How Activation, Entanglement, and Searching a Semantic Network Contribute to Event Memory

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Abstract

Free association norms indicate that words are organized into semantic/associative neighborhoods within a larger network of words and links that bind the net together. We present evidence indicating that memory for a recent word event can depend on implicitly and simultaneously activating related words in its neighborhood. Processing a word during encoding primes its network representation as a function of the density of the links in its neighborhood. Such priming increases recall and recognition and can have long lasting effects when the word is processed in working memory. Evidence for this phenomenon is reviewed in extralist cuing, primed free association, intralist cuing, and single-item recognition tasks. The findings also show that when a related word is presented to cue the recall of a studied word, the cue activates it in an array of related words that distract and reduce the probability of its selection. The activation of the semantic network produces priming benefits during encoding and search costs during retrieval. In extralist cuing recall is a negative function of cue-to-distracter strength and a positive function of neighborhood density, cue-to-target strength, and target-to-cue strength. We show how four measures derived from the network can be combined and used to predict memory performance. These measures play different roles in different tasks indicating that the contribution of the semantic network varies with the context provided by the task. We evaluate spreading activation and quantum-like entanglement explanations for the priming effect produced by neighborhood density.

Navigating a complex world requires many kinds of knowledge, and we rely on fast, efficient access to information while engaging hundreds of mental operations, including remembering, thinking, reading, driving, and so on. The brain seems to be wired to respond automatically to cues in its environment by simultaneously activating neighborhoods of related knowledge. We see a friend and her name comes readily along with related information, hear the word *Atom* and automatically *electron*, *neutron*, and *bomb* are activated. In each instance related word knowledge is activated, but most of it remains in the shadow of awareness, available but not apparent. Later, some cue reminds us of a prior event and activates it along with related knowledge, e.g., suppose we write a check to the electric company, seal it and put it on the desk. We get ready for work, rush out, and stop the car at the end of the driveway after noticing the mailbox. Our findings indicate that Check and Envelope remind us of associated words, *bill, money, mail* and the Mailbox cue activates links to *bill*, *mail,* and *mailman*. Mailbox succeeds as a cue because it implicitly activates words associated to a momentarily forgotten task that reminds us to pay the bill.

In our research we ask people to study words and then provide word cues to remind them of what they studied. We use free association norms to determine what related words are likely to be activated when a word is experienced, and in this article we describe how free association can be used to measure the probabilities of links between words and how such links reveal a large and organized associative/semantic network of words. Our motivating thesis is that the brain stores and retrieves experience with objects and events, and words are invented to represent such information. As experiences and the words that represent them are repeated they link together in interconnected semantic neighborhoods. Such neighborhoods differ in both size and

connective density with some neighborhoods so dense that they generate category names such as "fruit" or "topics" such as alcohol or drug abuse (Goldman, 1999; Griffiths, Steyvers, & Tenenbaum, 2007; Stacy, 1997).

One purpose of this paper is to show how the semantic network contributes to episodic memory for recently experienced word events. The findings show that experiencing a familiar word during a study episode activates related words that prime its activation state in this network and make it easier to recall and recognize. We review evidence from data pooled over many experiments suggesting that cognitive processes operate on this network and we evaluate equations based on measures taken from the network to predict recall in the presence of a related cue. We show how the effects of word knowledge change during encoding and retrieval, with test delay, and semantic context, and we discuss how priming effects related to automatic activation can persist over long intervals. In the second purpose of the paper we address the issue of how network activation works when a word is processed during study. We challenge the spreading activation explanation for priming effects and suggest that experiencing a word simultaneously activates links that encompass the word's local neighborhood. We present a quantum-like entanglement model that describes and predicts how parallel activation captures neighborhood density and the resulting priming effects.

The Semantic Network

Semantic/associative networks (shortened to semantic) can be constructed by presenting lists of words to subjects asked to produce the first word to come to mind that is meaningfully or associatively related (e.g., Cramer, 1968; Deese, 1965; DeDeyne & Storms, 2008a,b; Nelson, Dyrdal, & Goodmon, 2005; Nelson, McEvoy, & Schreiber, 2004). Free association measures what one group of brains knows about semantic relationships and predicts what other groups of

brains are likely to know. It is a direct way to measure what related words are likely to come to mind when a word is experienced, and the validity of such measures depends on how well they predict performance in word processing tasks.

Free association to a word produces an array of associated words that vary in probability and number. First response associates are highly reliable (r = .89) even for responses produced by only two subjects and we assume that they index a word's nearest neighbors (Nelson, McEvoy & Dennis, 2000). We collected such norms on 5,000 words over more than 20 years using more than 6,000 subjects, with an average of about 150 subjects responding to each word. Words were normed for addressing specific research questions that evolved over time, and initially, we collected norms to study the effects of cue-target relationships in the extralist cuing task. In this task participants study a list of unrelated words that are not directly associated to one another, called targets (T), and the recall of each target is prompted during testing by a semantically related word cue (Q). Early interest focused on the effects of two free association measures, forward *cue-to-target strength* and backward *target-to-cue strength* (see Table 1 for abbreviations and calculations of these and other variables). The experimental findings show that extralist cued recall increases as a positive function of each link (e.g., Nelson, Fisher, & Akirmak, 2007). Recall is more likely when a cue strongly activates a target in free association, and in addition, an associate that is strongly activated by the target is a more effective cue during test than a weakly activated associate.

Other findings show that words vary in terms of how many different associates they produce in free association and that the number of response alternatives produced by a word that is used as a test cue has a robust but negative effect on recall (called the *cue set size effect* in our experiments). The more associates a cue has the less the chances are of recovering one of its

associates that has been studied as the target. This finding generalizes across word types, taxonomic category names, word stems, rhymes, and pictures (Nelson & McEvoy, 1979; Nelson & Castano, 1984; Nelson, Walling, & McEvoy, 1979). Cue set size, however, is an inclusive measure that includes the target, indirect facilitating links that join the cue and target (mediators and shared associates), and alternative responses. In this article we create a relative index that separates alternative responses responsible for negative effects from the target and indirect links in the statistical analyses of the data from the earlier experiments. Alternative responses are now called *distracters*, and as indicated in Table 1, they are computed as proportions that measure relative *distracter strength*. The probability of selecting a distracter instead of the target increases as distracter strength increases.

Cue set size findings created a need to norm more words, and this task became routine after learning that studied *targets with more links among their associates are more likely to be recalled and recognized* (e.g., Nelson, McKinney, Gee, & Janczura 1998; Nelson, Bennett, Gee, Schreiber, & McKinney, 1993; Nelson, Zhang, & McKinney, 2001). This phenomenon was called *connectivity* in these experiments but to be more consistent with the literature on related topics, we will refer to it in Figure 1and elsewhere as *neighborhood density*. Measuring neighborhood density required us to norm a word in order to identify its closest associates, and then to norm each of its associates using independent samples of subjects. Figure 1a shows a toy network for Word T that produces 3 directly related associates and the 4 links that connect them. Figure 1b illustrates this network as an *nxn* asymmetrical adjacency matrix for Word T that represents its neighborhood. Placing T's closest associates (A) on the columns and again on the rows defines its neighborhood in matrix form. Each of T's associates is normed separately and we measure whether a link connects these associates or not {1, 0}, e.g., reading along the rows

$A_{12} = 1$, and $A_{13} = 1$ indicating that A_1 is linked to A_2 and A_3. Figure1c calculates neighborhood density by summing the number of associate-to-associate links in the matrix and dividing by the number of possible links. As with cue-to-target, target-to-cue, and distracter strengths, neighborhood density is a relative index of strength that varies from 0.0-1.0. Density increases as the number of links among the target's associates increase relative to the size of its neighborhood. Neighborhood density theoretically measures *primed target strength* on the assumption that targets with higher neighborhood densities are primed to higher activation levels within the semantic network. For example, *Trombone* has 85 out of 240 possible links among its associates whereas *Basket* has 10 out of a possible 342 links. Their respective primed strengths are .354 and .029 and the findings show that, with other variables controlled, words such as Trombone are more likely to be recalled and recognized than words like Basket. In the last section of this article we focus on neighborhood density in predicting recall and recognition and propose a quantum-like model for explaining its effects.

What does free association measure? In free association response production is not really "free" in the sense that any response is always acceptable. Free association is restricted because the instructions bias responses toward the very general--any word--to the very specific--category instances, properties, rhymes, feelings, topics like "alcohol makes me feel," and so on (e.g., Battig & Montague, 1969; Cramer, 1968; MacRae, Seidenberg, & McNorgen, 2005; Reich & Goldman, 2005). Because the task is so familiar, individuals can access and generate any type of related word based on instructions that set a comprehensible goal that defines a context for eligible words. Different biases produce different semantic maps, and at this time there is no single "best" map for predicting the effects of all types of mental operations on all types of word

knowledge (Maki & Buchanan, 2008). Our norms request a response that reflects meaning or association, and it allows responses to be based on a variety of semantic relationships.

The second word in the task name, "association," is also misleading because it implies that cue-to-target strength is determined only by an association formed by co-experiencing words Q and T in the same context. Association by learning is critical, but observing the existence of a link reveals nothing about its source. Free association indicates the probability that one word produces another and tells us nothing about the information used to produce the response. The observation could be generated though learned association, recency, imagery, semantic similarity, or contrast. Several studies show that semantic information concerning categories, properties, emotions, and so on, are well represented in free association data (Borge-Holthoefer, & Arenas, 2010; Brainerd, Yang, Reyna, Howe, & Mills, 2008; De Deyne & Storms, 2008a; Hutchison, 2003; Monaco, Abbott, & Kahana, 2008; Steyvers, Shiffrin, & Nelson, 2005). Most importantly, when we refer to "the semantic network" we are referring to the normalized network that emerges from our free association procedure. Furthermore, we assume that every person has a variant of such a network in memory and that processes like activation and search operate directly on this representation.

Organization of the Semantic Network. In many sciences networks tend to be large, asymmetric, and irregular structures that are well suited for describing complex systems (Newman, 2003). Networks describe links between people (Moreno, 1934), computers (Barabási, 2002), neurons (Watts & Strogatz, 1998), metabolic states (Jeong, Tombor, Albert, Oltvai, & Barabási (2000), and words (Steyvers & Tenenbaum, 2005). Their topological structure helps scientists understand how different kinds of entities communicate in interactive systems, and they have been used to describe a wide range of processes, including percolation,

spread of disease, phase transitions, protein interactions, computer search, as well as activation and search (Barabási, 2002; Nelson et al., 1998; Newman, 2003). Networks are also useful to scholars investigating complexity itself (e.g., Barabási, 2002; Palla, Derényi, Farkas, & Vicsek, 2005; Steyvers & Tenenbaum, 2005; Strogatz, 2003; Watts & Strogatz, 1998).

Research across disciplines indicates that different networks are organized in strikingly similar ways. By treating networks as graphs and borrowing the terminology and mathematics of graph theory researchers have shown that networks built from different entities and types of links tend to have similar statistical profiles. Of particular interest Steyvers and Tenenebaum (2005) used our norms to create a semantic network by generating a 5018 x 5018 word matrix in which normed cues are represented on the rows and responses are shown on the columns as in Figure 1b. Their analysis shows that the network is sparsely linked, with each word being directly connected to an average of only 12.7 other words. Furthermore, short path links are characteristic of all small-world networks (Watts & Strogatz, 1998). The average directed path length from any one word in our norms to any other takes only 4.27 links or "steps" so the semantic network qualifies as a small-world network. More importantly for this article, a property termed *clustering* in graph theory is described in this article by neighborhood density, the relative number of links among a word's associates (Figure 1c).

The network analyses indicate that words in the semantic network are directly connected to only a few other words, but on average, they are connected to nearly all other words in the net within a few mediating links. The network has a *small-world structure* comprised of words with varying levels of neighborhood density that are linked by short paths to and from other words. As a network, words are represented as a system of nodes and links as opposed to isolated pairs, and theoretically, a mental process operating on one word in the system has the potential to

change the states of related words in the network. The system in which words reside is distributed but there can be many alternative paths to any single word, and short paths provide shortcuts that may affect the activation states of distant concepts (Watts & Strogatz, 1998).

We assume that the semantic network is a dynamically evolving, complex system. Complexity arises because we know thousands of words that are linked in semantic memory in ways that can affect how well a given word will be remembered. Dynamics arise because portions of the system are always growing or weakening in response to experience (Hills, Maouene, Riordan, & Smith, 2010; Steyvers & Tennenbaum, 2005). The network is also dynamic in terms of how it responds to the contexts provided by different tasks. We review findings showing that a target's neighborhood density has different effects depending on the task and the semantic context in which it is experienced.

Knowledge by Context Interactions

In this section, we review how the semantic network is engaged in a variety of tasks, including cued recall, primed free association, intralist cuing, and word recognition. We focus on the extralist cuing task resembling the mailbox example because of its importance to everyday memory events and because it is more interesting from a network perspective. Pooling the results over dozens of extralist cuing experiments provides a database on thousands of word pairs that we use to identify the most important network variables and how they can be incorporated into an equation that effectively predicts recall.

Extralist cuing

During the study phase of the *standard* extralist task a list of unrelated familiar words is presented one at a time for 3s, and subjects read each word aloud and attempt to remember as many as possible. Test instructions are provided immediately after the last study word. During

testing, another set of words is presented one at a time at a self-paced rate, and the instructions

ask subjects to use each cue to recall a related target word from the study list (e.g., use the cue

"Proton" to recall the target "Atom"). The procedure is called "extralist" because test cues are

physically unavailable during study, and hence successful recall depends on the cue accessing

the target in the semantic network. This characteristic makes extralist cuing an ideal

"reminding" paradigm for studying how prior knowledge captured by a single word can be used

to respond to the environment.

Table 1 presents a list of 8 variables shown to affect recall in extralist cuing that have

been incorporated into a statistical prediction algorithm called Pier2, standing for "Processing

implicit and explicit representations" (e.g., see Nelson & Zhang, 2000; Nelson, Goodmon, &

Ceo, 2007 for a description and computational examples). One purpose of this article is to report

a simplified computation that grew out of two problems with Pier2. It over predicts recall, and

the 8 variables in its prediction equation are not on the same scale, with some representing

strengths such as cue-to-target strength and others representing sums of strengths. Although the

equation is well correlated with recall, we thought that transforming each variable to the same

scale would solve the over prediction problem. Just as importantly, given correlations among the

variables, not all of them may be necessary for predicting recall thus simplifying the problem of

incorporating them into a prediction equation. As we will show, transforming our past measures

into proportions unexpectedly forced us to re-conceptualize Pier and to revise our interpretation

of both cue and target set size effects.

All 8 variables shown in Table 1 were transformed to free association-determined

strengths that ranged from 0.0-1.0, and were entered into an extralist cuing database comprised

of 4,068 cue-target pairs re-scored at the item level[1]. In the articles that report these experiments

the data are pooled over items and the usual subject-based analysis of variance procedures are

applied to determine what variables are significant. In contrast, in this article the data are pooled

over subjects in all analyses. The number of subjects who correctly recalled a target relative to

the number of subjects who studied it computes the probability of recalling each cue-target pair

(see Nelson & Zhang, 2000). Both subject- and item-analyses indicate whether a variable is

important, but item-analyses are critical for predicting the probability of recalling a given cue-

target pairing. This type of analysis allows us to determine the influence of a variable over

thousands of cue-target pairs, which is important when the goal is to determine how and how

much the network contributes to memory for recent word events. In addition, the item-analysis

allows us to use regression analyses that statistically control correlations among the variables.

In the database the cue-target pairs are shown in two columns with other columns

representing the observed and predicted probabilities of correct recall, information on how the

list was studied, measures of the 8 variables, and other related information. The analyses are

restricted to 2,803 pairs studied in the *standard task*, and a preliminary analysis is used to

determine whether the new scaling procedure eliminates some variables when correlations with

other variables are statistically controlled in a simultaneous multiple-regression. Probability of

correct recall is the dependent measure and measures of the 8 variables serve as predictors.

The preliminary analysis results indicate that the first 4 variables shown in Table 2 are

more important for predictive purposes. The regression is significant [$F(8, 2794) = 205.30$,

$MS_{res} = .042$, $R = .61$, $R^2 = .37$], and the partial correlations shown in the bottom row of Table 2

indicate the variables represented in the first 4 columns are more strongly correlated with recall

than the last 4. The 4 variables having the largest effects are cue-to-target strength, S_{qt}, target-to-

cue strength, S_{tq}, cue-to-distracter strength, S_{qd}, and neighborhood density as a measure of

primed target strength, $S_{t'}$. Of the last four variables, shared associate strength and associate-to-target strength failed to have significant effects in this analysis, and mediator strength and target distracter strength had reduced effects because of correlations with other measures. These four variables were dropped from the prediction equations described later because they are redundant and reduce predictability when included. The failure of associate-to-target strength to affect recall is important to spreading activation theory and we return to this result later. The failure of target distracter strength deserves special notice because this variable played a key role in our earliest investigations of the semantic network. Many experiments focused on the effects of varying target set size because it has robust negative effects on cued recall, but as with cue set size, it is correlated with several variables that have positive effects (see Table 2). However, we are not dismissing target set size effects as irrelevant. In the conversion to proportions target set size determines the size of the associative matrix and hence the relative magnitude of neighborhood density. Given a fixed number of links among the target's associates, neighborhood density decreases as target set size increases so the negative effects of target set size are built into the density index.

The first row of Table 3 shows that the results of a second analysis limited to the 4 most important predictors of recall are significant overall and that each predictor has significant effects. The correlations, partials, and descriptive statistics are shown in Table 4. The partial correlations are shown in the bottom row and each variable is significantly correlated with recall after correlations among the variables are statistically controlled. Of the variance that can be explained, a separate unforced stepwise regression shows a highest to lowest ordering of cue-to-target strength $S_{qt} = 58.9\%$, neighborhood density $S_{t'} = 20.8\%$, cue-to-distracter strength $S_{qd} = 11.8\%$, and target-to-cue strength $S_{tq} = 8.5\%$. Recalling the target depends most on cue-to-target

strength S_{qt} and next most on neighborhood density $S_{t'}$. Target-to-cue strength S_{qt} has a smaller

positive effect, and only cue-to-distracter strength S_{qd} has negative effects on recall. All things

being equal, a cue that activates a higher proportion of distracters is more likely to fail.

Predicting extralist cued recall. Retrieving a target event from the semantic network

can be direct when cue-to-target strength is very strong but becomes a problem as the cues

become weaker and retrieval becomes less certain. For the most part, in our experiments cue-to-

target strength is generally weak (averaging .15) because we were manipulating several variables

in factorial designs and needed to keep recall off the ceiling. Given uncertainty, a test cue is

more likely to utilize all of the available information. In the Pier2 framework, measures of

variables known to affect recall have been combined in a single prediction equation. We update

this equation now because of the changes in the number of key measures and their underlying

scales, and we refer to the new approach as Pier3. There are many ways to combine 4 predictors

and we evaluated many plausible computations. The equation we report is the best general

predictor, and although it does not constitute a model in the same sense as general memory

models (e.g., SAM), it carries implications for how a cue reminds us to recover a recent word

event from the semantic network.

Figure 2 illustrates the positive and negative effects involved when a test cue activates its

associates given a goal of recalling a related and recent word event. We assume that the four

sources of strength represented in the figure act together in affecting probability of recall. The

target activates its associative network and this activation strengthens its representation in

semantic memory. By activating an array of related associates the test cue narrows the range of

potential targets and the target is selected from within the array. Cue-to-target (S_{qt}) and target-

to-cue (S_{tq}) strengths locate the primed target in the array, and its recall is more likely when

these links are stronger and when the target has been primed to a higher level during study ($S_{t'}$).

Theoretically, target priming makes its representation more distinct within the array of associates

activated by any related cue and increases the likelihood of its selection. In contrast, distracters

have negative effects on recall, and cue-to-distracter (S_{qd}) strength is interpreted as sampling

error. As distracter strength increases, the probability of sampling a distracter as opposed to the

target increases.

Equation 1 brings the four sources of information about the target together. Words in the

semantic network exist in a tangle of correlated links loosely organized into a complex system,

and recall in extralist cuing is based on more than just how strongly the test cue is related to its

target. Equation 1 is a SAM-like equation stating that the semantic network's contribution to

target recall in extralist cuing can be predicted by computing the probability of recalling a

primed target given the test cue. *P(T'/Q)* is a ratio of positive sources of information about the

target relative to the total amount of information activated (e.g., Raaijmakers & Shiffrin, 1981).

The probability of recalling a primed target is a function of total cue-target strength relative to

the total amount of information activated by the test cue, which includes total cue-target strength

and distracter strength. Total cue-target strength S(Q, T') is captured in Equation 2 by summing

cue-to-target and target-to-cue strengths, and adding the result to the target's neighborhood

density. Cue-distracter strength is defined in Equation 3 as the number of distracters relative to

the number of associates activated by the test cue (cue set size). Finally, Equation 4 measures

target priming as a function of its relative neighborhood density.

All of these sources of information are embedded in the semantic network and we assume

that target priming and cue-initiated search operate directly on this network. The predicted

probability of recalling a primed target from the semantic network given its test cue is:

$$P(T'/Q) = \frac{S(Q,T')}{S(Q,T') + S(Q,D)} \quad (1)$$

where total cue-target strength $S(Q, T')$ is:

$$S(Q,T') = S_{qt} + S_{tq} + S_{t'} \quad (2)$$

and cue-distracter strength $S(Q,D)$ is:

$$S(Q,D) = \frac{\sum_{i=1}^{d} D_i}{m} , d = distracters \; and \; m = \text{\# } cue \; associates \quad (3)$$

and target priming probability $P(T')$ for associates A_{ij} is:

$$S_{t'} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} A_{ij}}{n(n-1)} , n = number \; of \; target \; associates \quad (4)$$

Results. To test the predictions of Equation 1 we use the extralist cuing database for the

cue-target pairs learned under the standard condition (i.e., 3 second study, "remember"

instructions). The probabilities of observed and predicted recall are normally distributed around

means of .518 (SD = .26) and .392 (SD = .16), respectively. We compute the error distribution

by subtracting predicted from observed recall and plotting the results, and this distribution is

normal and shifted to the right because the equation underestimates recall.

The first row of Table 5 presents the results of multiple regression analysis with Equation

1 as the sole predictor, and it is well correlated with probability of recall, r = .567. Figure 3

shows observed and predicted recall as a function of four categories of Equation 1, and as can be

seen, it underestimates observed recall by about the same amount in each category. The

transformation to proportions solves the over prediction problem associated with Pier2.

Equation 1 uses fewer variables, predicts as well as Pier2, and explains 32.1% of the total

variance in extralist cuing. When the correlation is corrected for the reliability of free

association and extralist cuing tasks (Myers & Well, 1995, pp. 394-395, 472-473), the correlation

between predicted and observed recall rises from r = .567 to r = .703, and explained variance

rises to 49.5% (see Nelson & Zhang, 2000, p.6). Thus, nearly half of the total variance of

extralist recall is explained by free association measures based on links among words comprising

the semantic network. The network can contribute substantially to episodic recall.

Effects of Test Delay. Fifteen experiments show that recall in the extralist cuing task is

negatively affected by test delays filled with solving multiplication problems (e.g., Nelson, Bajo,

& Casanueva, 1985; Nelson, Goodmon, & Ceo, 2007; Nelson et al., 1998). The data are re-

scored at the item level and pooled over experiments in order to portray the effects of delays at 2,

7, 10, 12, 22, and 1,442 minutes. Two minutes are added to each delay to accommodate study-

to-test time that includes time for reading test instructions. A multiple regression analysis that

includes the 4 variables plus test delay as predictors is significant [$F(5, 2549) = 138.82$, $MS_{res} =$

.046, $R = .46$, $R^2 = 21.2\%$]. The coefficients or weights allocated to cue-to-target S_{qt}, target-to-

cue S_{tq}, distracter S_{qd}, neighborhood density $S_{t'}$, and delay by the regression equation are each

significant and the respective correlations between each source and observed recall are .32, .14,

-.21, .22, and -.19. When interactions between each source and delay are included as predictors,

none are significant. The absence of delay interactions is inconsistent with experimental findings

showing that the strong-weak difference for each variable declines as delay increases (also see

Sahakyan & Goodmon, 2010). Examinations of mean recall with the data split along strong-

weak levels for each variable indicate that this trend is apparent in the database but the effects,

though smaller, are apparent even after 24 hours. Finally, as shown in the second row of Table

5, Equation 1 and delay are significant predictors in a simultaneous multiple regression, and each

predictor is significantly correlated with recall, r = .40 and r = -.19.

A log-log plot of probability of recall and test delay approximates a straight line, and a

power function fitted to recall as a function of untransformed values explains 88% of the

variance that can be explained with an intercept constant of .541 and a slope of -.109. Effects of

delay are incorporated into Equation 1 by weighting it by $t^{-\propto c}$ where t is time in minutes, $\propto$ is

decay rate estimated by the power function, and c is a context parameter ($c \geq 1$) that is estimated

from the data and accounts for differences in how the retention interval is filled (e.g.,

multiplication problems, studying additional lists, or room and experimenter changes). When the

effects of test delay are taken into account Equation1 becomes:

$$P(T'/Q) = \left[\frac{S(Q,T')}{S(Q,T') + S(Q,D)} \right] (t^{-\propto c}) \qquad (5)$$

Figure 4 shows probability of recall as a function of test delay using Equation 5 with $c = 1$.

Recall declines sharply over the first 20m and levels out after 24 hours. When Equation 5 is

used as a single predictor of recall in the multiplication problem database it emerges as a

significant predictor, $F(1, 2{,}553) = 686.5$, $MS_{res} = .046$, $R = .46$, $R^2 = 21.2\%$.

We attribute the effects of test delay to decay and the loss of context information (e.g.,

Nelson & Goodmon, 2003; Nelson, Goodmon, & Akirmak, 2007; Nelson, Goodmon, & Ceo,

2007; Sahakyan & Goodmon, 2010). Theoretically, the target is primed and encoded in

conjunction with environmental context cues sampled during study, and asking subjects to

switch attention from the study list to math problems and the like disrupts the recovery of these

cues. Additional support for the importance of context comes from studies showing that changes

in the physical environment produced by changing rooms, experimenters or both between study

and test as well as by requiring the study of additional lists during the delay reduce the

probability of recall.   However, neighborhood density effects are attributed to target priming.

Forgetting *describes* why recall declines but it does not explain why priming effects are reduced

but still apparent after 24 hours when activation normally decays within milliseconds in speeded lexical and semantic decision tasks. In contrast to speeded tasks, density induced target-priming effects somehow persist in extralist cuing and we suggest a reason below.

Effects of Study Condition. Study conditions varied through presentation rate and instructions have robust effects on recall in extralist cuing. The database includes 1,265 pairs encoded under non-Standard conditions. In some experiments presentation rate is varied under the otherwise standard condition and recall increases with slower rates, averaging .47 (SE=.02, n=210 pairs), .52 (SE=. 01, n=2,803), and .60 (SE=.02, n=210) for rates of 1.5s, 3.0s, and 6.0s (e.g., Nelson, Schreiber, & McEvoy, 1992). With Equation 1 and rate as predictors, the results in the third row of Table 5 indicate that the regression and both predictors are significant. The correlations with recall for Equation 1 and rate are $r = .57$ and .08 and they explain 98.1% and 1.9% of the variance that can be explained. In extralist cuing, the contribution of semantic memory is substantially greater than the contribution of additional study time.

In other experiments different groups of subjects process the targets by naming their vowels, trying to remember them in the standard condition, or by rating their concreteness (e.g., Nelson, Fisher, & Akirmak, 2007). Recall increases with elaboration and averages .39 (SE=.02, n=210), .52 (SE=.01, n=2,803), and .68 (SE=.02, n=427) for naming vowels, remember instructions, and rating concreteness. We code instructions as -1, 0, and +1 and enter it along with Equation 1 as predictors in a multiple regression. Table 5 shows that the regression equation is significant and that Equation 1 and Study Instructions contribute significantly to recall. Equation 1 and Instructions are correlated with recall at $r = .56$ and $r = .23$, and an unforced stepwise regression indicates that they explain 87.9% and 12.1% of the variance that can be explained.

Consistent with study time, preexisting information in the semantic network contributes more to recall in extralist cuing than level of processing. Recall in extralist cuing relies on both semantic and episodic manipulations but it depends more on the contribution from the semantic network than on explicitly defined encoding procedures. The network captured in Equation 1 explains more variance because the test cue is absent during study and target recall hinges on using the test cue to access it within the semantic network. In experiments these two sources of information generally do not interact but when they do, the interaction is weak and potentially the result of ceiling effects. These results suggest that semantic network variables and episodic encoding operations (E) have additive effects on recall in the extralist task, and that total cue-target strength (Equation 2) can be re-represented as:

$$S(Q, T') = S_{qt} + S_{tq} + S_{t'} + E \qquad (6)$$

Developing an equation for E is beyond the scope of this article but we consider two implications of Equation 6. The first is that encoding operations applied according to the study instructions add their effects directly to total cue-target strength $S(Q, T')$. Total strength is greater when study instructions focus on semantic processing or remembering than when focused on naming vowels. The second implication is that two different types of information contribute to target recall in the extralist cuing task, one based on episodic encoding operations and one based on implicitly activated semantic information. The episodic processes are tied to how targets are encoded, study time, and general context cues and hence to recollective retrieval processes. The implicit processes are linked to the strength of the cue-target relationship and target priming and hence to automatic, unaware retrieval processes.

Pier incorporates both dual encoding and dual retrieval processes in explaining extralist cuing. Pier 3 assumes that the appearance of a target can prime its representation in the semantic

network in accordance with its neighborhood density, and that regardless of its primed state, a

target is automatically loaded into working memory and subjected to encoding operations

controlled by study instructions. Both target priming effects and the encoding processes applied

to it in working memory strengthen its representation in the semantic network. As illustrated in

Figure 5, the studied word Atom is represented in the network and its appearance in the

experimental setting activates this representation, with neighborhood density theoretically

affecting its primed strength. The application of working memory operations to a primed

representation of Atom adds to its strength in the semantic network so that any cue linked to it in

the network has an increased likelihood of selecting it as a response during testing. Importantly,

we assume that Atom's associates serve only to prime its representation in semantic memory and

they are not processed in working memory. We found small implicit associative strengthening

effects in an early experiment (Nelson, Bajo, McEvoy, & Schreiber, 1989), but several

unpublished experiments by Schreiber failed to replicate such effects.

As suggested in Figure 5 primed targets such as Atom are encoded in the presence of

elements of the environmental context that are simultaneously represented in working memory,

so context becomes associated with the primed target (cf., Raaijmakers & Shiffrin, 1981).

Atom's representation in the network is temporarily strengthened by all sources of information,

including priming, explicit encoding operations, and context. When Proton is presented as a

reminding cue it initiates a search through its associative array. Atom is now more likely to be

selected than Proton's other associates if it has been primed and explicitly encoded via study

instructions, and this encoding occurs in the presence of information about the context of the

experience. Relative to Proton's distracters, Atom now has a greater chance of being recalled

because its state in the semantic network has been strengthened via both episodic and implicit

processes, and this state explains why target priming effects can be long-lasting in extralist cuing. They last when target words are encoded in a primed state in working memory.

Primed free association. Primed free association and extralist cuing tasks are similar because the same list of targets and test cues can be used along with the same study conditions, and the hypothesis that primed information is retrieved from semantic memory predicts that the same variables will be important in both tasks. The main difference between these tasks occurs during testing. In primed free association, subjects are asked to free associate the first related word to come to mind for each test cue under a cover story suggesting that norms are being collected for another experiment, and they are not told that the test cues are related to the targets. To reduce the probability of discovering the relationship the test often begins with unrelated "cues," and then continues with a random mix of equal numbers of related and unrelated cues (e.g., Chappell & Humphreys, 1994; Humphreys, Tehan, O'Shea, & Bolland, 2000; Nelson & Goodmon, 2002; Zeelenberg, Shiffrin, & Raaijmakers, 1999). We focus on the probability of recalling the target as a function of the variables that comprise Equation 1 to determine whether they have similar effects in extralist cuing and primed free association. The intentional recall instructions used in extralist cuing make subjects aware of the relevance of the target words just seen in the study context and the cue-target relationship, whereas free association instructions relax awareness on both counts. Neither the study context nor the semantic relationships between cues and targets is ever mentioned in the test instructions. Relaxing awareness decreases recall, but variables that affect intentional recall should have similar effects in primed free association if both tasks are relying on the same semantic network.

Results. The experiments confirm this expectation and show that target recall is greater when cue-to-target S_{qt} and target-to-cue S_{tq} are stronger, and when primed target strength $S_{t'}$ is

higher. As in the extralist cuing task, they also show that target recovery is more likely when attention is directly focused on target meaning during study compared to standard remember instructions, and when testing is immediate as opposed to delayed (Goodmon & Nelson, 2004; Nelson & Goodmon, 2002; Nelson, Goodmon, & Akirmak, 2007).

Data from these and related experiments involving immediate tests were re-scored at the item level and used to create a primed free association database that included 470 cue-target pairs, probability of target recall, and the predictor measures. Although recall is very low in primed free association, the results of a simultaneous multiple regression analysis shown in Table 3 indicate that the regression is significant as are the effects of each of the 4 predictors. Table 6 presents the correlations for each variable and note that although cue-to-distracter S_{qd} is not varied in any experiments, it emerges as a significant negatively correlated predictor. As in extralist cuing, target recall significantly increases as a positive function of cue-to-target S_{qt}, target-to-cue S_{tq}, and primed target $S_{t'}$ strengths and it declines as cue-to-distracter strength S_{qd} increases. An unforced stepwise regression shows that recall is significantly affected by all 4 network variables, with S_{qt}, S_{tq}, S_{qd}, and $S_{t'}$ explaining 23.9%, 4.0%, 3.2%, and .4% of the total variance. The effects of all 4 variables are reduced in primed free association compared to extralist cuing, but each variable is significant, and though quite small, the effects of $S_{t'}$ indicate that target priming affects recall.

Predicting priming. A multiple regression analysis with the probability of target recall as the dependent measure and Equation 1 as the predictor is significant, but it over predicts recall, $[F(1, 468) = 118.36, MS_{res} = .023, R = .45, R^2 = 20\%]$. Mean predicted and observed recall is .33 and .19. Observed recall is very low in primed free association when directly compared to extralist cuing where recall can be twice as high (Nelson, Goodmon, & Akirmak,

2007). Low recall arises because subjects are unaware of the importance of the study episode and cue-target relationships. Weighting Equation 1 by .5 brings predicted mean target recall more in line with observed recall and, although it must be adjusted, Equation 1 explains 20% of the total variance and is an acceptable predictor of primed free association.   Target recall is based on the semantic network even in the absence of an intent to recall.

Studying Semantically Related Pairs

In extralist cuing each target is presented in the absence of semantic context during study but in this section we consider a task in which the target is studied in the context of a semantically related word.   A word seen in either context implicitly activates its closest associates (e.g., in lexical decisions, both meanings of a polysemous word are momentarily activated, Kintsch, 1988). However, the effects of this broad activation on recall could not be more different in the two contexts. When seen in isolation in the extralist task, target meaning is uncertain and the activation of related words provides an internally generated semantic context that primes the target's representation to varying degrees. Theoretically, this primed representation is loaded into and studied in working memory, thus preventing the rapid decay of target priming. For example, when Bolt is studied in isolation, both its "*fastener*" and its "*storm*" meanings support and prime its activation state, and because the target is rehearsed and encoded in this state, both meanings affect recall even when Bolt is cued by *Screw* or *Lightening*, which specify one meaning or the other (Gee, 1997). Both meanings contribute to Bolt's priming level during study so they affect recall even when search is initiated by only one of its meanings.

In contrast to semantic isolation, encountering a pair of semantically related words during study tends to produce a semantically specific encoding (Tulving & Thomson, 1973). For example in the intralist cuing task, after studying *Screw-Bolt*, *Screw* is an effective cue whereas

Lightening fails dramatically (Nelson, Walling & McEvoy, 1979). Following Kintsch (1988),

we assume that both the context cue *Screw* and its target *Bolt* activate their associates during

study and that this broad activation collapses to a specific meaning provided by the semantic

context implied by the word pairing. Because the target's meaning is specified during study in

intralist cuing its associates are no longer needed to support its semantic state, and as a

consequence the density of the target's semantic neighborhood has no effect. The cue-target

pairing can be directly loaded into working memory where it can be rehearsed and encoded.

Furthermore, in intralist cuing collapse is observed regardless of whether a target word has

multiple, distinct meanings or not because its meaning is more certain compared to when it is

semantically isolated (Nelson et al., 1979).

Three findings reinforce the collapse assumption. First, in intralist cuing the target is

studied in the presence of a semantically related context word that is used as the test cue, and

effects related to its associates are mostly eliminated (Holley & McEvoy, 1996; Nelson et al.,

1992). This collapse occurs when the pairing is studied and is not produced by the test cue itself

because collapse is observed even when recall is prompted by a rhyme cue linked to the target's

name (Nelson, Schreiber & McEvoy, 1992). Second, the presence and timing of the semantic

context word in relation to its target is critical (Nelson, Gee & Schreiber, 1992). When the

context word appears slightly before or after the target, effects related to the target's associates

are apparent once again, but the extent of these effects falls between the context-absent and the

context-simultaneous conditions.   Short delays in the appearance of the context word introduce

semantic uncertainty and reveal the effects of the target's associates. Total collapse of the

target's associates depends on simultaneously experiencing the cue-target pair. Finally,

compared to when unrelated facts are memorized, facts organized around a semantic theme

eliminate FAN effects (Anderson, 1983; Reder & Anderson, 1980). FAN effects are distracter

effects, and as with word pairs, encoding facts in a specific semantic context sharply reduces

distracter effects.

Based on these findings, we suspected that of the 4 predictors in Equation 1 only cue-to-

target S_{qt} should affect intralist cued recall because the test cue must be used to recover the cue-

target pair in the semantic network.   In order to evaluate the effects of the 4 components of

Equation 1 on a larger scale we rescored data from 12 intralist cuing experiments and created a

database of 802 pairs. In the first analysis, the four variables are used as predictors and the data

are restricted to pairs presented at a 3s rate and studied under instructions to remember the pair

and that the word appearing on the left will be the test cue. The regression is significant as

shown in Table 3, and cue-to-target strength S_{qt} is the only significant predictor. In a second

analysis we include cue-to-target S_{qt}, presentation rate, and target frequency as predictors. The

regression is significant [$F(3, 798)=40.78$, $MS_{res}=.035$, $R=.37$, $R^2=13.0\%$], as are all 3 predictors.

For S_{qt}, presentation rate, and frequency the coefficients are .31 (t=9.24), .18 (t= 5.30), and -.14

(t=-4.15) and they explain 8.4%, 2.8%, and 1.8% of the total variance. Mean recalls at study

times of 1.5s, 3.0, 5.0s and 6.0s are .75 (SE=.02, n=93), .74 (SE=.01, n=590), .81 (SE=.02, n=47)

and .87 (SE=.02, n=93).

Compared to extralist cuing, in intralist cuing cue-to-target strength and study time have

much reduced effects and target-to-cue, cue-to-distracter, and importantly, the target's

neighborhood density have no observable effects. These contrasts indicate that the semantic

network responds dynamically to the context provided by the task at hand. In extralist cuing a

word's meaning as encoded during study tends to be distributed across its semantic contexts

whereas in the intralist task it tends to be confined and specific, which comes as no surprise (e.g.,

Tulving & Thomson, 1973). What is most interesting is the extralist cuing result showing that the semantic network supplies meaning when a word is experienced out of context and it delivers what it has activated to a working memory system that encodes this information for future use. The semantic network responds dynamically to context and to memory systems that have evolved for encoding recent events. Next, we consider effects of neighborhood density in single item recognition.

Recognition

In single-item recognition subjects study a long list of words followed by a second list that is usually twice as long and includes an equal number of studied and new words. During study subjects process the words in some way and the second list tests recognition by having them separate the test words into two categories, "old" and "new." In this task, the test cue is the target itself so of the 4 variables used in cued recall studies, only neighborhood density is relevant. Nelson, Zhang, and McKinney (2001) asked subjects to study words that varied in density and printed word frequency (also see Fisher & Nelson, 2006; Nelson et al., 1998). Theoretically, targets with greater density are more likely to be correctly recognized when "old" and correctly rejected when "new." This finding holds across variations in frequency and differences in study instructions (rate concreteness, name vowels, or remember).

To deepen our understanding of these results and to control for the effects of correlations between the predictor variables, we set up a recognition database that includes the targets from all our experiments. Targets are represented in one column with four measures of recognition performance (d', A', hits, false alarms) and the predictor variables represented in the remaining columns. Table 3 shows the results of a simultaneous multiple regression of the pooled data and indicates that all of the manipulated variables significantly predict d' (and the other measures).

Printed frequency effects are not shown in the table but as expected they have very strong effects with coefficients of -.36, SE = .031, t = -17.13. Study instructions (rate concreteness, name vowels, remember), frequency and neighborhood density are significantly correlated with d' at r = .38, r = -.37, and r = .12 and these correlations explain 50.6%, 46.9%, and 1.7% of the variance that can be explained. Although the effect is small, higher levels of neighborhood density are positively correlated with single-item recognition.

In the recognition task, word frequency explains more variance than neighborhood density. A similar analysis on extralist cuing discloses a reversed pattern. Of the explained variance, frequency and target density explain 2.7% and 49.1%, respectively. In both tasks study instructions explain about the same amount of variance, but recognition is more affected by distinctive letter patterns (e.g., Malmberg, Steyvers, Stephens, & Shiffrin, 2002; Shiffrin & Steyvers, 1997), whereas extralist cuing is more affected by neighborhood density and target priming effects. Both tasks rely on non-semantic and semantic information, but the same information plays different roles in the two tasks. In recognition the target is used as a cue for itself and its orthographic features play a more important role than its semantic neighborhood. Alternatively, extralist cuing relies on an external cue and is forced to rely on the semantic network. Recognition appears to depend more on matching the target's name whereas extralist cuing depends more on searching the network (e.g., Humphreys, Bain, & Pike, 1989).

Summary of Neighborhood Density Effects

The experimental and correlational findings indicate that neighborhood density effects linked to the target facilitate target recall and recognition to varying degrees. As density increases, words are more likely to be recognized as studied and rejected when not-studied, and they are more likely to be recalled when prompted by extralist test cues. In all of these tasks a

target is experienced in semantic isolation during study and semantic memory responds by activating its semantic neighborhood. Observing density effects appears to be contingent on both the absence of semantic context during study and the presence of a related extralist cue or a self-cue that provides access to its primed and encoded representation in semantic memory.

The findings also show that the magnitudes of neighborhood density effects in extralist cuing do not interact with study time or level of processing manipulations. Density effects are manifested at short and long study times, and regardless of whether subjects are naming vowels, rehearsing, or rating semantic attributes. Though the effects are small, density also influences target recovery in primed free association where the importance of the study context and the cue-target relationship are never mentioned. Finally, although target recall declines quickly as a function of test delays, target density effects are reduced but still apparent after 24 hours.

However, target density effects are not evident when targets are presented simultaneously with a semantically related word that specifies their meanings, and though this can be interpreted as indicating that the neighbors are not activated, the speeded decision literature suggests otherwise (e.g., Kintsch, 1988). The target's associates appear to be activated but this activation rapidly collapses because the associates are irrelevant when target meaning is specified by the context. The processes underlying neighborhood density effects as well as their collapse appear to be automatic, unconscious, and fast. Activation affords rapid access to prior knowledge in the semantic network and is most relevant when the prevailing semantic context is non-existent or ambiguous. In order to comprehend what it is experiencing the brain rapidly provides potentially relevant semantic contexts. Although activation is normally treated in the speeded decision literature as an ephemeral event lasting milliseconds, we suggest that neighborhood density effects survive in semantically uncertain contexts because primed targets are encoded in working

memory. A target's primed representation functions as a foundation for encoding processes

performed upon it, and such encoding ensures longer lasting priming effects. The question of

why the semantic system operates this way seems straightforward. Given semantic uncertainty,

activating prior knowledge allows the system to quickly grasp the meaning of current events in

the broadest possible sense in order to anticipate unknown specific responses to future events.

When a future event arrives in the form of a retrieval cue, a primed and encoded target is more

likely to be selected within the test cue's noisy set of related distracters.

Source of Neighborhood Density Effects And Target Priming

The most important question about the effects of neighborhood density effects has been

postponed and it concerns the underlying process: When the target is studied in semantic

isolation, how does the relative density of the links comprising its neighborhood affect its recall

and recognition? We assume that neighborhood density primes the representation of the target to

greater or lesser degrees, but how does the activation of the target's associates *prime the target*?

In this section we offer two explanations: spreading activation and quantum-like entanglement.

Spreading activation. Initially, we turned to the Collins and Loftus (1975) spreading

activation explanation. Applied to target priming effects, spreading activation implies that seeing

the target spreads activation to and among its associates and then back to the target through

associate-to-target links (Nelson et al., 1998). Spreading activation is inherently a sequential

process whereby activation moves from one word to the next along the links in the network. To

illustrate this idea Figure 6 represents target T with links to two associates, one associate-to-

associate link, and one associate-to-target link. In the 2-step loop, activation spreads from T to

Associate 2 and back to T. In the 3-step loop, it travels to Associate 1, to Associate 2, and then

to T. According to this hypothesis, the effect of the link from Associate 1 to Associate 2, or

more generally, the effects of associate-to-associate links arise because they direct activation back to the target as opposed to words outside its neighborhood.

According to spreading activation, target priming effects are contingent on the probability of links back to the target, and this contingency predicts that effects of associate-to-associate links must be greater when more associate-to-target pathways exist. While reasonable, the results of several experiments that manipulated the proportions of both types of links in a factorial design reject this alternative (Nelson, McEvoy, & Pointer, 2003). They show that associate-to-associate effects are robust compared to associate-to-target effects, and more importantly, they indicate that the expected interaction between the two variables does not emerge. The target priming effects of associate-to-associate links are just as apparent when there are few associate-to-target links as when there are many. In addition, the preliminary regression analysis of extralist cuing shows that associate-to-target links are not significantly correlated to recall when other variables are controlled (Table 2). Moreover, Bruza, Kitto, Nelson, and McEvoy (2009) pooled the data from the above experiments and found that a spreading activation equation was a poor predictor of recall (r = .35) compared to Pier2 (r = .57). Hence, experiencing a word does not appear to activate its nearest neighbors sequentially. We assume that neighbors are activated in parallel, but this assumption begs the question of how such an event can be modeled, and we turned to the concept of quantum entanglement for an alternative explanation.

Semantic Entanglement. The mathematics of quantum mechanics is being used to generate a variety of models in the social sciences and the purpose of this section is to show how it can be used to model target priming in extralist cuing (Aerts, 2009; Busemeyer & Bruza, 2012; Busemeyer, Pothos, Franco, & Trueblood, 2011; Gabora & Aerts, 2002; Pothos & Busemeyer,

2009). Entanglement is a fundamental concept in quantum mechanics that arises when two

physical entities (such as electrons and photons) are subjected to "preparations" or what

cognitivists might call "procedures," and these preparations produce highly correlated

experimental findings. Once the entities are entangled, measuring the state of one of them

determines its state and simultaneously provides information about the state of the other entity,

even when it is so distant that communication between them is impossible (see Bruza et al., 2009

for more detail on how quantum theory is applied to primed target strength; Greenstein &

Zajonc, 2006 for an introduction to experimental work; LaLoe, 2001 for a review of quantum

theory; Maudlin, 1994 for a discussion of entanglement and its implications; Turvey & Moreno,

2006, for a rationale behind using physical metaphors to understand the semantic network).

Once entangled, the entities can be represented as a "superposition state" illustrated in the

following equation that describes a situation that arises *before* the spin states of two particles are

measured. Particle 1 has a potential of spinning "down" while Particle 2 is spinning "up," *or*

alternatively, Particle 1 has a potential of spinning "up" while Particle 2 is spinning "down:"

$$\psi_{before\ measurement} = \frac{1}{\sqrt{2}}[(\downarrow_1 \uparrow_2) + (\uparrow_1 \downarrow_2)]$$

This superposition represents an *indefinite* state, and the actual spin states of two entangled

electrons cannot be known until spin direction is measured. Measuring the state of one of the

electrons causes it to collapse to spinning "up" or "down". For example, if Particle 1 is

measured, the state could collapse to one or the other state:

$$\psi_{after\ measurment} = \frac{1}{\sqrt{2}}[(\downarrow_1 \uparrow_2)] \ OR \ \psi_{after\ measurment} = \frac{1}{\sqrt{2}}[(\uparrow_1 \downarrow_2)]$$

The important point is that measuring the state of Particle 1 predicts the state of Particle 2. In the

after measurement state, if Particle 1 is observed as spinning down, we know that Particle 2 is

spinning up regardless of its distance from Particle 1. Alternatively, if Particle 1 is observed as spinning up, we know that Particle 2 will be observed as spinning down. Once entangled, measuring the state of one particle determines its state and simultaneously predicts the state of the other particle.

To say the least words differ from physical entities, but there are abstract similarities that make the comparisons worth considering. For example, both scientific disciplines entangle entities in some context, and measuring the state of one of them simultaneously provides information about its state and the states of correlated entities. In our case, observing target-priming effects reveals the activation states of its associates. Our findings show that links among the target's associates prime its representation in accordance with its neighborhood density. They also suggest that neighborhood density effects are contingent on parallel activation. An entangled state has to be "prepared," and this state emerges when the target's neighborhood in the semantic network is simultaneously activated. Theoretically, simultaneous activation generates an indefinite superposition state in the experimental context, and quantum-like entanglement provides a plausible hypothesis for explaining how neighborhood density effects emerge from links among its associates (Bruza et al., 2009; Busemeyer & Bruza, 2012; Galea, Bruza, Kitto, Nelson, & McEvoy, 2011).

The preparation phase occurs during study when the target appears on the screen. Its appearance puts the target's network representation into a superposition state with its associates. The model assumes that each of its associates is activated with a probability of 0.0 *and* each of its associates is activated with a probability of 1.0. A word's representation is recovered from the network in an indefinite state in which each of its associates *is not and is* activated. This state collapses to one activation state or the other when it is observed in context, and

theoretically, this occurs when the representation appears in working memory where it is observed, read aloud, and rehearsed, or rated on some attribute. The superposition collapses to a definite state of being not primed *or* primed when the observer becomes aware of its existence in the experimental context. Becoming aware of a word in the setting is analogous to "measuring" the state of an electron in the sense that this measurement produces a definite state.

Model details. We first illustrate how target priming is computed in the Entanglement Model, and then describe the underlying conceptualization. Table 7 presents a matrix representation of target T and its 3 associates. It shows how the probability of activating each associate is calculated in the bottom row, and how these associates affect target priming. Theoretically, each probability measures the degree to which an associate is activated by links from T's other associates, and Equation 14 shows how the Entanglement Model combines the probabilities and predicts target priming. Note that the equation indicates that each associate contributes to priming regardless of its semantic distance from the target (readers may wish to skip ahead to superposition Equation 11 after examining this table).

The model treats the associates as "qubits" in a many-bodied system. A qubit is a "quantum bit," and is a quantum analog of a classical bit. In classical probability theory a bit takes on a definite value of 0 or 1, whereas a qubit exists as a weighted sum of both of these states that defines the superposition. A classical bit represents information in a binary fashion based on logic states of "off" *or* "on." In contrast, *a qubit can represent multiple states simultaneously for brief periods* because both alternative outcomes are concurrently represented along with a weighting term that relates to their probability of occurring.

In quantum theory "off" and "on" are represented in kets $|0\rangle$ and $|1\rangle$ that are called basis

states that represent the context of a quantum measurement[2]. Hence, the superposition state of a

system ψ is written as:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle,$$

where α and β represent "probability amplitudes." When α and β are squared they are

probabilities, e.g., α^2 is the probability that a value of 0 is found, and β^2 is the probability that a

value of 1 is found. In quantum probability theory the indefinite superposition state collapses to

one of the specified states when a "measurement" is applied. In our case, the activation state of a

target is indefinite until it comes into awareness, which causes its superposition state to collapse

to the "not activated" $|0\rangle$ or to the "activated" state $|1\rangle$.

Figure 7 illustrates the system of related associates shown in Table 7 as a set of 3 qubits.

Each qubit provides a spatial representation for one of the target's associates, represented as a

vector of length 1.0 for each associate. The probability of a qubit collapsing to one state or the

other is related to the squared projection of the qubit state (the vector) down to the basis state

defined by the horizontal axis. This projection can be envisioned as drawing a perpendicular line

from the tip of the vector onto the basis state. In quantum theory probabilities are based on the

Pythagorean theorem $a^2 = b^2 + c^2$, so taking the square root of the probability amplitudes

produces probabilities. Thus, the probability of an activated target is equal to the square root of

the projection onto the $|1\rangle$ basis state, and the probability of a non-activated state is equal to the

square root of the projection to the $|0\rangle$ basis state. These ket states take the context of activation

into account, so the model is inherently contextual because the probability of activation changes

with changes in context (Isham, 1995). Making use of this procedure, we can write a

superposition state for each of the target's associates a_1, a_2, and a_3 as:

$$\left|a_1\right\rangle = \sqrt{\overline{p}_{a1}}\left|0\right\rangle + \sqrt{p_{a1}}\left|1\right\rangle \qquad (8)$$

$$\left|a_2\right\rangle = \sqrt{\overline{p}_{a2}}\left|0\right\rangle + \sqrt{p_{a2}}\left|1\right\rangle \qquad (9)$$

$$\left|a_3\right\rangle = \sqrt{\overline{p}_{a3}}\left|0\right\rangle + \sqrt{p_{a3}}\left|1\right\rangle \qquad (10)$$

where a bar over p indicates not activated.

We take all three states in Equations 8-10 and combine them by using a tensor product to

produce the indefinite superposition state. Such operations result in a complete set of possible

states (i.e., $\left|000\right\rangle, \left|100\right\rangle .... \left|111\right\rangle$. However, because of our assumption that either none or all of

the associates are activated, the only states that can occur are $\left|1\right\rangle \otimes \left|1\right\rangle \otimes \left|1\right\rangle = \left|111\right\rangle$ and

$\left|0\right\rangle \otimes \left|0\right\rangle \otimes \left|0\right\rangle = \left|000\right\rangle$, respectively. Given this restriction, *the activation state of the whole*

system can be written as an entangled state:

$$\left|\psi_t\right\rangle = \sqrt{p_0}\left|000\right\rangle + \sqrt{p_1}\left|111\right\rangle \qquad (11)$$

Equation 11 describes an entangled state representing the target in its indefinite form, where p_0

and p_1 represent the probabilities that none $\left|000\right\rangle$ or that all of the associates are activated $\left|111\right\rangle$,

respectively. We can extract values for p_0 and p_1 by making the following observations using

the law of total probability:

$$p_0 = \overline{p}_{a1}\overline{p}_{a2}\overline{p}_{a3} \qquad (12)$$

and therefore,

$$p_1 = 1 - p_0 = 1 - \bar{p}_{a1}\bar{p}_{a2}\bar{p}_{a3} \qquad (13)$$

Given this activation assumption, the remaining probability mass contributes to *primed target strength* as a whole. Consequently,

$$p_1 = 1 - (1 - p_{a1})(1 - p_{a2})(1 - p_{a3}) \qquad (14)$$

so in Table 7,

$$p_1 = 1 - (1 - .167)(1 - .167)(1 - .333) = .537$$

Equation 14 can be generalized for targets having any number of associates, and we identify it and its assumptions as the "entanglement model" or $EMS_{t'}$ for predicting target priming effects described by S_t' (Equation 4). $EMS_{t'}$ is successful to the extent that it is correlated with S_t', and to evaluate the model we used Equation 14 to compute primed target strength for all targets studied in the Standard condition in the extralist cuing database. The correlation between $EMS_{t'}$ and S_t' is r = .987, n = 2,803, and R^2 = 97.4% so nearly all of the variance of our intuitive descriptive statistic is predicted by the entanglement model. When we enter $EMS_{t'}$ in place of $S_{t'}$ along with S_{qt}, S_{tq}, and S_{qd} as predictors of recall in a multiple regression analysis the results are nearly identical [F(4, 2798) = 390.97, MSres = .043, R = .599, R^2 = .358] compared to when $S_{t'}$ is used (Table 3). The correlations with probability of recall for $EMS_{t'}$ and $S_{t'}$ are r = .264 and r = .256, respectively. Because the results are so similar, Equation 1 predicts that the two methods for computing target activation will have similar correlations with recall and similar predictions of mean recall, and this is the case. Recall probability is correlated r = .567 for both measures $EMS_{t'}$ and $S_{t'}$, and mean recall is .392 (SD = .159) and .390 (SD = .162). The mean differences between $S_{t'}$ and $EMS_{t'}$ tend to be very small, averaging .01, because $EMS_{t'}$ tends to predict more low values of target activation than $S_{t'}$ for a few targets that have only several associates (as in the example calculation in Table 7).

The entanglement model is successful because it captures the effects of links among the target's associates as well as the intuitive measure $S_{t'}$. According to the model, the appearance of the target during study puts it into an indefinite superposition state where its associates are simultaneously activated and not activated in the experimental context until the target's representation enters working memory where it is observed and can be rehearsed or its properties can be judged. As soon as the target appears in working memory subjects become consciously aware of its existence in the experimental setting and the superposition state collapses to either a non-primed or a primed state. This interpretation assumes that a miniscule amount of time elapses between when a word appears on the screen and when it is observed. During this interval the target is retrieved from the semantic network as a superposition state. When the superposition collapses to its primed state, priming effects emerge, and encoding a target in this state in working memory links it to the contextual cues available in the setting. In this approach, encoding processes applied in accordance with the study instructions operate on the target's representation in working memory regardless of the value of its primed state in this system. When all the target's associates are activated a primed representation of T is loaded into working memory, and when none are activated an unprimed representation of T is loaded into this system.

Another similarity that makes the comparison interesting between physical and semantic states of entanglement concerns the effects of semantic context. Quantum research indicates that superposition states are not permanent. Particles and other objects existing in entangled states suddenly collapse to one or the other state when measured (LaLoe, 2001). Analogously, seeing a target in semantic isolation locates it in its semantic neighborhood and creates a superposition state in the experimental setting that collapses to activating none or all of its associates when a subject becomes consciously aware of it in working memory. In contrast, when the target is seen

in the context provided by a semantically related word, neighborhood density effects are not apparent because the target's meaning is specified by the context. Seeing a semantically related cue-target pairing creates an entangled state in which the target's associates are activated or not, but this state immediately collapses to the non-activated state when this representation reaches working memory. The target's superposition state prior to appearing in working memory is the same as when it is seen in isolation, but when seen in an appropriate semantic context, the superposition state collapses to a non-activated state when observed in working memory. Although derived from an unusual source for the field of memory, the entanglement model fairs better as a model of target activation effects than spreading activation because it is based on a parallel activation process that is sensitive to environmental context.

General Discussion

Both experimental and correlational findings show how the semantic network contributes to event memory in tasks involving a semantically isolated target and a cue that is related to the target or that is the target in a physical sense. The magnitude of the network contribution based on variance explained differs across tasks depending on the semantic context during encoding, context awareness during testing, and the nature of the cue. Importantly, in extralist cuing the network contributes more to recall than does study time or how the target is encoded during study. Recall in this task is affected by both semantic and episodic information and the semantic information is critical because recall is based on a test cue that is both absent during study and semantically related to the target. The network provides semantic information during study that defines the meaning of an isolated word event, and during testing it provides information that guides the search for this event. During both study and test familiar words act as reminding cues

that reliably and quickly activate the prior semantic contexts of these words. In what follows, we consider four general and partially overlapping conclusions.

The semantic network. The first conclusion is that a semantic network exists in memory as a complex system of words and links that functions as a repository of word knowledge. Words are not randomly connected in this system (Collins & Loftus, 1975; Steyvers & Tenenbaum, 2005). They cluster around similar experiences involving thousands of direct links and tens of thousands of indirect links that may provide shortcuts across the domain (Watts & Strogatz, 1998). This system continually interacts with familiar words, objects, and events by automatically activating related words. Automatic parallel activation provides the informational bases for comprehension, priming, and encoding, as well as for search, recall and recognition. Episodic encoding and retrieval depend to varying degrees on the semantic network to provide word knowledge needed in each of these processes, and more specifically, the findings show that measures based on the network are correlated with memory performance in several event memory tasks. Of the four key measures taken on the network, word recognition relies only on target activation, intralist cuing relies only on cue-to-target strength, and extralist cuing depends on all four measures. Taken together, the findings provide strong evidence for the hypothesis that words are represented and processed in a vast dynamic semantic storage system that contributes to and that can be used to predict the recall and recognition of episodic events.

Free association and semantic context. The second general conclusion is that free association to thousands of words can be used to generate a semantic network that measures what related words are likely to come to mind when experiencing a word, measures that are reliable and valid, and that are sensitive to semantic context. It is reliable because re-norming the same word tends to produce the same associates for even weaker associates, and it is valid

because measures taken from this network predict behavior in various memory tasks. Finally,

the network is sensitive to context because the same word takes on different shades of meaning

when influenced by different cues. For example, in our free association norms *food* is produced

as a response by 324/ 5,018 different cues and its meaning varies for each cue. Each cue that

produces *food* as an associate also produces related words that vary substantially across cues so it

means something different in the context of different words. Both Dinner and Hamburger

produce *food* as an associate but otherwise their associates are completely different indicating

that it activates a different semantic sense in the contexts provided by Dinner and Hamburger.

Free association norms capture context-driven differences in meaning because a word with

exactly the same name appears among different associates for each cue that generates it in free

association. We suggest that the semantic network generated via free association is highly

sensitive to semantic context differences because cues being normed activate not just a single

word but an array of related words out of which one or more words can be selected.

       Activation, search, and memory task. The third conclusion concerns the distinction

between activation associated with priming effects and search. The most advanced memory

models of recall generally do not explicitly incorporate activation in the modeling because the

research is based on the free recall of *unrelated* words, defined as words that are not directly

associated (e.g., Gillund & Shiffrin, 1984; Shiffrin & Steyvers, 1997). The study phases in free

recall and extralist cuing tasks are essentially identical so it is reasonable to assume that the

target words are loaded into working memory as primed or not, but the testing phases are

different. In free recall, subjects are asked to recall all list words in any order whereas in cued

recall, a semantically related cue is used to prompt the recall of each one. In extralist cuing the

semantic cue provides access to an array of response alternatives that include the target, whereas

in free recall the first word recalled is cued by context and the remaining words are cued through a combination of context and episodic associations between the words produced by rehearsal during study (Raaijmakers, & Shiffrin, 1981). In the free recall of unrelated words what is activated in the semantic network serves no apparent purpose. There is no reason to believe that the activation of related words by the target or the cue might be important so the priming literature and the concept of activation have been largely and reasonably ignored in modeling free recall.

The results of three experiments that compare the two tasks directly using the same materials and study conditions justify this position (Nelson, Akirmak, & Malmberg, in preparation). These experiments show that neighborhood density and the resulting priming effects are strong in extralist cuing and absent in free recall. Although both tasks involve search, what is being searched is different: In free recall memory for the study list is searched using a recalled word as a cue for recalling another word from the study list based on an episodically created link (Raaijmakers & Shiffrin, 1981). In contrast, in extralist cuing the cue activates its associates in the semantic network and search is limited to this set. The network becomes involved in recall when a test cue is semantically linked to its prospective target, and the task comparison suggests that target-priming effects are contingent on recovering the target from its storage in this network. Target priming effects may be observed only when searching the network that created these effects in the first place.

These findings suggest that the network plays a critical role in recall that is cued by a meaningfully related word but no role whatsoever when the recall of one list word is cued by an unrelated word. They also indicate that, when the semantic system is utilized, effects of related words can be apparent during both study and test. Related words are not physically presented so

some brain mechanism must be providing them and findings here and in the priming literature

suggest that implicit activation is that mechanism. The evidence reviewed here suggests that the

semantic memory system supports the recognition and recall of episodic events by activating

related words that serve as the basis for comprehension and search processes in some but not all

episodic memory tasks. In the extralist cuing task, the simultaneous activation of the target's

associates during the study phase provides the semantic context for a word seen in isolation, and

during testing the cue activates a set of potential responses that is likely to include the target and

that initiates a search for the target within this set. Activation plays a role in both phases, but the

study phase is largely concerned with comprehension and following the study instructions. The

key network variable in this phase is neighborhood density and its influence on target priming.

In contrast, the test phase is largely concerned with search and the key network variables are cue-

to-target strength, cue-to-distracter strength, and target-to-cue strength. Variables associated

with the semantic network contribute in different ways to both phases of extralist cuing and in

different ways to recognition and intralist cuing, suggesting that the network responds

dynamically to the contexts provided by different ways of measuring memory. Semantic

memory is a fast acting dynamic system that reminds us about what we know. To return to the

beginning, our findings indicate that the electric company is paid because Check, Envelope, and

Mailbox activate related words that allow Mailbox to succeed as a cue by reminding us to pay

the bill.

       Pier3 and Entanglement. Equation 1 provides an algorithm for predicting extralist

cuing that evolved from the Pier framework, and we refer to it as Pier3. Pier3 computations are

derived from measures made on the semantic network that are combined in a ratio rule that

predicts the contribution of the semantic system to probability of recall. Pier3's core rationale is

motivated by SAM (search of associative memory, Raaijmakers & Shiffrin, 1981), but it is

incomplete as a SAM model because it does not incorporate the effects of the environmental

context or the effects of encoding operations in calculating its predictions. In addition, it differs

from SAM in that search is based on a semantic network of links acquired in interactions with

the world as opposed to an episodic network of associative links established during recent study.

In addition, Pier3 makes probabilistic predictions for specific cue-target pairs. By computing

mean predicted recall and the SD for pairs linked to a specific semantic manipulation (e.g.,

neighborhood density), it predicts the contribution of the semantic network to recall in extralist

cuing experiments. In extralist cuing once a list is prepared it is possible to compute a recall

prediction for each cue-target pair, and by averaging over the pairs in a given condition, it is

possible to predict recall for that condition. Finally, among other things, Pier3 differs from SAM

in how it aggregates links among related words, but despite the differences, both approaches

assume that recall is based on searching memory for recently encoded information. Given this

commonality it might be possible to develop a SAM model for extralist cuing that incorporates

simulations of episodic encoding processes using predictions based on semantic relationships. In

Bayesian terms, Pier3 predictions could serve as the prior probability, and a to be developed

measure of the contribution of episodic memory could serve as the posterior probability.

      In Pier3 the test cue initiates a search of the semantic network and this search is

facilitated when the cue and its target are more strongly linked relative to all of the information

relevant to its selection, including the error introduced by the cue's distracters. Recall is more

likely when cue-to-target and target-to-cue strength are high, and when cue-to-distracter strength

is weak. It is also more likely when target priming is higher, when the target is studied longer,

and when it is studied with a more effective procedure. Pier3 assumes that both target priming

and encoding strengthen its representation in the semantic network and that this elevation decays over time unless refreshed.

The target priming effect is in many ways a most interesting phenomenon because it is founded on links among the target's associates. Classic spreading activation theory predicts that this result arises because activation in the target's network returns to the target as opposed to spreading outside its neighborhood. This interpretation, however, is countered by evidence indicating that target priming effects are independent of the presence of associate-to-target links. Target priming effects do not appear to arise from a sequential activation process but from a parallel process that simultaneously activates the target's neighborhood. Words exist in a tangled network of associative/semantic links and when context fails to provide a specific semantic sense, the network activates and temporarily encodes its most immediate senses. The Entanglement Model captures this process effectively because it is based on an indefinite superposition state that is sensitive to context represented in the probabilities that none *and* all of its associates are activated. The model assumes that the physical appearance of a word puts it into a superposition state that collapses to a specific sense when it reaches working memory and an individual becomes aware of its existence. The target becomes entangled with its associates, and such entanglement occurs when the target and its associates are simultaneously activated. When applied to the extralist cuing database the model explains 97.4% of the variance of the intuitive measure of neighborhood density. Although rarely used in psychological research this result indicates that the superposition assumption can be productively used to study difficult problems involving indefinite semantic states and, possibly, other indefinite psychological states involving uncertainty (Busemeyer & Bruza, 2012).

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Notes

[1] All databases mentioned in this article are available on request from the first author.

[2] The symbol $\left| \ \right\rangle$ is called a "ket." In quantum mathematics kets provide a context for describing probabilities, e.g., $\left|0\right\rangle$ and $\left|1\right\rangle$ are read as "ket 0" and "ket 1.

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Table 1

Variables and their computations shown to affect extralist cued recall

Variables	Computation
Cue-to-target strength, S_{qt}	#Subjects producing target in free association ÷ sample size
Target-to-cue strength, S_{tq}	#Subjects producing cue in free association ÷ sample size
Cue-to-distracter strength, S_{qd}	#cue distracters ÷ # cue associates*
Primed Target strength, $S_{t'}$	#links among target's associates ÷ #possible links
Mediator strength, S_m	#mediators ÷ #cue associates
Shared-Associate Strength, S_{sa}	#shared associates ÷ #target associates
Associate-to-target strength, S_{at}	#associate-to-target links ÷ #target associates
Target-to-distracter strength, S_{td}	#target distracters ÷ # target associates

* Distracters exclude the target, mediators, and shared-associates. Mediators provide indirect links from the test cue to the target (e.g., Proton→ $electron$ → $Atom$). Shared associates occur when the cue and target have the same associate in common (e.g., Proton→ $electron$ and Atom→ $electron$).

Table 2

Correlations (above diagonal) and partial correlations (below

diagonal) among the 8 network variables that affect extralist cued recall

	S_{qt}	S_{tq}	S_{qd}	$S_{t'}$	S_m	S_{sa}	S_{at}	S_{td}	r with Prob. Recall
S_{qt}	---	-.01	-.29	-.04	.27	.04	.17	-.02	.46
S_{tq}	.01	---	.11	.20	-.20	.18	-.21	-.30	.19
S_{qd}	-.13	.13	---	-.16	-.73	-.43	-.11	.37	-.37
$S_{t'}$	-.10	.08	.07	---	.08	.63	.10	-.58	.26
S_m	-.02	.04	-.70	-.07	---	.23	.45	-.15	.30
S_{sa}	0.0	-.13	-.15	.34	.02	---	-.04	-.87	.34
S_{at}	.11	-.14	.31	.22	.51	-.02	---	.11	.10
S_{td}	.06	-.25	.08	-.06	.05	-.76	.08	---	-.33
Partial r with Prob. Recall	.42	.19	-.10	.11	.06	.02	.02	-.07	

Table 3

Results of regression analyses evaluating the effects of the four predictors as a

function of memory task

	F	MS_{res}	R	adj R^2	S_{qt} Std. Coeff. Std. Error t-Value	S_{tq} Std. Coeff. Std. Error t-Value	S_{qd} Std. Coeff. Std. Error t-Value	$S_{t'}$ Std. Coeff. Std. Error t-Value	Study Cond.
Extralist Cuing	$F_{(4,2803)}$ = 387.36	.043	.597	.355	.395 .034 24.81	.183 .028 11.64	-.246 .022 15.08	.194 .034 12.26	_____
Primed Free Assoc.	$F_{(5, 464)}$ = 47.42	.019	.583	.332	.441 .100 10.77	.162 .069 4.19	-.225 .037 -5.18	.081 .087 2.07	.145 .007 3.76
Intralist Cuing	$F_{(4, 509)}$ = 13.17	.037	.306	.087	.263 .085 5.78	.011 .052 .246 ns	-.090 .049 -1.91 ns	-.056 .001 -1.24 ns	_____
Recog-nition	$F_{(3,1647)}$ = 221.02	.919	.536	.286	_____	_____	_____	.071 .143 3.37	.381 .033 18.33

Table 4

The 4 strongest predictors of extralist cuing, with correlations (above diagonal) and partial

correlations (below) in the first 5 columns and descriptive statistics in the last 3 columns.

	S_{qt}	S_{tq}	S_{qd}	$S_{t'}$	Prob. Recall	Mean	SD	Range
S_{qt}	---	-.01	-.29	-.04	.46	.152	.120	0.0-.818
S_{tq}	-.05	---	.11	.20	.19	.099	.144	0.0-.917
S_{qd}	-.15	.21	---	-.16	-.37	.605	.192	.091-1.00
$S_{t'}$	-.18	.17	-.13	---	.26	.152	.118	0.0-1.00
Prob. Recall	.43	.22	-.27	.23	---	.518	.258	0.0-1.00

Table 5

Results of regression analyses for Equation 1 as the sole predictor in the first row, and regression

comparisons between Equation 1 against test delay, presentation rate, and study instructions in

the successive rows

	F	MS_{res}	R	adj R^2	Std. Coeff.	Std. Error	t-Value
Regression Equation 1	F(1, 2801) = 1,326.00	.045	.567	.321	.567	.025	36.41
Regression Equation 1 Test Delay	F(2, 2552) = 285.07	.048	.427	.182	.384 -.164	.026 .000	21.43 -9.15
Regression Equation 1 Rate	F(2, 3220) = 778.08	.045	.571	.325	.565 .084	.023 .010	39.02 5.81
Regression Equation 1 Instructions	F(2, 369) = 930.25	.045	.597	.356	.551 .207	.022 .009	39.78 14.93

Table 6

Correlations (above diagonal) and partial correlations (below) for

Primed Free Association

	S_{qt}	S_{tq}	S_{qd}	$S_{t'}$	Study Condition	r with Prob. of Recovery
S_{qt}	---	-.10	-.37	.02	-.13	.49
S_{tq}	-.12	---	.12	.07	.12	.11
S_{qd}	-.21	.15	---	-.31	.17	-.37
$S_{t'}$	-.14	.10	-.29	---	-.11	.16
Study Condition	-.14	.07	.13	-.09	---	.06
Partial r with Prob. of Recovery	.45	.19	-.23	.09	.17	---

Table 7

Matrix representation of Target T with three associates *a*, the links among them reading along

each row, and the probabilities (p) that an associate will be activated

Target	a_1	a_2	a_3
a_1	---	1	1
a_2	1	---	1
a_3	0	0	---
Probabilities	$P_{a1} = 1+0 \div 3(3\text{-}1)$ $= .167$	$P_{a2} = 1+0 \div 3(3\text{-}1)$ $= .167$	$P_{a3} = 1+1 \div 3(3\text{-}1)$ $= .3333$

Figure Legends

Figure 1. Measuring primed target strength on the basis of neighborhood density.

Figure 2. Recovering primed target T' from its test cue Q. Cue-to-target strength (S_{qt}) is represented in the arrow from the test cue to the target, and target-to-cue strength (S_{tq}) is represented in the arrow from the target to the test cue. Both strengths are taken directly from free association norms. Primed target strength ($S_{t'}$) is calculated by example in Figure 1 (also see Equation 4 in the text). Cue-distracter strength in this figure is determined by dividing the number of distracters by the total number of responses produced to the cue in free association after eliminating mediators and shared associates. Mediators and shared associates facilitate recall and are not counted as distracters, and because there are none in the figure, distracter strength is 1/6 or .167.

Figure 3. Observed and predicted probability of recall as a function of Equation 1 predictions in four categories.

Figure 4. Observed and predicted probability of recall as a function of minutes of test delay.

Figure 5. The representation of *Atom* in semantic memory can be strengthened by priming effects produced by its neighborhood density in the network and by encoding processes in working memory. Although priming effects are generally short-lived, they can be long lasting when a primed version of a target word is encoded in working memory.

Figure. 6. Target T activates target-to-associate, associate-to-associate, and associate-to-target links.

Figure 7. The system of related associates shown in Table 7 represented as a set of three qubits.

Measuring neighborhood density on the basis of associate-to-associate links

a. Graph depicting Word T, its 3 associates, and their 4 connecting links
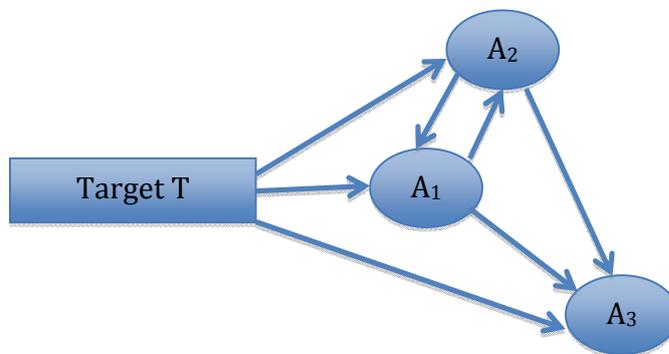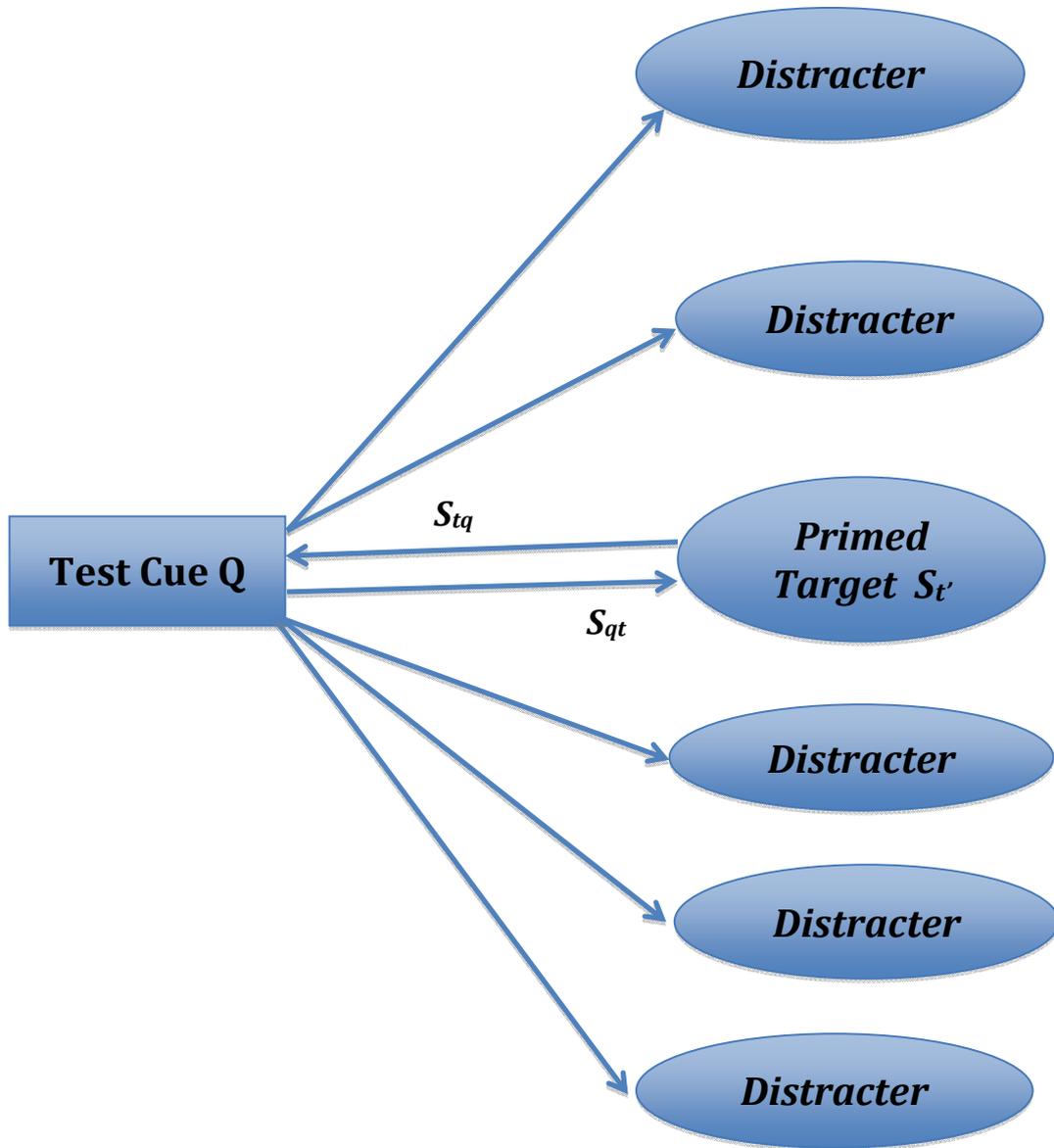

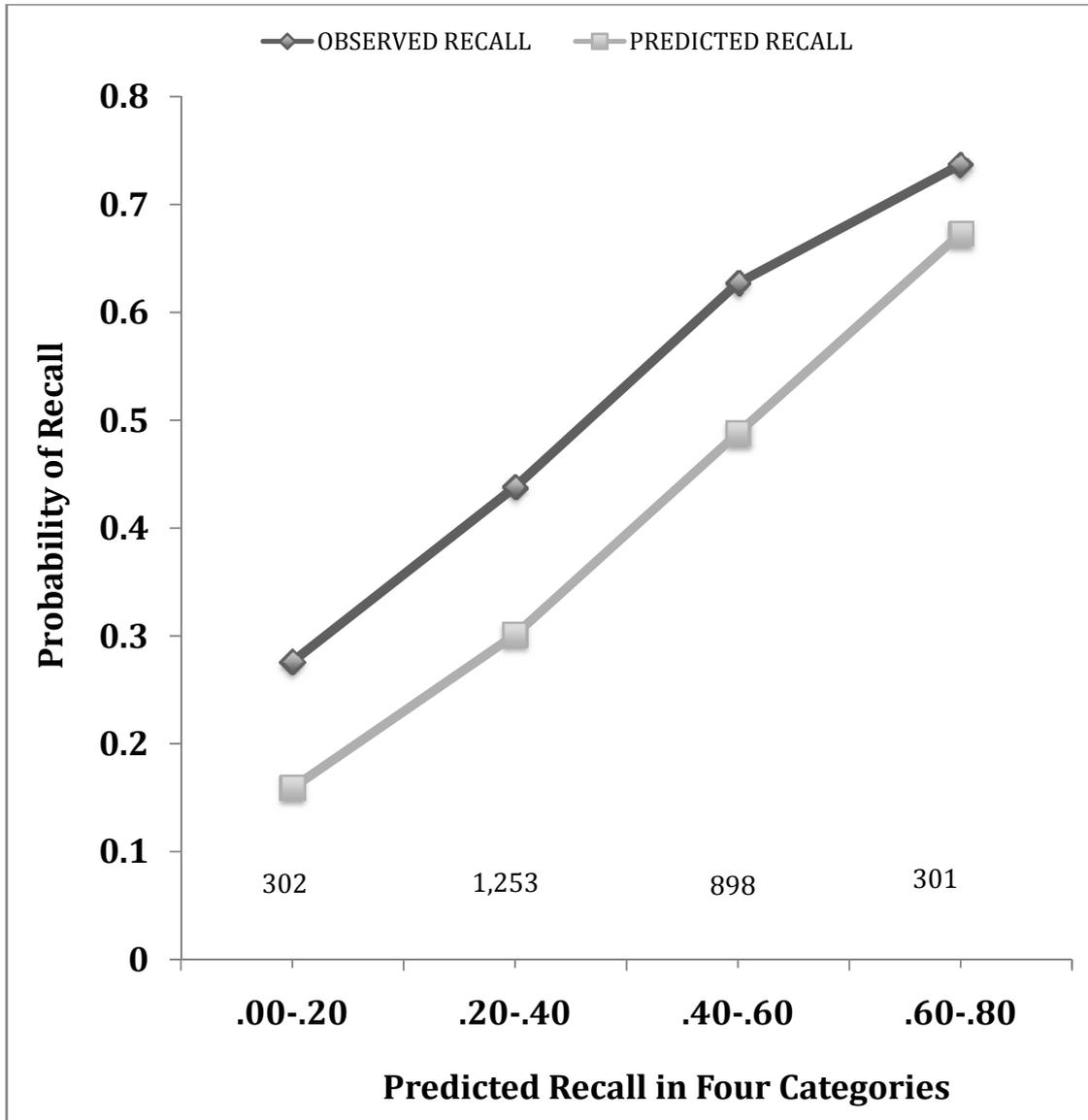b. Asymmetric adjacency matrix depicting links among T's associates
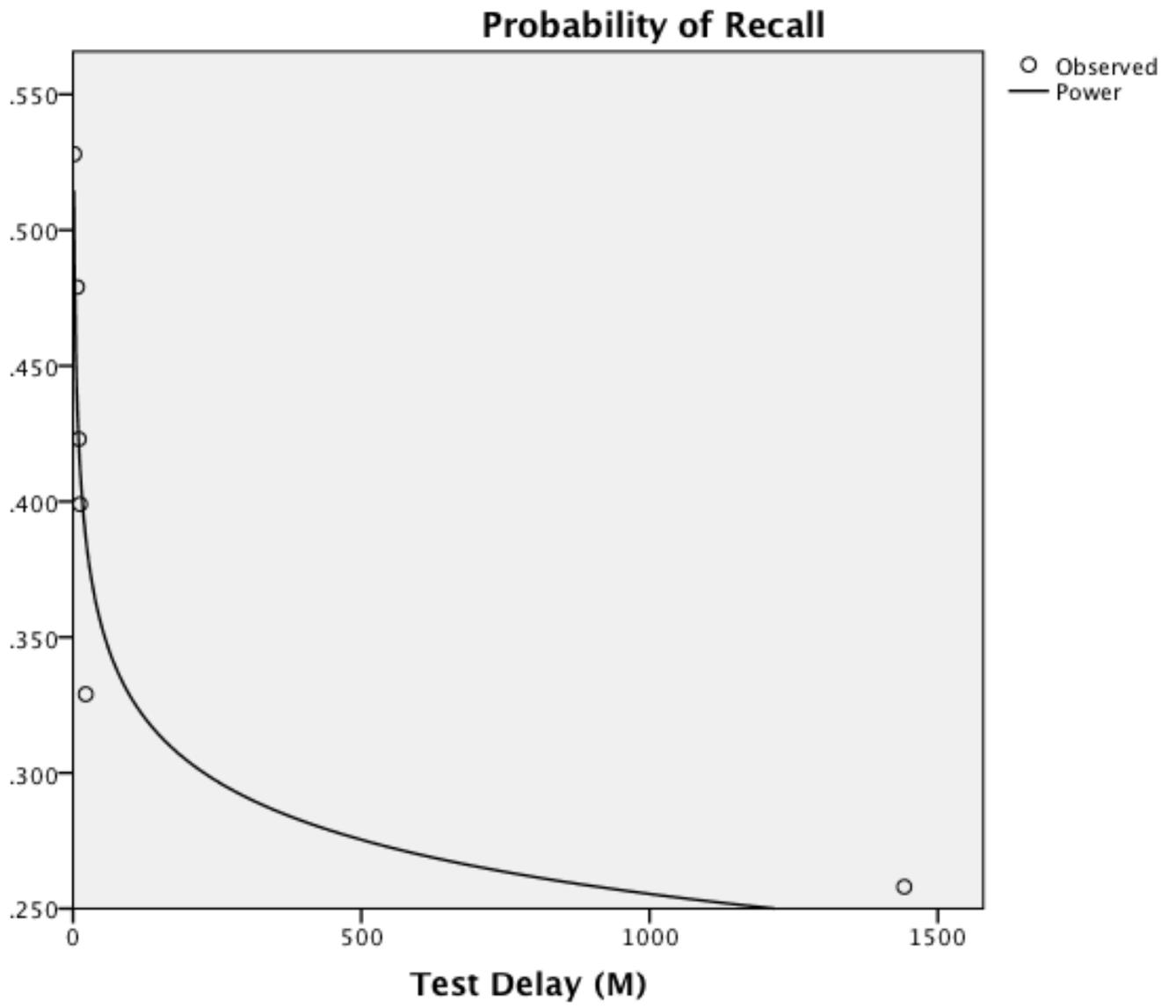
Normed Associates of T

		Target T	A_1	A_2	A_3
Associates	A_1		---	1	1
Normed	A_2	1		---	1
As Cues	A_3	0		0	---

c. Primed target strength, $S_{t'}$

$$S_{t'} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} A_{ij}}{n(n-1)} = \frac{4}{3(3-1)} = .667$$

Semantic Memory

Molecule

Atom

Proton

Rehearsal

ATOM

context

context

context

Name Vowels

Working Memory

Rate
Concreteness