 Interaction between Activation Waves

Recall that in the learning phase simulation of SEMANT (section 3.3.1), two words are first presented to the model with a certain SOA and two activation waves then spread independently. Such independence is a severe deficit of the current version of SEMANT as a biologically plausible model. In order for two (or more) waves to spread in the same system without interaction, the waves should be somehow "labeled" (or "colored") to carry the information that identifies their source throughout their propagation. Moreover, in the current version of SEMANT, the association strength between the two concepts is determined based on the sum of the intersections of the activation wave throughout the trial and, hence, only after the trial is ended. Again, in order for such mechanism to take place, the wave should be labeled and should carry the information regarding their source throughout the trial. Note, however, that such labeling scheme can be avoided if the enhancement of the association strength between the two words based on the summation of waves' intersection is done in "real-time", while the waves are propagating and while the sensory input (or echoic input) that originated the activation is still valid. Nevertheless, in order to prevent the waves from interacting, some labeling scheme seems inevitable.

A possible justification for labeling comes from the spreading activation theory of Collins and Loftus. According to their theory, activation spreads from the two concepts along the connection of the semantic network until the two activations meet. At that point, an association is formed between the two concepts. The waves, therefore, should be labeled to carry the information regarding their source throughout the propagation.

Collins and Loftus's semantic network theory is a cognitively driven theory for semantic memory. However, SEMANT is intended to be more biologically plausible (although still at the conceptual level, as opposed to suggest a direct implementation in the brain hardware). Since such a labeling mechanism is not likely to exist in reality, it is less suitable to be implemented in SEMANT. Moreover, it is also less likely that two (or more) activation waves would propagate through the same system (semantic memory) without interacting. Hence, the more plausible assumption is that the waves that originate from different sources interact in some manner, and that the propagation of one wave affects the propagation of the other during the trial. Changing SEMANT to support unlabeled interacting activation and still replicating human behavior is a challenging future computational research direction.

5.4.4 Semantic and Phonetic Maps

Words that rhyme are associated more easily regardless of their semantic distance (Baddeley, 1999). SEMANT suggests an architecture that supports the facilitation of association formation based on a measurable relative property of the words, namely, their semantic distance. In an analogy to the role of semantic distance in SEMANT, a *phonetic distance* measure can be defined such that a model similar to SEMANT with self-organizing feature maps based on phonetic distance will be successful in replicating experimental results on rhyming words.

Miikkulainen (1991, 1993) suggested a simple encoding scheme for building distributed representations for words that would reflect their phonetic distance. In his encoding scheme, each letter of the alphabet was given a value between 0.0 and 1.0 according to its darkness, measured by counting the black pixels in its bitmap representations. The darkness values of each word's letters were then concatenated into a representation vector. In effect, the representation is an extremely blurred bitmap of the words. This encoding scheme grounds the representation into the sensory experience and satisfies the requirements for modeling the phonetic map. Each written word has a unique representation and words that are similar in their phonetics have similar representations.

In a natural next step, in addition to a phonetic model, the two models could be combined to form a more comprehensive model of the human lexicon. Miikkulainen (1993) suggested such a model, DISLEX, which consists of two separate maps: semantic and phonetic, which are inter-linked with all-to-all bi-directional connections. The activation of a node in one map causes an activation of the relevant node (and its neighborhood) in the other map. Using activation waves that spread separately on the two maps, a much richer range of phenomena of the facilitation of association formation based on both semantic and phonetic relatedness could be addressed (Figure 26).

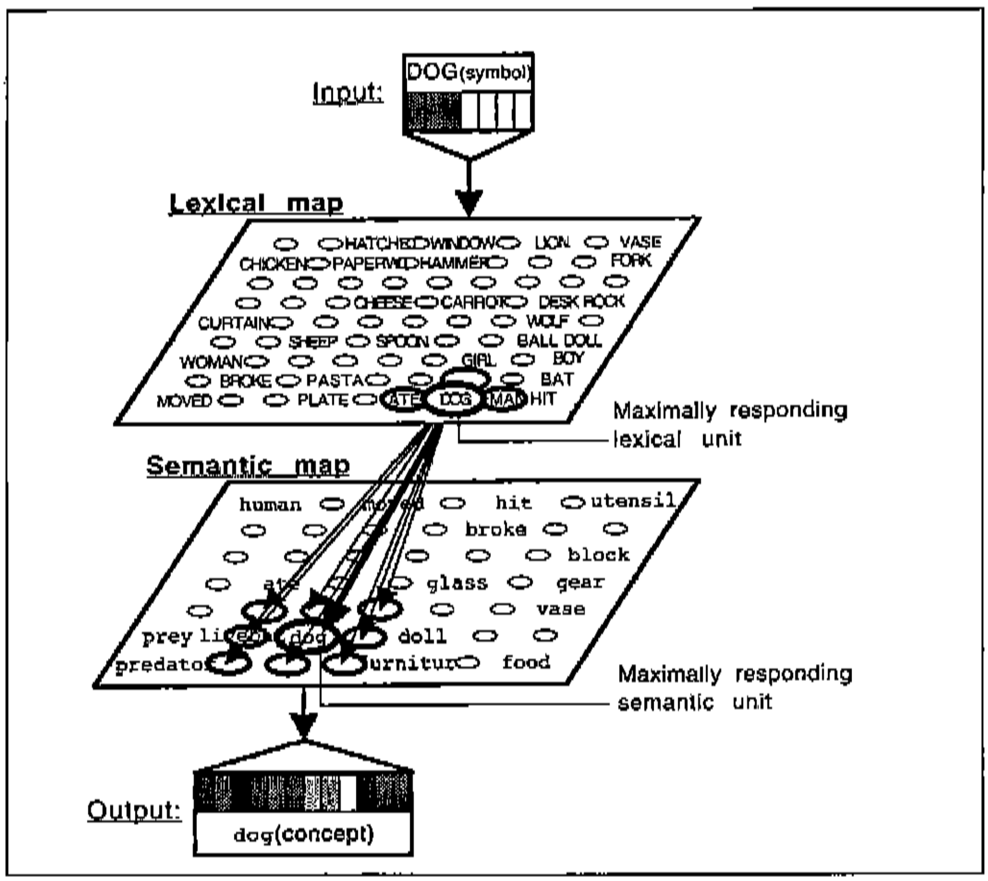

Figure 26: An illustration of lexical and semantic maps with many-to-many inter-connections. SEMANT could be expanded to include a phonetic map in addition to the semantic map (from Miikkulainen, 1993).

Assume, for example, that the strength of the association that is formed between two concepts that are activated sequentially depends not only on the intersection of the two activation waves that spreads over the semantic map, but also on the intersection of the two activation waves that spread over the phonetic map. In such a case, it should be easier to form an association between LEG and BEG (based on phonetic similarity) than between LEG and COW, as it is easier to form an association between LEG and EAR (based on semantic similarity) than between LEG and COW (section 2.7).

5.4.5 The Effect of Attention

The research in this dissertation was focused on incidental learning. Therefore, the effect of attention on learning was not studied experimentally and was not modeled. However, in the Pilot Experiment (section 2.3) a clear advantage for intentional learning was demonstrated. As discussed in the introduction chapter, most of the studies on association learning are based on intentional learning (section 1.4). It can be safely concluded that allocating attention to the learning process, either explicitly (i.e., intentional learning) or implicitly (i.e., priming) significantly improves the learning performance.

The most common theory of attention is based on the spotlight metaphor (Eriksen, 1990; Juola, 1991). At each given moment, our attention is directed to a certain process or area in the memory and shifting the attention is done serially in time as if a spotlight was pointing at only one target at each moment in time. This spotlight metaphor can be easily implemented in SEMANT to support the enhancement of learning by attention. At each moment in time, a certain limited area of the map can be activated by an outside source, i.e., the attention spotlight, such that the nodes in this area are partially activated regardless of the activation waves caused by the learning process. Consequently, should the items to be learned be localized in the spotlighted area, their activation should be stronger. Since the model suggests that episodic learning is achieved through the intersection of activation waves, it should be stronger when it happens in an attention-activated area. The spotlighted area over the map can be manipulated regardless of the learning procedure, as is done in experiments with human. Thus, further predictions on how attention and episodic learning processes interact can be derived. Moreover, extending the model in this manner makes it possible to compare intentional learning in a computational model with that in humans.

Confirming the predictions of such a model would provide computational support for the spotlight theory, as well as establish a more comprehensive model of associative learning.

5.4.6 Episodic vs. Semantic Recall

Recall that in the first behavioral experiments in this research (section 2.2.1) the participants were tested in two types of tests. The first, explicit, was a cued recall test, where the participants were presented with the first words in the pairs from the study phase and had to reply with the corresponding second word. The second test, implicit, was a free association test. In the simulations, however, only the first, explicit test was simulated (section 3.3.1).

The activation waves spread according to the same equations in two different manners: (1) ignoring the episodic components of the lateral connections, and (2) combining the full level of the episodic components of the lateral connections with the semantic component. The parameter τ implements the choice between the two processes:

$$L_{ij,uv} = S_{ij,uv} + \tau \cdot E_{ij,uv}, \qquad (10)$$

(section 3.2.5). During the learning phase, τ is set to 0 such that the activation propagates based only on the semantic components of the lateral connections. During testing, τ is set to 1 such that the activation propagates based both on the semantic and the episodic components of the lateral connections. In this way, cued recall is simulated since the simulated-participant takes into account the episodic information from the learning phase while trying to recall the answer. This parameter did not play a major role in the model thus far, but it could be used to simulate additional implicit tests in the future.

The additional testing phase in the Pilot Experiment (section 2.3), i.e., the implicit free associations test, could be simulated by selecting a middle value between zero and one for the τ parameter, e.g., 0.1. In this case, even in the testing phase, the simulated-participant will "try to ignore" the study phase and consequently will reply with his first, natural, association. However, as happens with real participants, the episodic components of the lateral connection affect the propagation of the activation wave to some extent, and sometimes the episodic pair word will be output as the first natural association. Such a mechanism would allow SEMANT to be compared to numerous free-association studies in humans (e.g., Palermo & Jenkins, 1964) and would allow scaling the computational parameters more accurately than is currently possible. Additionally, it will be possible to use SEMANT to model a variety of effects in free-associations tests (e.g., Postman & Phillips, 1965) and to predict others, thus contributing to our understanding of the fundamental process of free associations.

5.4.7 Forgetting

The dissertation did not address question concerning memory decay in general and forgetting episodic information in particular. Accordingly, no implementation for a forgetting mechanism was implemented in SEMANT. Such a mechanism can be added in various ways and the performance of the model could than better fit human data. One simple approach is to reduce the strength of all episodic connections in some small fixed quantity at the end of each learning trial. Thus, associations that will be learned later in time would have an advantage in being recalled. Using this implementation, the model would demonstrate the well known *recency effect* (Postman & Phillips, 1965). Note, however, that such a simple implementation would not support the *primacy effect* (in Baddeley, 1999). Extending SEMANT to demonstrate normal and pathological memory loss may turn it into a useful tool for investigating this less examined aspect of learning process and might even be useful in studying cognitive pathologies related to forgetfulness.

5.4.8 Map Organization with Episodic Associations

SEMANT is based on an already organized semantic map, modeling the human semantic memory. A fundamental question in cognitive psychology is how the semantic memory gets organized in the first place. The psychological experimental research described above does not address this question and, hence, the computational model it includes does not aim at solving it either. Several researchers have suggested that the sensory input that is related with each concept in the semantic memory serves as a *feature vector*. This vector enables the semantic memory to become organized such that semantic relatedness is reflected in the organization as illustrated in Figure 27 (Allen, 1990; Feldman et al., 1990; Harnad, 1990, 1992; Nenov, 1991; Regier, 1991a, 1991b, 1992; Sopena, 1988). Others proposed that all semantic knowledge is based on episodic learning (Postman, 1972). These researchers suggest that the organization of the semantic memory and the structure of episodic connection are differentiated only by the time scale in which they are established. Episodic connections are established quickly, sometimes even based on a single presentation, and the semantic organization develops slowly and gradually with time and is determined by the episodic connections.

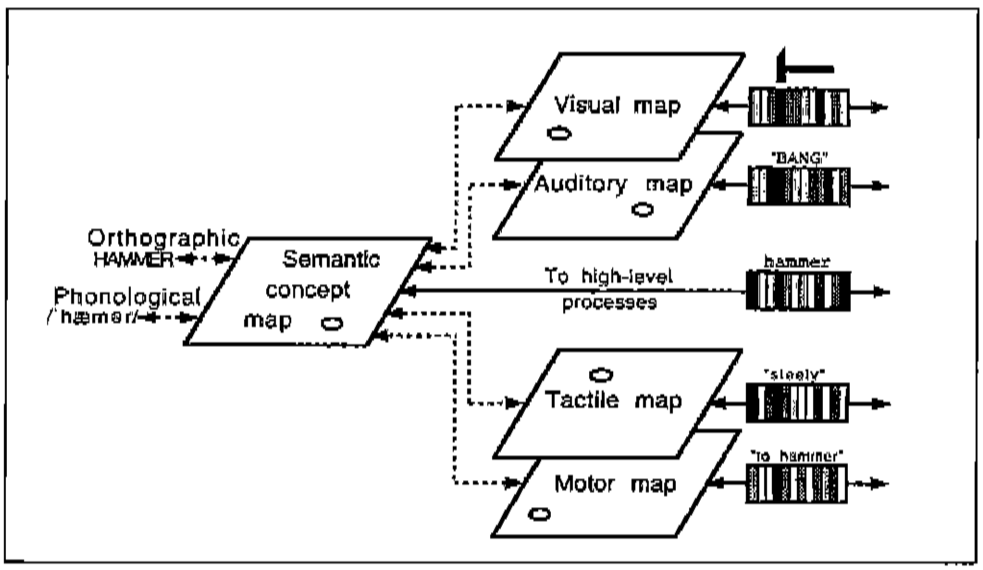

Figure 27: An illustration of a conceptual map with reciprocal connection with sensory maps. The sensory input serves as a feature vector, enabling a meaningful organization of the conceptual map (from Miikkulainen, 1993).

In the current version of SEMANT, the episodic connections do not affect the organization of the semantic map. However, activation flows through both semantic and episodic connections such that the outside observer cannot isolate the influence of the two types of connections. This modeling approach better reflects the feature vector assumption, as the semantic map is organized according to outside (possibly sensory) information and is not affected by the episodic connections. Another version of the model could be designed such that the episodic connections in long time scales affect the organization of the semantic map. This alternative design better reflects the idea that semantic knowledge is actually episodic information over long time scales. Comparison of predictions of human behavior of the two alternative designs with actual human performance may supply evidence to support one approach or the other.

5.4.9 Conclusion of Computational Future Work

As elaborated in this section, there are many interesting directions for expanding and modifying SEMANT to overcome its limitations and to expand it to further aspects of human behavior. Implementing the extensions suggested above and other possible modifications and additions should allow us to better understand the basic process of human associations in particular and the nature of the human memory and thinking in general.

6 Conclusion

The empirical findings in this study demonstrate that an interaction between the organization of the human semantic system and the formation of new episodic associations between words exists. Furthermore, the experiments unveiled several characteristics of the process association formation, focusing on the contribution of the semantic memory organization to this process:

a. Human capacity to simultaneously form new associations is limited. An attempt to incidentally form an overwhelming number of new episodic associations simultaneously, would fail.

b. Deep processing of word stimuli, by activating their meanings, dramatically increases the probability that new incidental associations would be formed between them.

c. Prior semantic relations between the to-be-associated stimuli facilitate the process of the association formation between them, regardless of whether attention is directed to the words' meanings.

d. Semantic relatedness facilitates each association learning episode. Hence, the organization of the semantic system influences the actual dynamics of the association formation process.

Based on existing theories and constrained by the empirical findings stated above, I developed a computational, neural-network based model, SEMANT, which suggests a plausible mechanism for the process of forming associations and demonstrates in detail a possible dynamics of the above interaction. The psychological plausibility of this model was demonstrated by simulations which accurately replicated the empirical results. Furthermore, the model predicted a set of testable patterns of associative learning:

a. It should be easier to form an association from a word with few semantic neighbors to a word with many semantic neighbors than vice versa.

b. It should be easier to associate words that are semantically related to other words that are already associated.

c. A less focused activation wave such as that implicated in schizophrenic thought disorder should decrease the advantage of associating semantically related pairs over unrelated pairs.

In further behavioral experiments, the first two of these predictions were validated with human participants.

Together, these theoretical and empirical findings suggest that, while the semantic and episodic memories are based on different principles, they are highly intertwined and interact during learning. Furthermore, the current work strongly supports the idea that forming associations is not a purely episodic process but relies heavily on semantic memory organization.

On the basis of the strong support that it received from human experimentation, the SEMANT model can provide a theoretical framework for many additional studies aimed at understanding associative learning. As such, the present study is a successful demonstration of a multidisciplinary approach to studying human cognition. Nevertheless, there are several open questions that await empirically based answers. Among those are:

a. Do the same rules that govern the process of association formation between nouns apply to other parts of speech, whose semantic representation might be differently organized?

b. Is SEMANT prediction concerning STD patients valid, and what can we learn from the behavior of STD patients in similar experiments about the nature of schizophrenia?

c. Is an interaction similar to the one found between the episodic formation of associations and semantic information found with other types of information (e.g., morpho-phonological)?

d. What is the effect of attention on the process of forming new associations and how does it interact with the mechanisms discussed in this dissertation?

e. What rules govern the decay and forgetting of associations?

f. How do episodic associations affect the organization of the semantic system over large time scales?

Answering these questions would lead us further towards understanding the organization of human semantic system, and human memory and thinking in general.

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Appendix A – Stimuli

Experiment 1: The Effect of Memory Load

1.	לפת - בעל	Turnip - Husband
2.	מצע - פרא	Platform - Savage
3.	נהר - חרס	River - Clay
4.	סלע - רחש	Rock - Whisper
5.	יער - צבע	Forest - Paint
6.	גמד - סמל	Dwarf - Symbol
7.	ענב - עמק	Grape - Valley
8.	פרק - קסת	Chapter - Inkstand
9.	גזר - כלא	Carrot - Jail
10.	גרב - קצה	Sock - Edge

Experiment 2: The Effect of the Level Of Processing

1.	נהר - גמל	River - Camel
2.	גרב - יער	Sock - Forest
3.	ספה - גזר	Sofa - Carrot
4.	קטר - שדה	Locomotive - Field
5.	דלת - פרח	Door - Flower
6.	ברז - ילד	Tap - Child
7.	אהל - מחק	Tent - Eraser
8.	ענב - ספל	Grape - Mug
9.	כלב - אגס	Dog - Pear
10.	בצל - בגד	Onion - Garment

Experiment 3: The Effect of Semantic Relatedness

1.	דגדוג - נשיקה	Tickling - Kiss
2.	גרב - חזיה	Sock - Brassiere
3.	פרפר - יתוש	Butterfly - Mosquito
4.	דלקת - שפעת	Inflammation - Flew
5.	אבטיח - תפוז	Watermelon - Orange
6.	שרוך - כפתור	Shoelace - Button

7.	אוטובוס	-	קטר	Train-engine	-	Bus
8.	מילון	-	ירחון	Monthly journal	-	Dictionary
9.	חרדל	-	חמאה	Butter	-	Mustard
10.	שמנת	-	דיסה	Porridge	-	Cream
11.	דלק	-	חשמל	Electricity	-	Fuel
12.	טירה	-	בקתה	Hut	-	Castle
13.	באר	-	צנצנת	Jar	-	Well
14.	מרצפת	-	משקוף	Lintel	-	Tile
15.	תחבושת	-	זריקה	Injection	-	Bandage
16.	לחם	-	פשטידה	Casserole	-	Bread
17.	חרוט	-	מעוין	Rhombus	-	Cone
18.	מצעד	-	מסדר	Parade	-	March
19.	נשיא	-	גזבר	Treasurer	-	President
20.	פרסה	-	רסן	Bridle	-	Horseshoe
21.	מדחום	-	מאזניים	Scales	-	Thermometer
22.	סל	-	ארגז	Crate	-	Basket
23.	חמר	-	מתכת	Metal	-	Clay
24.	מפל	-	אוקיינוס	Ocean	-	Waterfall
25.	תרבוש	-	קסקט	Cap	-	Tarbush
26.	קוסם	-	מוקיון	Clown	-	Magician
27.	מרק	-	יוגורט	Yogurt	-	Soup
28.	מחבת	-	מזלג	Fork	-	Pan
29.	תרמיל	-	ארנק	Wallet	-	Satchel
30.	צווארון	-	שרוול	Sleeve	-	Collar
31.	זגג	-	סנדלר	Shoemaker	-	Glazier
32.	נענע	-	אורגנו	Oregano	-	Meant
33.	מחק	-	צבע	Paint	-	Eraser
34.	דולפין	-	תמנון	Octopus	-	Dolphin
35.	לימונדה	-	קפה	Coffee	-	Lemonade
36.	אגס	-	תות	Strawberry	-	Pear
37.	משחה	-	לפיד	Torch	-	Ointment
38.	נחל	-	מסור	Saw	-	Stream
39.	גיטרה	-	היאבקות	Wrestling	-	Guitar

40.	כדורסל	-	אפודה	Vest	-	Basketball
41.	קשמיר	-	דאון	Glide	-	Cashmere
42.	חללית	-	סיר	Pot	-	Spaceship
43.	שש-בש	-	גלולה	Pill	-	Backgammon
44.	עלה	-	מלונה	Kennel	-	Leaf
45.	רפת	-	עפיפון	Kite	-	Dairy barn
46.	נקניק	-	כיפה	Yarmulke	-	Cold cut
47.	ברווז	-	אננס	Pineapple	-	Duck
48.	מכתב	-	חבל	Rope	-	Letter
49.	גופיה	-	זרקור	Spotlight	-	Undershirt
50.	צלם	-	מעטפה	Envelope	-	Photographer
51.	מצנח	-	מחברת	Notebook	-	Parachute
52.	פנקס	-	יוטה	Jute	-	Notepad
53.	מעיל	-	אקליפטוס	Eucalyptus	-	Coat
54.	צלוחית	-	אוהל	Tent	-	Saucer
55.	ארגמן	-	מפית	Napkin	-	Purple
56.	סדין	-	אפור	Gray	-	Sheet
57.	מיקרופון	-	יונה	Dove	-	Microphone
58.	ריסוס	-	מקלע	Machine gun	-	Spraying
59.	תפילה	-	אבוקדו	Avocado	-	Prayer
60.	אהיל	-	ציציות	Fringes	-	Lampshade
61.	קרפדה	-	חוטם	Nose	-	Toad
62.	אפרסק	-	צמרת	Treetop	-	Peach
63.	מימיה	-	צלי	Roast	-	Canteen
64.	מטלית	-	שמלה	Dress	-	Rag
65.	קסדה	-	קציר	Harvest	-	Helmet
66.	טיל	-	פאזל	Puzzle	-	Rocket
67.	גזר	-	מגבת	Towel	-	Carrot
68.	קן	-	כינור	Violin	-	Nest
69.	אזוב	-	ינשוף	Owl	-	Hyssop
70.	בורג	-	סופר	Writer	-	Screw
71.	חכה	-	שורש	Root	-	Fishing rod
72.	בוהן	-	בריכה	Pool	-	Thumb

73.	מצבר - דקל	Battery - Palm tree
74.	בובה - גשר	Doll - Bridge
75.	תרנגול - כרוב	Cock - Cabbage
76.	אגרטל - כומתה	Vase - Beret
77.	אקדח - שלג	Pistol - Snow
78.	אזניה - עוגה	Earphone - Cake
79.	עמק - מקרר	Valley - Refrigerator
80.	אשוח - תותח	Fir - Cannon
81.	בדיל - מחשב	Tin - Computer
82.	פקודה - מעיין	Order - Spring
83.	כיור - טרקטור	Sink - Tractor
84.	חלב - חרגול	Milk - Grasshopper
85.	חבילה - נשר	Package - Eagle
86.	פרעוש - כוס	Flee - Cup
87.	סלרי - רמקול	Celery - Loudspeaker
88.	משי - מחסן	Silk - Warehouse
89.	יומן - צוללת	Diary - Submarine
90.	סלון - כדור	Living room - Ball
91.	מנוף - מגרש	Crane - Court
92.	אגזוז - זהב	Exhaust - Gold
93.	מזכירה - חרצית	Secretary - Chrysanthemum
94.	שושנה - תינוק	Rose - Baby
95.	שרב - מכבש	Hot weather - Press
96.	גבעה - פעמון	Hill - Bell
97.	מפוחית - שידה	Harmonica - Chest of drawers
98.	רפסודה - יין	Rhapsody - Wine
99.	ברד - כסא	Hail - Chair
100.	ישיש - שוקולד	Old person - Chocolate
101.	מכונית - דפדפת	Car - Loose leaves
102.	ספריה - תנור	Library - Oven
103.	גבינה - קטורת	Cheese - Incense
104.	מפעל - ענן	Factory - Cloud
105.	שטיח - קיוסק	Rag - Kiosk

106.	גלויה	-	מגדל	Tower	-	Postcard
107.	נהר	-	גן	Garden	-	River
108.	צמר	-	מרשמלו	Marshmallow	-	Wool
109.	רקפת	-	סיגלית	Violet	-	Cyclamen
110.	חודש	-	רגע	Moment	-	Month
111.	עכבר	-	נמר	Tiger	-	Mouse
112.	שוקו	-	סודה	Soda	-	Hot chocolate
113.	סוללה	-	שקע	Socket	-	Battery
114.	שופט	-	רופא	Doctor	-	Judge
115.	דיו	-	סרגל	Ruler	-	Ink
116.	שפירית	-	ציפור	Bird	-	Dragonfly
117.	אש	-	רוח	Wind	-	Fire
118.	קרס	-	דוקרן	Spike	-	Hook
119.	מחרוזת	-	צמיד	Bracelet	-	Necklace
120.	מחבט	-	שער	Hair	-	Racket
121.	סיכה	-	נזם	Nose ring	-	Pin
122.	עתון	-	כרזה	Poster	-	Newspaper
123.	מסלול	-	שוליים	Margins	-	Path
124.	חמצן	-	אבץ	Zinc	-	Oxygen
125.	היפופוטם	-	כבשה	Ship	-	Hippopotamus
126.	מסגרת	-	תערוכה	Show	-	Frame
127.	משרד	-	חנות	Shop	-	Office
128.	גמל	-	פרה	Cow	-	Camel
129.	צייר	-	משורר	Poet	-	Painter
130.	הל	-	כורכום	Turmeric	-	Cardamom
131.	דלעת	-	צנונית	Small radish	-	Pumpkin
132.	חרסינה	-	בטון	Concrete	-	Porcelain
133.	אמבטיה	-	מרפסת	Balcony	-	Bath
134.	ספרות	-	כלכלה	Economy	-	Literature
135.	בשר	-	ביצה	Egg	-	Meat
136.	אלמוג	-	כריש	Shark	-	Coral
137.	קיר	-	גג	Roof	-	Wall
138.	קנאה	-	תמהון	Amazement	-	Jealous

139.	דוגית - מעבורת	Dinghy - Ferry
140.	קיטבג - מזוודה	Kitbag - Suitcase
141.	ציפורן - שיער	Hair - Nail
142.	סרנדה - קונצרט	Serenade - Concert
143.	אסימון - אגורה	Token - Penny
144.	תוף - חצוצרה	Drum - Trumpet

Experiment 4: A Semantic Boost for Episodic Association

1.	גמל - פרה	Camel - Cow
2.	יער - שדה	Forest - Field
3.	ענב - זית	Grape - Olive
4.	מרק - חלב	Soup - Milk
5.	נשק - חרב	Weapon - Sword
6.	זמר - טבח	Singer - Cook
7.	סלק - גזר	Beet - Carrot
8.	רגל - זנב	Foot - Tail
9.	עגל - כלב	Calf - Dog
10.	אגס - שסק	Pear - Loquat

Experiment 5: A Semantic Boost – Forced Choice Paradigm

List A:

Semantically unrelated pairs:

1.	משרד - צמיד	Office - Bracelet
2.	נענע - משורר	Mint - Poet
3.	חצוצרה - אשוח	Trumpet - Fir
4.	מעיל - גיטרה	Coat - Guitar
5.	מחרוזת - תות	String - Strawberry
6.	דקל - מסדר	Palm tree - Parade
7.	מצעד - אורגנו	March - Oregano
8.	צייר - ארנק	Painter - Wallet
9.	אגס - שמלה	Pear - Dress
10.	יתוש - משי	Mosquito - Silk
11.	צמר - פרפר	Wool - Butterfly

12.	חנות	-	תרמיל	Bag	-	Store

Semantically related pairs:

1.	פרה	-	גמל	Camel	-	Cow
2.	אקדח	-	תותח	Cannon	-	Pistol
3.	חשמל	-	דלק	Fuel	-	Electricity
4.	גג	-	קיר	Wall	-	Roof
5.	גבינה	-	שוקולד	Chocolate	-	Cheese
6.	שרב	-	שלג	Snow	-	Heat wave
7.	רופא	-	שופט	Judge	-	Doctor
8.	פוקר	-	דמקה	Checkers	-	Poker
9.	סודה	-	שוקו	Hot Chocolate	-	Soda
10.	גלולה	-	משחה	Ointment	-	Peel
11.	אבוקדו	-	גזר	Carrot	-	Avocado
12.	בובה	-	כדור	Ball	-	Doll

List B (Counter-Balanced):

Semantically unrelated pairs:

1.	פרה	-	כדור	Ball	-	Cow
2.	אקדח	-	משחה	Ointment	-	Pistol
3.	חשמל	-	גזר	Carrot	-	Electricity
4.	גג	-	שלג	Snow	-	Roof
5.	גבינה	-	גמל	Camel	-	Cheese
6.	שרב	-	תותח	Cannon	-	Heat wave
7.	רופא	-	שוקולד	Chocolate	-	Doctor
8.	פוקר	-	דלק	Fuel	-	Poker
9.	סודה	-	שופט	Judge	-	Soda
10.	גלולה	-	דמקה	Checkers	-	Peel
11.	אבוקדו	-	קיר	Wall	-	Avocado
12.	בובה	-	שוקו	Hot chocolate	-	Doll

Semantically related pairs:

1.	צמיד	-	מחרוזת	String	-	Bracelet
2.	משורר	-	צייר	Painter	-	Poet
3.	אשוח	-	דקל	Palm tree	-	Fir tree

4.	גיטרה	-	חצוצרה	Trumpet	-	Guitar
5.	תות	-	אגס	Pear	-	Strawberry
6.	מסדר	-	מצעד	March	-	Parade
7.	אורגנו	-	נענע	Mint	-	Oregano
8.	ארנק	-	תרמיל	Bag	-	Wallet
9.	שמלה	-	מעיל	Coat	-	Dress
10.	משי	-	צמר	Wool	-	Silk
11.	פרפר	-	יתוש	Mosquito	-	Butterfly
12.	חנות	-	משרד	Office	-	Store

Experiment 6: Implicit Asymmetry

Semantically unrelated pairs:

Forward:

1.	צינור	-	תנוך	Lobe	-	Pipe
2.	מטפחת	-	מטאטא	Broom	-	Kerchief
3.	אגודל	-	חדק	Trunk	-	Thumb
4.	זנב	-	הלצה	Joke	-	Tail
5.	עיפרון	-	פעמון	Bell	-	Pencil
6.	מעדר	-	שלולית	Puddle	-	hoe
7.	גלידה	-	גיר	Chalk	-	Ice-cream
8.	קריצה	-	ממטרה	Sprinkler	-	Wink
9.	דייסה	-	מחרוזת	Necklace	-	Porridge
10.	דודה	-	דבורה	Bee	-	aunt
11.	אקורדיון	-	איבה	Loathing	-	Accordion
12.	צופר	-	נכד	Grandson	-	Siren

Backward:

1.	סוכרייה	-	בוז	Scorn	-	Candy
2.	עברית	-	אגם	Lake	-	Grammar
3.	נקניקיה	-	קרחת	Bold	-	Sausage
4.	סנדלר	-	חשבון	Arithmetic	-	Shoemaker
5.	אלומיניום	-	יתוש	Mosquito	-	Aluminum
6.	מצילתיים	-	מטבח	Kitchen	-	Drums

7.	בלורית	-	זהב	Gold	-	Forelock
8.	אמבטיה	-	קרקס	Circus	-	Bath
9.	תאטרון	-	איכר	Farmer	-	Theater
10.	אוניה	-	צבא	Army	-	Boat
11.	טלפון	-	אוטובוס	Bus	-	Cucumber
12.	מדינה	-	טלוויזיה	Television	-	State

Semantically related pairs:

Forward:

1.	צופר	-	פעמון	Bell	-	Siren
2.	עיפרון	-	גיר	Chalk	-	Pencil
3.	דודה	-	נכד	Grandson	-	Aunt
4.	אגם	-	שלולית	Puddle	-	Lake
5.	צינור	-	ממטרה	Sprinkler	-	Pipe
6.	חשבון	-	עברית	Grammar	-	Arithmetic
7.	קריצה	-	הלצה	Joke	-	Winkle
8.	אוטובוס	-	אוניה	Boat	-	Bus
9.	איכר	-	סנדלר	Shoemaker	-	Farmer
10.	מטבח	-	אמבטיה	Bath	-	Kitchen
11.	זהב	-	אלומיניום	Aluminum	-	Gold
12.	קרחת	-	בלורית	Forelock	-	Bold

Backward:

1.	נקניקיה	-	דייסה	Porridge	-	Sausage
2.	מטאטא	-	מעדר	Hoe	-	Broom
3.	תנוך	-	אגודל	Thumb	-	Lobe
4.	תאטרון	-	קרקס	Circus	-	Theater
5.	חדק	-	זנב	Tail	-	Truck
6.	איבה	-	בוז	Scorn	-	Loathing
7.	מדינה	-	צבא	Army	-	State
8.	סוכרייה	-	גלידה	Ice-cream	-	Candy
9.	מחרוזת	-	מטפחת	Kerchief	-	Necklace
10.	מצילתיים	-	אקורדיון	Accordion	-	Drums
11.	טלפון	-	טלוויזיה	Television	-	Telephone

12.	יתוש - דבורה	Mosquito - Bee

Experiment 7: Implicitly Mediated Associations – Cued Recall

List A:

Intensive:

Same:

1.	סיר - ספר	Pot - Book
2.	שיר - כלב	Song - Dog
3.	שלג - אריה	Snow - Lion
4.	חולצה - טלויזיה	Shirt - Television
5.	קפה - שמש	Coffee - Sun
6.	דלת - הר	Door - Mountain

Different:

1.	אוניה - עגבניה	Boat - Tomato
2.	פטיש - עט	Hammer - Pen
3.	יד - ים	Hand - Sea
4.	לחם - זהב	Bread - Gold
5.	שולחן - רובה	Table - Rifle
6.	כדורגל - ילד	Football - Boy

Target:

Same:

1.	מחבת - מחברת	Pan - Notebook
2.	סיפור - חתול	Story - Cat
3.	ברד - נמר	Hail - Tiger
4.	מכנסיים - רדיו	Pants - Radio
5.	תה - ירח	Tea - Moon
6.	חלון - גבעה	Window - Hill

Different:

1.	סירה - ילדה	Boat - Girl
2.	מסמר - מלפפון	Nail - Cucumber
3.	רגל - עיפרון	Leg - Pencil
4.	חמאה - בריכה	Butter - Pool

5.	כסא - כסף	Chair - Silver
6.	כדורסל - אקדח	Basketball - Pistol

List B (Counter-Balanced):

Intensive:

Same:

1.	סיר - כלב	Pot - Dog
2.	שיר - אריה	Song - Lion
3.	שלג - טלויזיה	Snow - Television
4.	חולצה - שמש	Shirt - Sun
5.	קפה - הר	Coffee - Mountain
6.	דלת - ספר	Door - Book

Different:

1.	אוניה - ילד	Boat - Boy
2.	פטיש - עגבניה	Hammer - Tomato
3.	יד - עט	Hand - Pen
4.	לחם - ים	Bread - Sea
5.	שולחן - זהב	Table - Gold
6.	כדורגל - רובה	Football - Rifle

Target:

Same:

1.	מחבת - מחברת	Pan - Notebook
2.	סיפור - חתול	Story - Cat
3.	ברד - נמר	Hail - Tiger
4.	מכנסיים - רדיו	Pants - Radio
5.	תה - ירח	Tea - Moon
6.	חלון - גבעה	Window - Hill

Different:

1.	סירה - ילדה	Boat - Girl
2.	מסמר - מלפפון	Nail - Cucumber
3.	רגל - עיפרון	Leg - Pencil
4.	חמאה - בריכה	Butter - Pool

5.	כסף	-	כסא	Chair	-	Silver
6.	אקדח	-	כדורסל	Basketball	-	Pistol

Experiment 8: Implicitly Mediated Associations – Reaction Time

Study:

List A:

1.	סיר	-	ספר	Book	-	Pot
2.	שיר	-	לחם	Bread	-	Song
3.	שלג	-	אריה	Lion	-	Snow
4.	חולצה	-	טלויזיה	Television	-	Shirt
5.	קפה	-	שמש	Sun	-	Coffee
6.	דלת	-	הר	Mountain	-	Door
7.	אוניה	-	אבא	Father	-	Boat
8.	פטיש	-	עגבניה	Tomato	-	Hammer
9.	יד	-	עט	Pen	-	Hand
10.	כלנית	-	ים	Sea	-	Anemone
11.	שולחן	-	זהב	Gold	-	Table
12.	כדורגל	-	רובה	Rifle	-	Football
13.	כפר	-	אופנוע	Motorcycle	-	Village
14.	מדורה	-	משרד	Office	-	Bonfire
15.	סנדלר	-	שרשרת	Chain	-	Shoemaker
16.	שמיכה	-	תפוח	Apple	-	Blanket

List B (Counter-Balanced):

1.	שמיכה	-	ספר	Book	-	Blanket
2.	סיר	-	לחם	Bread	-	Pot
3.	שיר	-	אריה	Lion	-	Song
4.	שלג	-	טלויזיה	Television	-	Snow
5.	חולצה	-	שמש	Sun	-	Shirt
6.	קפה	-	הר	Mountain	-	Coffee
7.	דלת	-	אבא	Father	-	Door
8.	אוניה	-	עגבניה	Tomato	-	Boat
9.	פטיש	-	עט	Pen	-	Hammer

10.	ים - יד	Sea - Hand
11.	זהב - כלנית	Gold - Anemone
12.	רובה - שולחן	Rifle - Table
13.	אופנוע - כדורגל	Motorcycle - Football
14.	משרד - כפר	Office - Village
15.	שרשרת - מדורה	Chain - Bonfire
16.	תפוח - סנדלר	Apple - Sandal

Test:

Unrelated:

Part 1 (*Same* – for study list A, *Different* – for study list B)

1.	מחבת - מחברת	Pan - Notebook
2.	פיתה - סיפור	Pita-bread - Story
3.	נמר - ברד	Hail - Tiger
4.	רדיו - מכנסיים	Radio - Pants
5.	ירח - תה	Moon - Tea
6.	גבעה - חלון	Hill - Window
7.	אח - סירה	Brother - Dinghy
8.	מלפפון - מסמר	Cucumber - Nail
9.	עפרון - רגל	Pencil - Leg
10.	בריכה - ורד	Pool - Rose
11.	כסף - כסא	Silver - Chair
12.	אקדח - כדורסל	Pistol - Basketball
13.	אוטובוס - עיר	Bus - City
14.	מפעל - אש	Factory - Fire
15.	צמיד - נגר	Bracelet - Carpenter
16.	אגס - סדין	Pear - Sheet

Part 2 (*Same* – for study list B, *Different* – for study list A)

1.	דפדפת - כרית	Loose-leaves - Pillow
2.	לחמנייה - קערה	Bun - Bowl
3.	פנתר - אגדה	Panther - Legend
4.	עיתון - גשם	Newspaper - Rain
5.	כוכב - גופיה	Star - Undershirt

6.	שוקו	-	תל	Barrow	-	Hot-chocolate
7.	קיר	-	אמא	Mother	-	Wall
8.	צוללת	-	גזר	Carrot	-	Submarine
9.	מסור	-	טוש	Saw	-	Marker
10.	אצבע	-	אגם	Lake	-	Finger
11.	שושנה	-	פלטינה	Platinum	-	Rose
12.	ארון	-	מקלע	Machine-gun	-	Cupboard
13.	כדוריד	-	מכונית	Handball	-	Car
14.	קיבוץ	-	חנות	Shop	-	Kibbutz
15.	שריפה	-	טבעת	Ring	-	Fire
16.	חייט	-	תפוז	Orange	-	Tailor

Related:

1.	כף	-	מזלג	Fork	-	Spoon
2.	דשא	-	שיח	Bush	-	Grass
3.	דבורה	-	יתוש	Mosquito	-	Bee
4.	סנדל	-	מגף	Boot	-	Sandal
5.	סבון	-	שמפו	Shampoo	-	Soap
6.	מדרכה	-	כביש	Road	-	Pavement
7.	חבל	-	חוט	String	-	Rope
8.	מטאטא	-	מגב	Squeegee	-	Broom
9.	פלפל	-	אורגנו	Oregano	-	Pepper
10.	גרניט	-	שיש	Marble	-	Granite
11.	דחיפה	-	סטירה	Slap	-	Push
12.	ספל	-	כוס	Cup	-	Mug
13.	מיקרופון	-	רמקול	Loudspeaker	-	Microphone
14.	תינוק	-	ילד	Boy	-	Baby
15.	גבינה	-	חמאה	Butter	-	Cheese
16.	חמור	-	פרה	Cow	-	Donkey
17.	טיח	-	סיד	Pan	-	Notebook
18.	יממה	-	חודש	Month	-	Day
19.	מדפסת	-	מקלדת	Keyboard	-	Printer
20.	אוגר	-	שפן	Coney	-	Hamster

21.	מנורה - פנס	Flashlight - Lamp
22.	מצית - גפרור	Match - Lighter
23.	פסנתר - גיטרה	Guitar - Piano
24.	דאון - מסוק	Helicopter - Glider
25.	קוניאק - ויסקי	Whiskey - Cognac
26.	סורג - מנעול	Lock - Grate
27.	עורב - יונה	Dove - Crow
28.	בית - דירה	Apartment - House
29.	אדמה - חול	Send - Soil
30.	תה - חלב	Milk - Tea
31.	מברק - מעטפה	Envelope - Telegram
32.	זריחה - דמדומים	Twilight - Sunrise

Appendix B – MatLab Code

The Function Organize

```
%function [output] = organize()
close all;
clear all;
output=1;

rand('state', sum(100*clock))

% ---------- General Documentation ----------
% Organizing SOM in 2 stages.

pack
load kid_sub

% ---------- Parameters ----------
semantic_map_size = 40       % size of the square semantic map
display_step = 8*num_words;            % VISUALIZATION: after how
many steps to update the figure on the screen
t_max1 = semantic_map_size*num_words;   % # of iterations in 1st
organization stage
t_max2 = 3*semantic_map_size*num_words; % # of over all iterations
neighb_size1_i = semantic_map_size;     % initial "radius" of
neighborhood
neighb_size1_f = 3;% final "radius" of neighborhood for 1st stage
neighb_size2_i = neighb_size1_f;        % initial "radius" of
neighborhood for the second stage
neighb_size2_f = 0;          % final "radius" of neighborhood
epsilon = 0.5;               % base learning rate
init_w = 0.2;                % initial maximal size of the weights

% ---------- Data ----------
w = init_w.*rand(semantic_map_size, semantic_map_size,
size(attributes,1)); % the initial random weights of the SOM

% VISUALIZATION: Prepare the figure
figure(1);
set(1,'Units','normalized');
set(1, 'Position',[0.1 0.1 0.8 0.8]);
set(1, 'color','w');
colormap(white);
image(ones(semantic_map_size,semantic_map_size,3));
axis off;
title('Semantic Map');
hnd_t =
text(0.25,0.25,num2str(0),'HorizontalAlignment','center','color','
b','fontsize',10,'EraseMode','xor');
% Calculate the semantic map
for word = 1:num_words, % for each item find which is the most
responsive node (MAX of dot product of Wij and input vector)
   input = attributes(:,word);
   for i = 1:size(input),
      input_mat(:,:,i) = input(i)*ones(semantic_map_size);
   end
   [y,row] = max(sum(input_mat.*w,3),[],1);
```

```
   [y,col] = max(y);
   row=row(col);
   hnd(word) =
text(col,row,char(words(word)),'HorizontalAlignment','center','col
or','b','fontsize',8,'EraseMode','xor');
end
drawnow;

% -- Self-Organizing Learning - Phase I - Gross Organization----
for t = 1:t_max1,
   t
   input = attributes(:,ceil(rand*num_words)); % take as the
current input one column from the input matrix randomly
% create a matrix of the size of w where each column contains the
input vector that was selected, to make the w.x more elegant
   input_mat = shiftdim(input',-1);
   input_mat =
input_mat(ones(1,semantic_map_size),ones(1,semantic_map_size),:);
   [y,row] = max(sum(input_mat.*w,3),[],1);         % perform the
dot matrix for each node and find the maximal response
   [y,col] = max(y);
   row=row(col);
   neighb = round(neighb_size1_i - (neighb_size1_i -
neighb_size1_f)*t/t_max1);
   for i = max(1,row-neighb):min(semantic_map_size,row+neighb), %
for each node in the neighborhood do...
      for j = max(1,col-neighb):min(semantic_map_size,col+neighb),
         d2 = (i-row)^2+(j-col)^2;                 % compute the
distance between current node and the winner node
         h = 1-d2/(2*neighb^2);                    % compute the
neighborhood function
         w(i,j,:) = squeeze((1-epsilon*h)*w(i,j,:)) +
epsilon*h*(input); % Kohonen learning rule
      end
   end
%%%% USE FOR LONG PROCESS
%   if mod(t,display_step)==0
%      save big_map t num_words semantic_map_size words w;
%      save big_mapCPY t num_words semantic_map_size words w;
%   end
% VISUALIZATION: Calculate the semantic map
   if mod(t,display_step)==0
      set(hnd_t,'string',num2str(t));
      for word = 1:num_words,
         input = attributes(:,word);
         for i = 1:size(input),
            input_mat(:,:,i) = input(i)*ones(semantic_map_size);
         end
         [y,row] = max(sum(input_mat.*w,3),[],1);
         [y,col] = max(y);
         row=row(col);
         set(hnd(word),'position',[col row]);
      end
      drawnow;
   end
end

% --------- Self-Organizing Learning - Phase II - Fine Tunning --
for t = t_max1+1:t_max2,
```

```
   t
   input = attributes(:,ceil(rand*num_words)); % take as the
current input one column from the input matrix randomly
% create a matrix of the size of w where each column contains the
input vector that was selected, to make the w.x more elegant
   input_mat = shiftdim(input',-1);
   input_mat =
input_mat(ones(1,semantic_map_size),ones(1,semantic_map_size),:);
   [y,row] = max(sum(input_mat.*w,3),[],1);         % perform the
dot matrix for each node and find the maximal response
   [y,col] = max(y);
   row=row(col);
   neighb = round(neighb_size2_i - (neighb_size2_i -
neighb_size2_f)*(t-t_max1)/(t_max2-t_max1));
   for i = max(1,row-neighb):min(semantic_map_size,row+neighb), %
for each node in the neighborhood do...
      for j = max(1,col-neighb):min(semantic_map_size,col+neighb),
         d2 = (i-row)^2+(j-col)^2;                  % compute the
distance between current node and the winner node
         h = 1-d2/(2*neighb^2+0.0000000000001);    % compute the
neighborhood function (the small constant is added to prevent
division by zero)
         w(i,j,:) = squeeze((1-epsilon*h)*w(i,j,:)) +
epsilon*h*(input); % Kohonen learning rule
      end
   end
%%%% USE FOR LONG PROCESS
%   if mod(t, display_step)==0
%      save big_map t num_words semantic_map_size words w;
%      save big_mapCPY t num_words semantic_map_size words w;
%   end
   % VISUALIZATION: Calculate the semantic map
   if mod(t, display_step)==0
      set(hnd_t,'string',num2str(t));
      for word = 1:num_words,
         input = attributes(:,word);
         for i = 1:size(input),
            input_mat(:,:,i) = input(i)*ones(semantic_map_size);
         end
         [y,row] = max(sum(input_mat.*w,3),[],1);
         [y,col] = max(y);
         row=row(col);
         set(hnd(word),'position',[col row]);
      end
      drawnow;
   end
end

% ---------- VISUALIZATION: Display of Results ----------
set(hnd_t,'string',num2str(t));
for word = 1:num_words,
   input = attributes(:,word);
   for i = 1:size(input),
      input_mat(:,:,i) = input(i)*ones(semantic_map_size);
   end
   [y,row] = max(sum(input_mat.*w,3),[],1);
   [y,col] = max(y);
   row=row(col);
   semantic_map(row,col) = words(word);
```

```
   set(hnd(word),'position',[col row]);
end
drawnow;
semantic_map

words_not_mapped = 0;
if num_words ~= size(semantic_map(find(1-
cellfun('isempty',semantic_map)))',2)
   words_not_mapped = 1;
   fprintf('\nSOME WORDS WERE NOT MAPPED !!!\n\n');
   for i=1:num_words
      word1pos = get(hnd(i),'position');
      for j=1:i-1
         word2pos = get(hnd(j),'position');
         if word1pos(1,1:2,1)==word2pos(1,1:2,1)
            fprintf('Both word #%.0f %s and word #%.0f %s are
located at (%.0f,%.0f).\n',...

i,upper(char(words(i))),j,upper(char(words(j))),word1pos(1,2,1),wo
rd1pos(1,1,1));
         end
      end
   end
end

new_words = semantic_map(find(1-
cellfun('isempty',semantic_map)))';
num_words = size(new_words,2);
new_att = zeros(size(attributes,1),num_words);
for i=1:num_words
   new_att(:,i) = attributes(:,find(strcmp(new_words(i),words)));
end

words = new_words;
attributes = new_att;

save big_map t num_words semantic_map words w attributes
words_not_mapped;
save big_mapCPY t num_words semantic_map words w attributes
words_not_mapped;

% Zoom in
%init_axis = axis;
%button = questdlg('Would you like to rescale the map or
exit?','EpiSim','Rescale','Exit','Rescale');
%while strcmp(button,'Rescale'),
%   waitforbuttonpress;
%   finalRect = rbbox;
%   xmin = floor(finalRect(1) .* semantic_map_size) + 0.5;
%   xmax = ceil((finalRect(1) + finalRect(3)) .*
semantic_map_size) + 0.5;
%   ymin = floor(((1-finalRect(2)) - finalRect(4)) .*
semantic_map_size) + 0.5;
%   ymax = ceil((1-finalRect(2)) .* semantic_map_size) + 0.5;
%   axis([xmin xmax ymin ymax]);
%
%   waitforbuttonpress;
%   axis(init_axis);
%
```

```
%   button = questdlg('Would you like to rescale the map again or
exit?','EpiSim','Rescale','Exit','Rescale');
%end
```

The Function Learning

```
%function [output] = learning()
clear all;
pack;
output=1;

% ---------- General Documentation ----------
%This program simulates the spreading activation from two words
%and the formation of episodic associations between them as the
%sum of overlapping activity.

% ---------- Parameters ----------

SOA = 3;
t_max = 8;
forget = 0;

%sem_sft = 0.02;  %NORMALS
sem_sft = 0.04   %SCHIZO El
sem_slp = 100    %NORMALS
%sem_slp = 7      %SCHIZO SHAL
sem_amp = 1      %NORMALS
%sem_amp = 1.2048 %SCHIZO El
%sem_amp = 0.0721 %SCHIZO Sh #1 7
%sem_amp = 0.0836 %SCHIZO Sh #2 7
%sem_amp = 0.0821 %SCHIZO Sh #3 7
%sem_amp = 0.086  %SCHIZO Sh #4 7
%sem_amp = 0.0838 %SCHIZO Sh #5 7
%sem_amp = 0.0843 %SCHIZO Sh #6 7
%sem_amp = 0.069  %SCHIZO Sh #7 7
%sem_amp = 0.0728 %SCHIZO Sh #8 7
%sem_amp = 0.0758 %SCHIZO Sh #9 7
%sem_amp = 0.0742 %SCHIZO Sh #10 7
%sem_amp = 0.0743 %SCHIZO Sh #11 7
%sem_amp = 0.0891 %SCHIZO Sh #12 7

bub_rad = 98;
bub_slp = 70;
bub_amp = 0.2;

epis_factor = 0.005;
think_epis = 0;

dist2Dwght = 0;

% ---------- Data ----------
fid = fopen('insert-lrn.txt');
num_of_pairs = fscanf(fid,'%i',1);
num_of_reps = fscanf(fid,'%i',1);
num_of_trials = num_of_pairs*num_of_reps;
fprintf('\n%.0f pairs x %.0f repetitions = %.0f trials.   SOA =
%.0f.\n',num_of_pairs,num_of_reps,num_of_trials,SOA);
%fseek(fid, 2, 0);
load big_map semantic_map w num_words words attributes;
```

```
semantic_map_size = size(semantic_map,1);
episodic =
zeros(semantic_map_size,semantic_map_size,semantic_map_size,semant
ic_map_size);
sem_empty=cellfun('isempty',semantic_map);
sem_ind = find(sem_empty==0);
[sem_dbl_ind1,sem_dbl_ind2] = find(sem_empty==0);
shrt_sem_map = char(semantic_map(sem_ind));
shrt_sem_map = cellstr(shrt_sem_map(:,1:5));

% calculate the all-to-all semantic distances between the nodes of
the map
% 100D distance - All vectorized version
%temp1 = shiftdim(w,-2);
%temp2 =
temp1(ones(1,semantic_map_size),ones(1,semantic_map_size),:,:,:);
%temp3 =
permute(temp1(ones(1,semantic_map_size),ones(1,semantic_map_size),
:,:,:),[3 4 1 2 5]);
%dist100D = squeeze(sum(((temp2-temp3).^2),5));

% 100D distance - Semi-vectorized version
fprintf('\nPreparing Data... %3.0f%%',0);
dist100D =
zeros(semantic_map_size,semantic_map_size,semantic_map_size,semant
ic_map_size);
for i = 1:semantic_map_size
   for j = 1:semantic_map_size
      temp =
w(i*ones(1,semantic_map_size),j*ones(1,semantic_map_size),:);
      dist100D(i,j,:,:) = squeeze(sum((temp-w).^2,3));
%       fprintf('\b\b\b\b%3.0f%%',100*((i-
1)*semantic_map_size+j)/(semantic_map_size^2));
   end
end
fprintf('\b\b\b\bDone\n');

% 2D distance
%temp4 = [1:semantic_map_size];
%temp5 = temp4';
%tempi =
temp5(:,ones(1,semantic_map_size),ones(1,semantic_map_size),ones(1
,semantic_map_size));
%tempu = shiftdim(tempi,2);
%tempj =
temp4(ones(1,semantic_map_size),:,ones(1,semantic_map_size),ones(1
,semantic_map_size));
%tempv = shiftdim(tempj,2);
%dist2D = (tempi-tempu).^2+(tempj-tempv).^2;
%dist2D = dist2D./max(max(max(max(dist2D))));
%clear temp*;
%semantic = sem_amp/(1+exp(( dist2Dwght*dist2D+(1-
dist2Dwght)*dist100D - sem_sft)*sem_slp));

semantic = sem_amp/(1+exp((dist100D-sem_sft)*sem_slp));

clear temp* dist*
pack;
```

```
% locate the word-pairs
for trial = 1:num_of_pairs
   l_prm(trial) = cellstr(fscanf(fid,'%s',1));
   tmp = fscanf(fid,'%1c',1);
   l_tgt(trial) = cellstr(fgetl(fid));
   [l_prm_loc(trial,1),l_prm_loc(trial,2)] =
find(strcmp(l_prm(trial),semantic_map));
   [l_tgt_loc(trial,1),l_tgt_loc(trial,2)] =
find(strcmp(l_tgt(trial),semantic_map));
   [l_prm_ind(trial,1),l_prm_ind(trial,2)] =
find(strcmp(l_prm(trial),words));
   [l_tgt_ind(trial,1),l_tgt_ind(trial,2)] =
find(strcmp(l_tgt(trial),words));
end
save loc l_prm_loc l_tgt_loc
% replicate pairs for number of repetitions
l_prm = l_prm(:,ones(1,num_of_reps)'*[1:num_of_pairs]);
l_tgt = l_tgt(:,ones(1,num_of_reps)'*[1:num_of_pairs]);
l_prm_loc = l_prm_loc(ones(1,num_of_reps)'*[1:num_of_pairs],:);
l_tgt_loc = l_tgt_loc(ones(1,num_of_reps)'*[1:num_of_pairs],:);
l_prm_ind = l_prm_ind(ones(1,num_of_reps)'*[1:num_of_pairs],:);
l_tgt_ind = l_tgt_ind(ones(1,num_of_reps)'*[1:num_of_pairs],:);

% randomize the trials
%perm = randperm(num_of_trials);
%l_prm = l_prm(perm);
%l_tgt = l_tgt(perm);
%l_prm_loc = l_prm_loc(perm,:);
%l_tgt_loc = l_tgt_loc(perm,:);
%l_prm_ind = l_prm_ind(perm,:);
%l_tgt_ind = l_tgt_ind(perm,:);

% VISUALIZATION: prepare the 3 activation images
figHND = figure;
set(figHND,'units','normalized','position',[0.3 0.07 0.4 0.85]);
sp1HND = subplot(3,1,1);
im1HND = image(zeros(semantic_map_size));
text(semantic_map_size+2,-
4,'Time','HorizontalAlignment','center','color','k','fontsize',6,'
EraseMode','xor');
text(-1,-
4,'Trial','HorizontalAlignment','center','color','k','fontsize',6,
'EraseMode','xor');
tHND = text(semantic_map_size+2,-
2,num2str(0),'HorizontalAlignment','center','color','k','fontsize'
,6,'EraseMode','xor');
trHND = text(-1,-
2,num2str(0),'HorizontalAlignment','center','color','k','fontsize'
,6,'EraseMode','xor');
tx1HND =
text(sem_dbl_ind2,sem_dbl_ind1,shrt_sem_map,'HorizontalAlignment',
'center','color','w','fontsize',5,'EraseMode','none');
axis off;
tl1HND = title('','fontsize',7);
set(im1HND,'erasemode','none');
sp2HND = subplot(3,1,2);
im2HND = image(zeros(semantic_map_size));
```

```
         tmp = prm_act(:,:,t);
         bub_sft = prctile(tmp(:),bub_rad);
         prm_act(:,:,t) = bub_amp./(1+exp(-((prm_act(:,:,t)-
bub_sft)*bub_slp))); % Use logsig to narrow the activity bubble
      else
         % for each node make one step of the prime activation and
one step for the target activation
         prm_act(:,:,t) =
act_step(prm_act,t,t,semantic,episodic,think_epis);
         tgt_act(:,:,t) = act_step(tgt_act,t,t-
SOA+1,semantic,episodic,think_epis);
      end
      if t==SOA
         input = attributes(:,l_tgt_ind(trial,2));
         input_mat = shiftdim(input',-1); % create a matrix of the
size of w where each column contains "input", to vectorize the w.x
         input_mat =
input_mat(ones(1,semantic_map_size),ones(1,semantic_map_size),:);
         tgt_act(:,:,t) = sum(input_mat.*w,3);
% perform the dot matrix for each node
%         bub_sft = (1-bub_rad)*max(max(tgt_act(:,:,t)));
         tmp = tgt_act(:,:,t);
         bub_sft = prctile(tmp(:),bub_rad);
         tgt_act(:,:,t) = bub_amp./(1+exp(-((tgt_act(:,:,t)-
bub_sft)*bub_slp))); % Use logsig to narrow the activity bubble
      end
      % add the sum of mutual activation to the episodic assoc of
this pair

episodic(l_prm_loc(trial,1),l_prm_loc(trial,2),l_tgt_loc(trial,1),
l_tgt_loc(trial,2)) =...

episodic(l_prm_loc(trial,1),l_prm_loc(trial,2),l_tgt_loc(trial,1),
l_tgt_loc(trial,2)) + ...
         epis_factor *
sum(sum(min(prm_act(:,:,t),tgt_act(:,:,t))));
      % VISUALIZATION: update the activation images
      set(tHND,'string',num2str(t));
      set(tx1HND,'visible','off');
      set(im1HND,'cdata',prm_act(:,:,t)*63+1);
      set(tx1HND,'visible','on');
      set(tx2HND,'visible','off');
      set(im2HND,'cdata',tgt_act(:,:,t)*63+1);
      set(tx2HND,'visible','on');
      set(tx3HND,'visible','off');

set(im3HND,'cdata',min(prm_act(:,:,t),tgt_act(:,:,t)).*63+1);
      set(tx3HND,'visible','on');
      drawnow;
   end
   episodic = episodic*(1-forget);
end

save epis episodic semantic

close all;

% VISUALIZATION: Display the episodic map
```

```
% calculate the episodic map
%for i = 1:num_words
%   for j = 1:num_words
%       [i_loc(1),i_loc(2)] = find(strcmp(words(i),semantic_map));
%       [j_loc(1),j_loc(2)] = find(strcmp(words(j),semantic_map));
%       episodic_map(i,j) =
round(episodic(i_loc(1),i_loc(2),j_loc(1),j_loc(2)));
%   end
%end

%% display the episodic map
%figHND = figure;
%set(figHND,'units','normalized','position',[0.3 0.3 0.4 0.4]);
%image(zeros(size(episodic_map)));
%title('Episodic Map');
%axis off;
%text(-2,-1,'PRIME', 'HorizontalAlignment', 'right', 'color', 'k',
'fontsize', 7);
%for i = 1:size(words,2),
%   text(-2,i,char(words(i)), 'HorizontalAlignment', 'right',
'color', 'k', 'fontsize', 7);
%end
%text(size(words,2)+1,size(words,2)+2,'TARGET',
'HorizontalAlignment', 'left', 'color', 'k', 'fontsize', 7);
%for i = 1:size(words,2),
%   text(i,size(words,2)+1,char(words(i)), 'HorizontalAlignment',
'left', 'color', 'k', 'fontsize', 7, 'rotation', 270);
%end
%for i = 1:size(words,2)
%   for j = 1:size(words,2)
%       if episodic_map(i,j)>0
%           text(j,i,num2str(episodic_map(i,j)),
'HorizontalAlignment', 'center', 'color', 'w', 'fontsize', 7);
%       end
%   end
%end
```

The Function Testing

```
%function [output] = testing()
clear all;
pack;
output=1;

% ---------- General Documentation ----------
%This program simulates the spreading activation from a prime word
which
%takes into account both semantic and episodic associations and
search
%for the first association which is the first word that
%reach some activation level.

% ---------- Parameters ----------
num_of_assoc = 5;
t_max = 8;
recall_thresh = 0.98;

bub_rad = 98;
bub_slp = 70;
bub_amp = 0.2;

think_epis = 1;

repetitions = 20

% ---------- Data ----------
fid = fopen('insert-lrn.txt');
num_of_pairs = fscanf(fid,'%i',1)
num_of_reps = fscanf(fid,'%i',1);
%fseek(fid, 2, 0);
load big_map semantic_map w attributes words;
load epis episodic semantic;
episodic=episodic.*repetitions;
semantic_map_size = size(semantic_map,1);
sem_empty = cellfun('isempty',semantic_map);
sem_ind = find(sem_empty==0);
[sem_dbl_ind1,sem_dbl_ind2] = find(sem_empty==0);
recall_rel=0; recall_unrel=0;
fwid = fopen('testing-res.txt','w');
%fwid = 1;
% loacte the word-pairs
for trial = 1:num_of_pairs
   t_prm(trial) = cellstr(fscanf(fid,'%s',1));
   tmp = fscanf(fid,'%1c',1);
   t_tgt(trial) = cellstr(fgetl(fid));
   [t_prm_loc(trial,1),t_prm_loc(trial,2)] =
find(strcmp(t_prm(trial),semantic_map));
   [t_tgt_loc(trial,1),t_tgt_loc(trial,2)] =
find(strcmp(t_tgt(trial),semantic_map));
   [t_prm_ind(trial,1),t_prm_ind(trial,2)] =
find(strcmp(t_prm(trial),words));
   [t_tgt_ind(trial,1),t_tgt_ind(trial,2)] =
find(strcmp(t_tgt(trial),words));
end
```

```
% VISUALIZATION: prepare the activation image
figHND = figure;
set(figHND,'units','normalized','position',[0.3 0.3 0.4 0.5]);
sb1HND = subplot('position',[0.1 0.2 0.8 0.7]);
imHND = image(zeros(semantic_map_size));
text(semantic_map_size+2,-
4,'Time','HorizontalAlignment','center','color','k','fontsize',6,'
EraseMode','xor');
text(-1,-
4,'Trial','HorizontalAlignment','center','color','k','fontsize',6,
'EraseMode','xor');
tHND = text(semantic_map_size+2,-
2,num2str(0),'HorizontalAlignment','center','color','k','fontsize'
,6,'EraseMode','xor');
trHND = text(-1,-
2,num2str(0),'HorizontalAlignment','center','color','k','fontsize'
,6,'EraseMode','xor');
txHND =
text(sem_dbl_ind2,sem_dbl_ind1,semantic_map(sem_ind),'HorizontalAl
ignment','center','color','w','fontsize',5,'EraseMode','none');
axis off;
tl1HND = title('','FontSize',7);
set(imHND,'erasemode','none');
sb2HND = subplot('position',[0.1 0.1 0.8 0.05]);
im2HND = image([0:0.01:1],'CDataMapping','scaled');
set(sb2HND,'YTick',[],'XTick',[1:10:101],'XTickLabel',([1:10:101]-
1)/100);
tl2HND = title('Legend','FontSize',7);
drawnow;

% ---------- Associative Testing ----------
for trial = 1:num_of_pairs

   prm_act = zeros(semantic_map_size,semantic_map_size,t_max);
   assoc_selected = zeros(semantic_map_size);
   assoc_selected(t_prm_loc(trial,1),t_prm_loc(trial,2)) = 1;
   fprintf(fwid,'\nTrial = %.0f Prime:
%s\n',trial,char(t_prm(trial)));
   % VISUALIZATION: add titles to the images
   set(trHND,'string',num2str(trial));
   set(tl1HND,'string',strcat('Activation of Prime Word:
"',upper(t_prm(trial)),'" Over the Semantic Map'));

   % spreading activation
   t = 0;
   tgt_found = 0;
   tgt_found_flg = 0;
   while (tgt_found < num_of_assoc) & (t < t_max)
      t = t + 1;
      tgt_found_flg = 1;
      if t == 1
         input = attributes(:,t_prm_ind(trial,2));
         input_mat = shiftdim(input',-1); % create a matrix of the
size of w where each column contains "input", to vectorize the w.x
         input_mat =
input_mat(ones(1,semantic_map_size),ones(1,semantic_map_size),:);
         prm_act(:,:,t) = sum(input_mat.*w,3); % perform the dot
matrix for each node
```

```
         tmp = prm_act(:,:,t);
         bub_sft = prctile(tmp(:),bub_rad);
         prm_act(:,:,t) = bub_amp./(1+exp(-((prm_act(:,:,t)-
bub_sft)*bub_slp))); % Use logsig to narrow the activity bubble
      else
         prm_act(:,:,t) =
act_step(prm_act,t,t,semantic,episodic,think_epis);
      end
      while tgt_found < num_of_assoc & tgt_found_flg == 1
         tgt_found_flg = 0;
         tgt_i = 1;
         tgt_j = 1;
         for i = 1:semantic_map_size
            for j = 1:semantic_map_size
               % if {there is a word in (i,j)} and {this word was
not selected already} and {activation(i,j)>thresh} and
               %  {[activation(i,j)>activation(previous target)]
or
               %   [activation(i,j)=activation(previous target)
and assoc of prm and(i,j) > assoc of prm and previous target]}
               %  then new target is (i,j)
               if (sem_empty(i,j) ~= 1) & assoc_selected(i,j)==0 &
prm_act(i,j,t) > recall_thresh &...
                  ((prm_act(i,j,t) > prm_act(tgt_i,tgt_j,t))|...
                   (prm_act(i,j,t) == prm_act(tgt_i,tgt_j,t) &...

(semantic(t_prm_loc(trial,1),t_prm_loc(trial,2),i,j)+think_epis*ep
isodic(t_prm_loc(trial,1),t_prm_loc(trial,2),i,j)) >...

(semantic(t_prm_loc(trial,1),t_prm_loc(trial,2),i,j)+think_epis*ep
isodic(t_prm_loc(trial,1),t_prm_loc(trial,2),tgt_i,tgt_j))))
                  tgt_found_flg = 1;
                  tgt_i = i;
                  tgt_j = j;
               end
            end
         end
         if tgt_found_flg == 1
            tgt_found = tgt_found + 1;
            tgt_row(tgt_found) = tgt_i;
            tgt_col(tgt_found) = tgt_j;
            assoc_selected(tgt_i,tgt_j) = 1;
            fprintf(fwid,'t = %.0f Association:
%s',t,char(semantic_map(tgt_i,tgt_j)));
            if strcmp(semantic_map(tgt_i,tgt_j),t_tgt(trial)) == 1
               fprintf(fwid,' *\n');
               if tgt_found == 1
                  if trial > num_of_pairs/2
                     recall_rel = recall_rel + 1;
                  else
                     recall_unrel = recall_unrel + 1;
                  end
               end
            else
               fprintf(fwid,'\n');
            end
         end
      end
      set(tHND,'string',num2str(t));
```

```
      set(txHND,'visible','off');
      set(imHND,'cdata',prm_act(:,:,t)*63+1);
      set(txHND,'visible','on');
      drawnow;
   end

   % if number of assoc found is too small, output those with the
highest activity
   while tgt_found < num_of_assoc
      max_act_found = 0;
      tgt_found = tgt_found + 1;
      for i = 1:semantic_map_size
         for j = 1:semantic_map_size
            if prm_act(i,j,t) > max_act_found & sem_empty(i,j) ~=
1 & assoc_selected(i,j) == 0
               max_act_found = prm_act(i,j,t);
               tgt_row(tgt_found) = i;
               tgt_col(tgt_found) = j;
            end
         end
      end
      assoc_selected(tgt_row(tgt_found),tgt_col(tgt_found)) = 1;
      fprintf(fwid,'t = %.0f Association:
%s',t,char(semantic_map(tgt_row(tgt_found),tgt_col(tgt_found))));
      if
strcmp(semantic_map(tgt_row(tgt_found),tgt_col(tgt_found)),t_tgt(t
rial)) == 1
         fprintf(fwid,' *\n');
         if tgt_found == 1
            if trial > num_of_pairs/2
               recall_rel = recall_rel + 1;
            else
               recall_unrel = recall_unrel + 1;
            end
         end
      else
         fprintf(fwid,'\n');
      end
   end
end

fprintf(fwid,'\nRecalled Related: %.0f Unrelated:
%.0f\n',recall_rel,recall_unrel);
recall_rel
recall_unrel

% display activity levels over time
%figHND = figure;
%set(figHND,'units','normalized','position',[0.3 0.3 0.4 0.4]);
%hold on;
%for i=1:semantic_map_size,
%   for j=1:semantic_map_size,
%      plot(squeeze(prm_act(i,j,:)));
%   end
%end
%plot(squeeze(mean(mean(prm_act))),'r');

% display the associative distances
% Calculate distances from target word over the sematic map
```

```
%dist_map =
squeeze(semantic(t_prm_loc(1),t_prm_loc(2),:,:)+episodic(t_prm_loc
(1),t_prm_loc(2),:,:));
%dist_map = squeeze(semantic(t_prm_loc(1),t_prm_loc(2),:,:));

%figHND = figure;
%set(figHND,'units','normalized','position',[0.3 0.3 0.4 0.5]);
%sb1HND = subplot('position',[0.1 0.2 0.8 0.7]);
%image(dist_map*63+1);
%title('Associative Distances from the Prime Word Over the
Semantic Map');
%axis off;
%text(sem_dbl_ind2,sem_dbl_ind1,semantic_map(sem_ind),'HorizontalA
lignment','center','color','w','fontsize',9,'EraseMode','none');
%text(t_prm_loc(2),t_prm_loc(1),semantic_map(t_prm_loc(1),t_prm_lo
c(2)), 'HorizontalAlignment', 'center', 'color', 'r',
'fontsize',9);
%sb2HND = subplot('position',[0.1 0.1 0.8 0.05]);
%im2HND = image([0:0.01:1]);
%set(sb2HND,'YTickMode','manual','CLim',[0 1]);
%set(im2HND,'CDataMapping','scaled');
%set(gca,'XTickLabel',[0.1:0.1:1])
%title('Legend');

fclose all;
close all;
```

The Function Act_Step

```
function [output] =
act_step(act,t,elapsed,semantic,episodic,think_epis)

% ---------- Parameters ----------
rfrct_strt    = 3;
rfrct_dur     = 3;
rfrct_factor = 5;

decay_sft     = 6;
decay_slp     = 1.5;

sig_sft       = 0.5;
sig_slp       = 9;

noise = 0;

% ---------- one step of spreading activation for one node -------
in_act = zeros(size(semantic,1));

mint = max(1,t-rfrct_strt-rfrct_dur+1);
maxt = t-rfrct_strt;

if maxt>=mint
   in_act = in_act - sum(act(:,:,mint:maxt),3).*rfrct_factor;
end

temp1 = shiftdim(act(:,:,t-1),-2);
temp2 =
shiftdim(temp1(ones(1,size(semantic,1)),ones(1,size(semantic,1)),:
,:),2);

%noisy links
%in_act = in_act +
squeeze(sum(sum(temp2.*(semantic+think_epis*episodic+noise*randn(s
ize(semantic)))...
%                   /(1+exp((elapsed-decay_sft)*decay_slp)))));

%not-noisy links
in_act = in_act +
squeeze(sum(sum(temp2.*(semantic+think_epis*episodic)...
                  /(1+exp((elapsed-decay_sft)*decay_slp)))));

% implement the neuron's activation function on the output

%linear transfer function
%output = max(0,min(1,in_act));

%sigmoid transfer function (no noise)
output = 1./(1+exp(-(in_act-sig_sft)*sig_slp));

%noisy sigmoid transfer funstion
%output = max(0, noise*randn(1) + 1./(1+exp(-(in_act-
sig_sft)*sig_slp)));
```

The File INSERT-LRN.TXT

```
24
1
necklace vanilla
painting train
van store
guitar cabbage
pear electricity
pepper song
coat violin
office dress
camel roof
oil cow
wall strawberry
carrot bracelet
bag purse
eye chin
butterfly bee
gun stone
lettuce chocolate
snow sunshine
doctor baker
dice cards
coffee soda
bandaid pill
ball doll
desert river
ORIGINAL
necklace vanilla
painting train
van store
guitar cabbage
pear electricity
pepper song
coat violin
office dress
camel roof
oil cow
wall strawberry
carrot bracelet
bag purse
eye chin
butterfly bee
gun stone
lettuce chocolate
snow sunshine
doctor baker
dice cards
coffee soda
bandaid pill
ball doll
desert river
REVERESED ORDER
vanilla necklace
train painting
store van
cabbage guitar
electricity pear
```

```
song pepper
violin coat
dress office
roof camel
cow oil
strawberry wall
bracelet carrot
purse bag
chin eye
bee butterfly
stone gun
chocolate lettuce
sunshine snow
baker doctor
cards dice
soda coffee
pill bandaid
doll ball
river desert
ASYMMETRY FORWARD
painting train
oil cow
bracelet carrot
sunshine snow
doctor baker
desert river
ASYMMETRY BACKWARD
train painting
cow oil
carrot bracelet
snow sunshine
baker doctor
river desert
RELATED PAIRS
necklace bracelet
painting song
van train
guitar violin
pear strawberry
pepper vanilla
coat dress
office store
camel cow
oil electricity
wall roof
carrot cabbage
bag purse
eye chin
butterfly bee
gun stone
lettuce chocolate
snow sunshine
doctor baker
dice cards
coffee soda
bandaid pill
ball doll
desert river
```

Appendix C – Model's Word List

Entire lexicon:

1. address
2. ale
3. answer
4. aquarium
5. back
6. bag
7. baker
8. balance
9. ball
10. band
11. band-aid
12. baseball
13. basement
14. bath
15. bathroom
16. bathtub
17. beard
18. bed
19. bee
20. bend
21. bin
22. birthday
23. blender
24. board
25. boom
26. bracelet
27. branch
28. bump
29. bush
30. butterfly
31. cabbage
32. camel
33. cards
34. carriage
35. carrot
36. castle
37. cheese
38. chin
39. chocolate
40. clay
41. coat
42. coffee
43. coke
44. collection
45. copy
46. cottage
47. cotton
48. counter
49. course
50. cow
51. cowboy
52. crack
53. crown
54. cube
55. dad
56. desert
57. dice
58. direction
59. dish
60. doctor
61. doll
62. dollar
63. door
64. downtown
65. dress
66. dresser
67. drill
68. drop
69. ear
70. earth
71. electricity
72. elevator
73. equipment
74. eye
75. factory
76. fall
77. farm
78. farmer
79. film
80. fireman
81. flag
82. flour
83. fly
84. fruit
85. game
86. garbage
87. gasp

Appendix C – Model's Word List

88. ghost
89. gown
90. group
91. guess
92. guitar
93. gun
94. haircut
95. hammer
96. hamster
97. hand
98. helicopter
99. hippopotamus
100. horse
101. hut
102. ice
103. ice-cream
104. iris
105. ironing
106. jeans
107. jelly
108. job
109. joke
110. jungle
111. key
112. kiss
113. kit
114. knock
115. lamb-chop
116. lasagna
117. letter
118. lettuce
119. lie
120. lollipop
121. machine
122. mail
123. mane
124. marble
125. material
126. math
127. means
128. microphone
129. monster
130. mountain
131. nail
132. nap
133. neck
134. necklace
135. office
136. oil
137. pack
138. page
139. painting
140. pajamas
141. palm
142. panda
143. parade
144. parking
145. part
146. party
147. pause
148. pay
149. pear
150. pepper
151. piano
152. picnic
153. pill
154. pineapple
155. pipe
156. pitch
157. play-dough
158. police
159. popcorn
160. popsicle
161. potato
162. power
163. price
164. prince
165. prize
166. pudding
167. purse
168. raccoon
169. racing
170. railroad
171. rake
172. refrigerator
173. ringing
174. river
175. road
176. robin
177. rock
178. roof
179. rose
180. sack
181. saddle
182. sailor
183. salad
184. scarf
185. school
186. second

187. shape
188. sign
189. slap
190. sleep
191. slide
192. snow
193. soap
194. soda
195. son
196. song
197. soup
198. squash
199. squirrel
200. squirt
201. stairs
202. steam
203. step
204. stew
205. stone
206. store
207. strap
208. straw
209. strawberry
210. string
211. sum
212. sunglasses
213. sunshine
214. sweater
215. sweatshirt
216. syrup
217. table
218. tail
219. temperature
220. throat
221. tick
222. ticket
223. toe
224. towel
225. train
226. trash
227. tree
228. tricycle
229. trouble
230. truth
231. tuba
232. tuna
233. van
234. vanilla
235. violin
236. wall
237. war
238. wash
239. washcloth
240. waste
241. wedding
242. whale
243. wheat
244. whisper
245. wine
246. wire
247. wool
248. worm
249. yawn
250. zoo

Word-pairs used in the simulations:

Semantically related:				Semantically unrelated:			
1.	necklace	-	vanilla	1.	bag	-	purse
2.	painting	-	train	2.	eye	-	chin
3.	van	-	store	3.	butterfly	-	bee
4.	guitar	-	cabbage	4.	gun	-	stone
5.	pear	-	electricity	5.	lettuce	-	chocolate
6.	pepper	-	song	6.	snow	-	sunshine
7.	coat	-	violin	7.	doctor	-	baker
8.	office	-	dress	8.	dice	-	cards
9.	camel	-	roof	9.	coffee	-	soda
10.	oil	-	cow	10.	bandage	-	pill
11.	wall	-	strawberry	11.	ball	-	doll
12.	carrot	-	bracelet	12.	desert	-	river

למודל משוער של הפרעות חשיבה בסכיזופרניה. הניבוי היה שפעילות סמנטית מפוזרת כמו זו המשפיעה על הפרעות מחשבה בסכיזופרניה אמורה להקטין את היתרון בזיווג זוגות קשורים סמנטית על פני זוגות לא קשורים.

במסגרת עבודת מחקר זו, בחנתי את שני הניבויים הראשונים בניסויים פסיכופיזיים נוספים. ניסוי 6 כוון לגלות את הא-סימטריה העקיפה שנובאה על ידי המודל. הזוגות ברשימת הלימוד הורכבו כך שבכל זוג למילה אחת היה מספר גדול יותר של אסוציאציות קדם-ניסוייות מאשר למילה השנייה. קביעה זו הסתמכה על נורמות של אסוציאציות חופשיות. למידת זוגות המילים המוצגים כאשר המילה עם מעט שכנים ראשונה הושוותה ללמידת זוגות המילים המוצגים כאשר המילה עם מספר רב יותר של שכנים ראשונה. כמו בניסויים ההתנהגותיים הקודמים, השתמשתי בלמידה מקרית ומשימת הזכרות מרומזת. התוצאות הראו שוב שמילים קשורות סמנטית זווגו באופן מובהק טוב יותר מזוגות לא קשורים סמנטית. אולם, היתרון שנובא חישובית של זוגות בכיוון "הלוך" על פני זוגות בכיוון "חזור" לא נימצא. אי-ההתאמה בין תוצאות ניסוי 6 והניבוי החישובי יכולה לנבוע מהעובדה שברשימת הלימוד של הניסוי ההתנהגותי צפיפות הסביבה הסמנטית נקבעה בהתבסס על מספר המילים האסוציאטיביות בנורמות של אסוציאציות חופשיות (כלומר, על ידי מידות אפיזודיות) בעוד שבמודל החישובי הסביבה הסמנטית נקבעה על ידי גורמים סמנטיים טהורים. עקב כך, עבודה ניסויית נוספת דרושה על מנת לקבוע את הצורך לשנות את ניבוי המודל והעקרונות הדינמיים שלו. שני ניסויים נוספים (7 ו- 8) הדגימו שכפי שהמודל ניבא, אסוציאציות חזקות בין שני מושגים לא קשורים סמנטית מקלות את היצירה המקרית של קשרים אסוציאטיביים חדשים בין שכנים של המילים עם האסוציאציה החזקה. ניסוי 7 הדגים אפקט זה על ידי שהראה הזכרות מרומזת טובה יותר של אסוציאציות חלשות כאשר זוג המטרה ייצג קטגוריות סמנטיות שקודם לכן קושרו על ידי אסוציאציות חזקות בין מושגים אחרים בקטגוריות אלו. ניסוי 8 הראה שיצירת אסוציאציה אפיזודית חזקה בין מושגים השייכים לקטגוריות סמנטיות שונות הקלה על העיבוד המשותף של זוגות מילים אחרים מאותן קטגוריות והובילה להחלטה סמנטית מהירה יותר, אפילו אם זוג המטרה לא הוצג בשלב הלימוד.

באופן כללי, תוצאות מחקר זה מעשירות את הידע שלנו על תהליך היווצרות אסוציאציות בין מילים. הראיתי, שלמרות שתהליך זה הוא אפיזודי מטבעו, המערכת הסמנטית מעורבת בו. יחד, ממצאים תאורטיים וניסויים אלו מרמזים שלמרות שהרשתות הסמנטית והאפיזודית מבוססות על עקרונות שונים, הן מאוד מקושרות בזכרון האנושי ומעורבות זו עם זו במהלך למידה. על בסיס התמיכה החזקה שקיבל בניסויים עם בני-אנוש, SEMANT יכול לספק מסגרת לעוד מחקרים רבים המכוונים להבין למידה אסוציאטיבית בפרט וזכרון אנושי וקוגניציה בכלל.

האינטראקציה הסמנטית/אפיזודית ביצירת אסוציאציות חדשות הגדירה והציבה אילוצים למודל החישובי שלי ליצירת אסוציאציות.

רוב המודלים החישוביים שרלוונטיים למחקר הנוכחי לא עסקו בתהליך יצירת אסוציאציות באופן ישיר. רובם מודלים של הארגון של המערכת הסמנטית וממדלים את ההיבטים הדינמיים של הטרמה סמנטית (Semantic Priming), שהיא התופעה הבולטת הנקבעת על ידי ארגון זה. באופן כללי, שתי מחלקות של מודלים הוצעו. מחלקה אחת של מודלים נקטה גישה לוקליסטית וקיבלה השראה מהתאוריה של רשתות סמנטיות (Collins & Loftus, 1975). במודלים אלו, המערכת הסמנטית מודלה על ידי רשת של צמתים כאשר מושגים (Concepts) מיוצגים כצמתים ברשת ויחסים בין המושגים מיוצגים על ידי קשרים של הרשת. המחלקה השניה של מודלים השתמשה ביצוגים מבוזרים. מודלים במחלקה זו מייצגים מושגים לא על ידי יחידות בודדות אלא על ידי דפוסי פעילות שונים על פני מספר רב של יחידות. כל יחידה המשתתפת ביצוג מייצגת תת-תכונית סמנטית ודמיון סמנטי לכן מתבטא כחפיפה בדפוסי הפעילות על פני קבוצת תת-תכוניות.

המודל אשר פיתחתי, שכינויו SEMANT (Semantic and Episodic Memory of Associations using Neural neTworks) הוא מודל מעורב בכך שהוא נוקט גם גישה לוקליסטית וגם גישה מבוזרת. המודל מניח רשת שבה מושגים דומים במשמעותם מיוצגים על ידי צמתים קרובים זה לזה על מפה סמנטית דו-מימדית המבוססת על ייצוגים רבי-מימדים. אסוציאציות אפיזודיות מיוצגות על גבי מפה זו כקשרים ישירים (רוחביים) בין הצמתים המזווגות. פעילות בין צמתים בארכיטקטורה זו מתפשטת לאורך קשרים סמנטיים ואפיזודיים. בהשראת הרעיון של למידה הבייאנית, החוזק של אסוציאציה הנוצרת בין שני צמתים המופעלים בו-זמנית מוגברת כאשר "גל" הפעילות המתפשט מצומת אחת חופף עם הפעילות המתפשטת מהשניה. מכיוון שפעילות מתפשטת דועכת עם המרחק מהמקור, ככל ששני המושגים קרובים יותר על פני המפה הסמנטית, גדולה יותר החפיפה בין פעילויותיהם. עקב כך, כאשר שתי מילים קשורות סמנטית מופעלות יחדיו, התוספת לחוזק הקשר האסוציאטיבי ביניהן גדולה יחסית. מילים שאינן קשורות סמנטית הן, על פי הגדרה, רחוקות יותר על המפה הסמנטית ופעילויותיהם חופפות פחות. לכן, החוזק המתווסף לאסוציאציה קטן יותר.

בסימולציה ראשונה SEMANT שיחזר בהצלחה את התוצאות הניסוייות באופן כללי ואת אלו של ניסוי 4 בפרט. לאחר קביעת הממשות הפסיכולוגית של SEMANT, הפעלתי באמצעות סימולציה שלושה ניסויים הנוגעים להתנהגות אנושית. ניסויים אלו הולידו ניבויים אשר נגזרו על ידי ניתוח המנגנונים בבסיסו של המודל ועל ידי שינוי הפרמטרים החישוביים.. הניבוי הראשון, "א-סימטריה עקיפה" (Implicit Asymmetry) הוא שיהיה קל יותר ליצור אסוציאציה ממילה עם מעט שכנים סמנטיים למילה עם הרבה שכנים סמנטיים מאשר להיפך. הניבוי השני, "תיווך סמנטי" (Semantic Mediation) מתבסס על עקרונות המודל. הנחה זו מנבאת שיהיה קל יותר לזווג מילים מסביבות סמנטיות של מילים אשר זווגו קודם לכן. לתשומת לב, ניבוי זה אינו תלוי בקשר סמנטי בין המילים המזווגות. הניבוי השלישי נוגע

(במטלת של הזכרות ברמיזה – Cued recall) בהשוואה לניסוי 1 הייתה דרמטית. עקב כך, הסקתי שהפעלת המערכת הסמנטית במהלך התהליך של היווצרות אסוציאציות, למרות שאינה הכרחית לתהליך האפיזודי של יצירת אסוציאציות, תורמת באופן משמעותי ליעילותו.

ההשפעה של גורמים סמנטיים על התהליך האפיזודי של היווצרות אסוציאציות שוכפלה והורחבה בניסוי שלישי. בנוסף לשימוש במטלת אוריינטציה ברמה סמנטית, השוויתי בניסוי 3 היווצרות של אסוציאציות חדשות בין זוגות קשורים סמנטית וזוגות שאינם קשורים סמנטית. בנוסף, בניסוי הנוכחי, חוזק האסוציאציות המקריות שנוצרו במהלך שלב הלימוד נבחן באופן עקיף על ידי הערכת השפעתם המסייעת על חזרה אחת של למידה אסוציאטיבית מכוונת עוקבת של זוגות אלה. הזכרות ברמיזה בעקבות הלמידה המכוונת היתה טובה יותר באופן מובהק בזוגות אשר זווגו במהלך שלב הלמידה המקרית. בשני התנאים, הזכרות מרומזת היתה טובה יותר לזוגות קשורים סמנטית מאשר לזוגות לא קשורים סמנטית. לפיכך, ניסוי זה גילה שזוגות קשורים סמנטית מזווגים ביעילות גבוהה יותר גם בלמידה מקרית וגם בלמידה מכוונת. תוצאה זו מעידה על כך שקיום קשרים סמנטיים טרם הניסוי בין המילים המיועדות לזיווג תורמת לתהליך הזיווג האפיזודי.

שני הסברים אפשריים ליתרון הקרבה הסמנטית שנצפה בניסוי 3 נבדקו בניסויים נוספים על ידי השוואת קצב למידה אסוציאטיבית של זוגות קשורים ולא קשורים סמנטית. לפי הסבר אחד, קשרים אסוציאטיביים חלשים קיימים בין מילים קשורות סמנטית. על פי הסבר זה, אסוציאציות אלה חלשות מדי מכדי להתגלות בשאלוני אסוציאציות מפורשים, אך הן מספקות יתרון התחלתי לזוגות הקשורים סמנטית. לפיכך, לפי הסבר זה, יתרון הקירבה הסמנטית צריך להיות קבוע במהלך תהליך הלמידה. ההסבר האפשרי האחר הוא שקירבה סמנטית מתערבת בתהליך האפיזודי ומיעלת כל אפיזודת למידה אסוציאטיבית. אם הסבר זה נכון, היתרון של זיווג אפיזודי של מילים קשורות סמנטית צריך לגדול עם מספר אפיזודות ההופעה המשותפת. ניסויים 4 ו- 5 תוכננו לבדוק את התקפות של ההסברים לעיל.

שני הניסויים הדגימו שקשרים סמנטיים בין המילים טרם הניסוי האיצו את ההיווצרות המקרית של אסוציאציות בהתבסס על מופעים משותפים חוזרים. בניסוי 4 מצאתי כי עד כ 10 חזרות של אפיזודות מופע משותף של המילים, היתרון של מילים קשורות גדל לינארית עם מספר החזרות. אינטראקציה זו מרמזת שמבנה המערכת הסמנטית משפיע על תהליך הלמידה האסוציאטיבית עצמו. בנוסף, ניסוי זה קבע את המהלך בזמן של אפקט זה. אינטראקציה דומה בין שיעור הלמידה האסוציאטיבית ובין האפקט של קשר סמנטי נמצאה בניסוי 5 בשימוש בזיהוי מרומז בבחירה כפויה (Forced-Choice Cued-Recognition). בעוד שתוצאות ההיזכרות המרומזת יכלו, בעקרון, לשקף הבדל בין אסטרטגיות שליפה שבהן השתמשו כדי למצוא זוגות קשורים ולא קשורים, הזיהוי המרומז בבחירה כפויה הפחיתה משמעותית אפשרות זו. לפיכך, התוצאות של ניסוי זה תומכות בהשערתי שהאצה סמנטית חלה בשלב הלימוד ולא היתה תוצאה של הבדלים באסטרטגיות שליפה בשלב הבחינה. מאפיינים אלו של

תקציר

מטרת המחקר הנוכחי היתה ללמוד גורמים המשפיעים על היווצרות אסוציאציות אפיזודיות חדשות בין מילים ולחשוף את המאפיינים הדינמיים של למידה אסוציאטיבית אפיזודית. במוקד העניין היתה ההשפעה של ידע סמנטי על יצירה של אסוציאציות חדשות על בסיס אפיזודי. כדי להשיג מטרה זו, שילבתי שיטות ניסוייות בפסיכולוגיה וטכניקות חישוביות בגישה מחקרית בין-תחומית. ראשית, בחנתי נבדקים אנושיים בסדרת ניסויים פסיכופיזיים וגיליתי מספר מאפיינים של למידת אסוציאציות חדשות בין מילים. שנית, פיתחתי מודל חישובי המבוסס על רשתות נוירונים מלאכותיות, תחת האילוצים שנקבעו על ידי התוצאות הניסוייות ועל ידי הידע הקיים בתחום. מודל זה אומת על סימולציית מחשב אשר התאימה להתנהגות האנושית. בעקבות אימותו, נוצל המודל לשם הפקת ניבויים חדשים הניתנים לבחינה לגבי למידת אסוציאציות אנושית. שלישית, בחנתי כמה מאותם ניבויים בניסויים פסיכופיזיים נוספים.

הנחת העבודה שלי היתה שרובן המכריע של האסוציאציות הנוצרות מחוץ למעבדות פסיכולוגיה קוגניטיבית נוצרות באופן מקרי, כלומר, לא כתוצאה של למידה מכוונת וללא הקצאת קשב לתהליך יצירת האסוציאציות. לכן, מחקרי התרכז ביצירה מקרית של אסוציאציות. הפרדיגמה הניסויית ברוב הניסויים הפסיכופיזיים הייתה דומה וכללה שלב למידה מקרית ושלב בחינה. במהלך שלב הלמידה, הנבדקים הועסקו במטלת אוריינטציה, שביצועה דרש החזקה חוזרת של זוגות מילים בזכרון העבודה למשך כשניה. בעקבות שלב הלמידה, הנבדקים התבקשו, באופן מפתיע לגביהם, לבצע מבחן זכרון שונה אשר כוון להערכת חוזק האסוציאציות שנוצרו בין המילים שזווגו בשלב הלימוד.

בניסוי מקדים, 50 זוגות מילים לא קשורות סמנטית ולא אסוציאטיבית הוצגו במטלת אוריינטציה אשר כיוונה את קשב הנבדקים לרמת האות של הגרויים. כל זוג חזר 10 פעמים במהלך שלב למידה זה. באופן מפתיע, בבחינת היזכרות מרומזת (Cued-Recall) שנתנה מיד אחרי שלב הלמידה, לא נמצאו עדויות ללמידה מקרית. מספר גורמים אשר מבדילים תנאי יום-יום מתנאי המעבדה בניסוי המקדים יכולים להסביר מדוע אסוציאציות לא נוצרו בנסיבות אלה. תנאים אלו נבחנו בסדרת ניסויים עוקבת.

ראשית, מתוך הנחה שבחיי יום-יום אנשים אינם נדרשים ליצור מספר רב כל כך של אסוציאציות בבת-אחת (50 בניסוי המקדים), בחנתי בניסוי 1 את ההשפעה של עומס הזכרון בשימוש בתכנון זהה לזה של הניסוי המקדים, מלבד השימוש ב 10 (לעומת 50) זוגות מילים שכל אחד חזר 20 (לעומת 10) פעמים. אחוזי ההיזכרות המרומזת של האסוציאציות שנוצרו במקרה היה מובהק וגבוה באופן ניכר מאשר בניסוי המקדים. תוצאה זו מעידה שעומס זכרון יכול היה להיות אחת הסיבות של כשלון נבדקי המקדים ללמוד אסוציאציות חדשות.

שנית, מכיוון שבחיי יום-יום אנשים מפנים קשב כברירת מחדל אל משמעות המילים המעובדות בעוד שמטלת האוריינטציה בניסוי המקדים דרשה עיבוד רמת האות, בחנתי בניסוי 2 את השפעת רמת העיבוד על היווצרות אסוציאציות חדשות. התכנון של ניסוי 1 הועתק עם שינוי בודד: מטלת האוריינטציה הפנתה את קשב הנבדקים אל משמעות המילים ולא אל רמת האותיות מהן הן מורכבות. העלייה באחוזי ההזכרות

תוכן העניינים

מחקר זה בוצע בהדרכת

פרופסור שלמה בנטין

ופרופסור ריסטו מיקוליינן

מאפיינים של היווצרות אסוציאציות אפיזודיות בין מילים

חיבור לשם קבלת תואר

דוקטור לפילוסופיה

מאת

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הוגש לסינט האוניברסיטה העברית בירושלים

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