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A synchronization account of false recognition

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ABSTRACT

We describe a computational model to explain a variety of results in both standard and false recognition. A key attribute of the model is that it uses plausible semantic representations for words, built through exposure to a linguistic corpus. A study list is encoded in the model as a gist trace, similar to the proposal of fuzzy trace theory (Brainerd & Reyna, 2002), but based on realistically structured semantic representations of the component words. The model uses a decision process based on the principles of neural synchronization and information accumulation. The decision process operates by synchronizing a probe with the gist trace of a study context, allowing information to be accumulated about whether the word did or did not occur on the study list, and the efficiency of synchronization determines recognition. We demonstrate that the model is capable of accounting for standard recognition results that are challenging for classic global memory models, and can also explain a wide variety of false recognition effects and make item-specific predictions for critical lures. The model demonstrates that both standard and false recognition results may be explained within a single formal framework by integrating realistic representation assumptions with a simple processing mechanism.

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1. Introduction

False recognition is one of the most empirically studied psychological phenomena in recent times, however, very little formal modeling has been conducted to explore the mechanisms that produce it. The dominant experimental paradigm to study false recognition in the laboratory is the

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Deese/Roediger–McDermott (DRM) task (Deese, 1959; Roediger & McDermott, 1995). In a DRM task, lists of words that are associated with a specific critical word are presented to subjects, and on subsequent memory tests the non-presented critical lures are falsely recognized and recalled at approximately the same level as studied items (Roediger & McDermott, 1995). For example, given *nurse*, *hospital*, *sick*, *cure*, etc. to remember, subjects are likely to produce a false alarm to the critical lure *doctor*.

False recognition is a very reliable effect (McDermott & Roediger, 1998). Many factors influence false alarms to semantic associates, including the number of studied items (Robinson & Roediger, 1997), the associative structure of study lists (Gallo & Roediger, 2002), level of processing (Thapar & McDermott, 2001), and instructional content (Brainerd, Wright, Reyna, & Mojardin, 2001), to identify just a few. Research using the DRM paradigm has demonstrated convincingly that humans use semantic information both to store and to retrieve memories, and that semantic confusions can lead to profound memory errors. Nevertheless, the exact mechanisms that underlie false recognition have evaded a formal explanation. Instead, researchers have focused more on conceptual frameworks of cognition, such as spreading activation (Anderson & Bower, 1972), fuzzy-trace theory (Brainerd & Reyna, 2002), and source monitoring (Johnson, Hashtroudi, & Lindsay, 1993).

Spreading activation theorists (e.g., Anderson & Bower, 1972) propose that the critical word becomes activated during study through the repeated exposure to semantically associated words. The increased activation in memory produces a higher probability of accepting the critical lure on a subsequent recognition test, and leads to the high levels of false recognition. In this sense, false recognition is explained by spreading activation in a fashion very similar to other types of semantic priming.

A related theory that has been very influential is the source monitoring framework (Johnson et al., 1993). Source monitoring theory proposes that the repeated exposure to related items increases the probability that the critical word is generated during the study phase. The increased probability may reflect spreading activation, or some other type of generation mechanism. At test, this generation during study leads to confusion about the source of the memory for the critical item (i.e. whether it was studied or not), which in turn leads to an increased false alarm rate for that item.

A competing theory to source monitoring is fuzzy trace theory (FTT; Brainerd & Reyna, 2002). FTT proposes that there are two types of memory traces stored for events: verbatim and gist traces. Verbatim traces are the surface forms of the items that are being studied, while gist traces contain the concepts (meanings, relations, and patterns) that are associated with the studied items. To explain false recognition in the DRM paradigm, FTT assumes that the semantic relatedness of studied items induces participants to rely on semantic information. False recognition reflects the high similarity of the critical lure to a gist trace that was formed through study of its associates.

Currently FTT and source monitoring are the two most influential theories of false recognition, and are commonly seen as competitor models. A complete review of these two approaches is beyond the scope of this article (but see Reyna & Lloyd, 1997, and Lindsay & Johnson, 2000, for a description of the strengths and weaknesses of both approaches). The formal model we propose has more in common with FTT, but we suggest in Section 5 how to build mechanisms of source monitoring into the same framework.

All three theories have evaded formal computational modeling. The main reason is that all three require a realistically structured lexical semantic representation for false recognition to be modeled. In spreading activation theories, a quantifiable associative connection needs to be made between word nodes within a semantic network to allow activation to spread to a critical item. The source monitoring framework requires a semantic representation for the critical word and its associates to allow the critical lure to be generated during study. FTT also requires semantic representations for words to allow gist traces to be created and confused with the representation of the critical lure.

The lack of a plausible semantic representation is problematic not only for these conceptual theories of false recognition, but also for standard computational recognition memory models. Most recognition models do not use a realistic semantic representation, but instead assume that lexical semantic structure can be approximated with random representations—each word's semantic representation is modeled as a randomly generated vector, created with a particular similarity structure. For instance, REM uses gamma vectors (Shiffrin & Steyvers, 1997), TODAM uses dense Gaussian vectors (Murdock 1982, 1993), BCDMEM uses sparse binary vectors (Dennis & Humphreys, 2001), and

MINERVA 2 uses dichotomous vectors (Hintzman, 1988). Arndt and Hirshman (1998) provided an existence proof that, as a process model, MINERVA 2 could account for some false recognition results by using randomly generated exemplar–prototype vectors. By assuming that semantically related items may be represented as random perturbations of a parent prototype vector (cf. the way Hintzman, 1986 simulates schema abstraction) Arndt and Hirshman were able to produce a variety of false recognition effects from MINERVA 2, suggesting that false recognition in the DRM paradigm may simply be a lexical version of schema abstraction (easily accounted for by a global memory process).

However, Johns and Jones (2010) recently conducted a series of simulations evaluating whether random representations provide a plausible approximation for the structure of lexical semantic memory. They compared the word-pair similarity distributions produced from random representations to those created by a variety of semantic memory models. The similarity distributions from plausible semantic memory models were much more positively skewed than the distributions generated from random representations—on average, two random words are relatively more dissimilar to each other than would be assumed using randomly generated representations. Standard signal detection models failed to fit human data when they used similarity distributions from the realistic semantic representations, indicating that they are overly reliant on a false assumption of random semantic structure.¹

Johns and Jones (2010) also evaluated how well the MINERVA 2 implementation of false recognition used by Arndt and Hirshman (1998) would fare with structured semantic representations when simulating false recognition data. They demonstrated that Arndt and Hirshman's success at simulating false recognition data using MINERVA 2 depended on the model's freedom to create random representational structure. It failed to reproduce even the qualitative trends in the human false recognition data when realistic semantic structure was used. Johns and Jones argued that the use of random representations in formal models might lead the theorist to accept an incorrect process model as having generated the data. A similar point has been made by Cree, McRae, and McNorgan (1999) in the realm of semantic priming, where they argued that the use of realistic representations reduces the degrees of freedom in the modeling exercise. Hence, it is important when evaluating a process account of recognition that it be implemented using representations that contain realistic semantic structure; this is particularly crucial for a paradigm such as the DRM for which the locus of the effect is thought to be largely semantic.

A variety of models have recently been developed to approximate the organization of semantic memory by observing statistical redundancies in linguistic corpora. These so called “semantic space models” (e.g., Landauer & Dumais, 1997) attempt to infer the structure of semantic memory from how words co-occur across linguistic contexts; they produce excellent candidate representations to be used in a model of standard and false recognition. Each word is represented by a vector in high-dimensional semantic space, with vector elements defined by the word's usage pattern in language, and proximity in the space is analogous to semantic similarity. In Arndt and Hirshman's (1998) simulation of false recognition using random representations within MINERVA 2, an assumption must be made that list items are uniformly distributed in their similarity to the critical lure (just as exemplars in Hintzman's (1986) simulation of schema abstraction were distributed as random perturbations of the prototype pattern). When representations from a semantic space model are used, however, the distribution of similarities between exemplars and the critical lure take on a much more realistic form and need not be uniform or even symmetric.

Semantic space models use a variety of mechanisms to learn their representations, including dimensional reduction (Landauer & Dumais, 1997), probabilistic inference (Griffiths, Steyvers, & Tenenbaum, 2007), holographic binding (Jones & Mewhort, 2007), random indexing (Kanerva, 2009), retrieval abstraction (Kwantes, 2005), and temporal context encoding (Howard, Shankar, & Jagadisan, 2011; Shankar, Jagadisan, & Howard, 2009). The representations learned from these models have been shown to contain semantic structure that mimics the structure of human semantic memory, accounting for a wide range of human data, such as synonymy tests (Landauer & Dumais, 1997), semantic similarity ratings (Jones & Mewhort, 2007; Recchia & Jones, 2009), association norms (Griffiths et al.,

¹ This criticism applies only to signal detection theories based on a single source of familiarity, but not those that integrate a recollection-based mechanism (e.g., Wixted & Mickes, 2010), or a different type of information, such as source memory (Banks, 2000).

2007), semantic priming (Hare, Jones, Thomson, Kelley, & McRae, 2009; Jones, Kintsch, & Mewhort, 2006), and word identification latency (Jones, Johns, & Recchia, 2012). However, the semantic representations cannot by themselves account for false recognition data—for example, LSA cosines between the critical word and associates from the norms of Stadler, Roediger, and McDermott (1999) and Gallo and Roediger (2002) have a non-significant correlation with the behavioral probability that the associate lists elicit the critical lure in DRM experiments. Instead, the semantic representations simply offer a plausible and constrained structure on which a process mechanism can operate.

To overcome these problems, a new computational model of recognition, the Recognition through Semantic Synchronization (RSS) model, will be introduced in the next section. RSS borrows components from other successful models of recognition memory, but also bases its decision process on plausible semantic representations for words developed with a semantic space model trained on a linguistic corpus. Using structured semantic representations, the model is more specified than if a particular structure was assumed or was simply fit to the behavioral data. Further, realistic representations allow the model to make word-specific predictions for lists, items, and lures, which can further illuminate the mechanisms responsible for both standard and false recognition and the interactions between memory structure and decision mechanism.

After describing the model and its process parameters, we turn to a set of simulations on basic recognition memory phenomena to demonstrate that RSS can account for effects that are considered to be standard benchmarks for a contemporary model of recognition. We then move onto simulating ten core effects from the false recognition memory literature and interpret parameter changes as reflecting principled mechanisms underlying false memory.

2. The Recognition through Semantic Synchronization (RSS) Model

Recognition through Semantic Synchronization (RSS) is a hybrid model based on previous accounts of semantic memory, recognition, and dynamic decision-making. RSS is based on three core assumptions about recognition memory, supported by current findings in the literature. First, we assume that any model of a process such as recognition must operate on a representation that contains plausible structure of the stimuli being used. If the stimuli are low-dimensional geometric figures generated by the experimenter, such as random dot patterns (e.g., Hintzman's (1986) simulation of Posner and Keele's (1968) stimuli) or colored shapes (e.g., Johns & Mewhort, 2002), it is an easy task to provide the model with vector representations that contain equivalent structure. Using the incorrect structural representation of the stimuli can lead the theorist to accept an incorrect process model as having generated the data (Johns & Jones, 2010). This caution also holds for stimuli that are not generated by the experimenter, such as words. Given that most recognition memory experiments use words as their stimuli, it is important to use realistic approximations of the orthographic, phonological, and semantic structure of the words being used in the model. Because we simulate false recognition here, we focus solely on semantic structure in this article, using as input semantic representations for words learned by a semantic space model. However, these types of representations can be extended to include information about the more physical characteristics of the words in a given experiment (see Cox, Kachergis, Recchia, & Jones, 2011).

Second, RSS assumes that recognition judgments are not made on a single dimension of familiarity, as is standard in classic signal detection theories, but that different sources of information drive *new* and *old* decisions. Specifically, the model assumes that the amount of contradictory information contained within a probe predicts *new* decisions, but *old* decisions seem to be based on the similarity of the probe to the list items (Hintzman & Curran, 1994; Johns & Mewhort, 2002, 2003, 2009; Mewhort & Johns, 2000; Rotello & Heit, 1999; Rotello, Macmillan, & Van Tassel, 2000). Mewhort and Johns (2005) propose a dual-criteria decision process to explain the pattern of results, and we borrow this dual criteria distinction and separate information sources for *old* and *new* decisions in RSS.

Third, RSS makes the assumption that information accumulation is continuous over time until a decision is made, an assumption common to successful dynamic models of decision making, such

as diffusion models (Ratcliff, 1978; Ratcliff & McKoon, 2008; Ratcliff & Rouder, 1998) and accumulator models (Brown & Heathcote, 2005; Usher & McClelland, 2001). In RSS, a probe word is compared to a composite memory of the list items using semantic representations, and information about similarity and contradiction is simultaneously sampled until one source of information reaches its criterion and a decision is made to respond *old* or *new*.

These two assumptions—separate information sources for old and new responses, and dynamic information accumulation—place this model in the general class of race models (Smith & Vickers, 1988; Vickers, 1979), a class commonly used to examine recognition memory (e.g. Lamberts, Brockdorff, & Heit, 2003; Luce, 1986; Nosofsky, Little, Donkin, & Fific, 2011). Race models typically assume that there is competition between different internal counters to make a decision. For instance, in Nosofsky et al.'s (2011) random walk model of short-term recognition, each item studied has a separate accumulator, and the accumulators racing to exceed some criterion produced an impressive account of a number of RT results within the Sternberg paradigm. Rather than a race between a set of studied items, we propose that recognition takes place through a race of information sources about whether the item occurred (assessed through similarity information) or did not occur (assessed through contradictory information).

A useful neural analogy to the underlying functioning of the RSS model is that of neural synchrony. Neural synchrony is the finding that spatially separated neural populations can become phase-locked in a millisecond time frame depending on anatomical connections between cortical areas and stimulus properties (Singer, 1999). For example, a classic study by Gray and Singer (1989) found that neurons in the visual cortex synchronized when activated by the same stimulus, but did not when they were activated by different stimuli moving in different directions. As Engel and Singer (2001, p. 24) discuss, the theoretical prediction of neural synchrony is that neurons that "... represent the same object or event might fire their action potentials in temporal synchrony in the millisecond range." Although neural synchronization has been employed primarily in models of perceptual processing (e.g. Eckhorn, Reitböck, Arndt, & Dicke, 1990) or as a potential solution to the binding problem (Engel & Singer, 2001), synchrony has also been studied in the field of memory. For example, single-cell recording studies have found gamma oscillations at the neural level in the hippocampus (Bragin et al., 1995) in rats. This is of interest to the model because the hippocampus (along with the medial temporal lobe) seems to be a primary processing hub for recognition memory (Manns, Hopkins, Reed, Kitchener, & Squire, 2003; Sporns, 2011).

In studies of human memory, researchers using electro-or-magnetoencephalography (EEG or MEG) have recorded systematic gamma oscillations under a variety of conditions pertaining to the maintenance and use of working, short-term, and long-term memory (Jensen, Kaiser, & Lachaux, 2007). For example, Sederberg et al. (2007) found distinct gamma oscillations during encoding to items that were correctly recalled, as opposed to items that were studied but not recalled. Sederberg et al. also found a like pattern at retrieval, allowing a system to distinguish retrieval of studied items vs. retrieval of non-studied items. Additionally, Burgess and Gruzelier (1997) found an increase in theta synchronization during a recognition memory decision, demonstrating that this type of finding also occurs during recognition. Such studies suggest that the synchronization of cell assemblies is an important property in memory processing.

The above findings point to a recognition process quite different from the classic view that a single global similarity value is computed between the probe and memory. Rather, similarity can be a gradual process where the synchrony between the probe and memory is assessed over time as a race between different information sources. Next, we describe a recognition model based on the principles of synchrony and information accumulation. Words are represented by a plausible representation of semantic structure, learned by a semantic space model. The encoding and processing mechanisms share conceptual similarities to FTT, enabling a connection to an established theory of false recognition. However, due to the complicated nature of the claims of FTT as a conceptual theory, it is not currently possible to formalize all aspects of FTT in a computational model. However, RSS attempts to utilize some of the key aspects of FTT within a computational framework, such as the usage of gist traces as composite storage for items on a list. Where applicable, the similarities between FTT and the RSS will be noted and expanded upon.

2.1. Item representation

The representation of words used by the model is based on a word-by-context vector learned from a text corpus. Following Dennis and Humphreys (2001), we assume that when making a recognition decision, the contextual representation is reinstated and recognition is based on the similarity between the reinstated representation and the construction of the current context. This vector is a sparse binary representation, where an element is coded as 1 if the word occurs within a specific document in the corpus and a 0 if it does not. We use a simply binary vector pattern rather than a frequency vector (i.e. the number of times that a word occurs in the document), because this type of representation produces better correspondence to human lexical data (for the theoretical reasons why, see Adelman, Brown, & Quesada, 2006; Jones et al., 2012).

Context vectors were created for each word using the TASA corpus (Landauer & Dumais, 1997). TASA consists of 37,600 documents, which also represents the total vector length of each word. Even though these are rather simple representations, it has been argued previously that sparse binary vectors are the correct assumption when modeling brain functions (e.g. Kanerva, 2009; Norman & O'Reilly, 2003). It has also been demonstrated that simple co-occurrence may give a better approximation to semantic behavior than complex representations (e.g., LSA) when allowed sufficient input (Louwerse & Connell, 2011; Stone, Dennis, & Kwantes, 2011; Recchia & Jones, 2009; Johns & Jones, 2012a).

2.2. Encoding

Based on the “gist” proposal of FTT, the RSS model encodes all items on a study list as a single composite representation. FTT proposes that a separate trace should be formed for each semantically related list during the study period; for simplicity, all lists in RSS will be collapsed to form a single representation. Computationally, this is identical to the proposals of composite recognition memory models (e.g., Murdock, 1982, 1993) and recall models (e.g. Howard & Kahana, 2002; Sederberg, Howard, & Kahana, 2008), which store multiple episodic traces within a single composite vector. The composite vector is then used in subsequent recognition operations.

There are three components to the encoding operation: (1) normalization, (2) encoding failure, and (3) noise. First, each word vector is normalized to unit length by dividing each element by the vector's total magnitude. Normalization ensures that each word adds an equal amount of information into the composite vector so that high-frequency words do not dominate the memory trace. Encoding failure is simulated by generating a uniform random number between 0 and 1 and multiplying it with the word's vector. In keeping with the proposals of Dennis and Humphreys (2001), noise in this model is not completely item dependent, but is simulated with a context noise vector. The context vector simulates the noise intrusions from extra-list contextual information. The noise vector is simply a vector with elements sampled randomly from a uniform distribution ranging from 0 to σ , where σ is a free parameter between 0 and 1.

More specifically, the use of a contextual co-occurrence representation actually produces two sources of context noise: (1) item noise—noise arising from overlap between the word's context representation and the composite vector (the studied items), and (2) extra-list context noise—noise intruding from outside of the particular study list. Extra-list context noise influences how well the composite may be reinstated at study. More noise indicates the intrusion of irrelevant information within the memory vector. This is similar to the item noise proposals of Criss and Shiffrin (2004; see also Criss, Malmberg, & Shiffrin, 2011), with the exception that item noise in this case is actually due to extra-list contextual overlap, resulting from the word-by-context representation. These two sources of noise play different roles in the false alarm rates for different types of lures, with extra-list context noise influencing false alarms to unrelated words, and item noise influencing false alarms to semantically associated words (due to a build-up of a similar representation in the gist trace). While there is an interaction between these two processes, the majority of the variance in false alarm rates is due to these separate sources of noise.

Formally, the encoding process is described as:

$$\mathbf{M} = \sum_{i=1}^n \mathbf{T}_i \gamma + \mathbf{R} \quad (1)$$

where \mathbf{M} is the composite memory vector for the list, \mathbf{T}_i is a normalized studied trace for word i , n is the number of traces studied, γ is a uniform random scalar between 0 and 1 to represent encoding failure, and \mathbf{R} is the context noise vector. This process generates the memory trace for the list used in both standard and false recognition simulations. The difference between the recognition processes will be how the memory trace is used. These differences will be explained in the parameters section.

2.3. The synchronization process

Synchronization is the searching mechanism that RSS uses to determine if a word occurred in a specific context, similar to the 'homing-in' mechanism of Mewhort and Johns (2005) or the resonance mechanism of Ratcliff (1978). As described previously, this process is inspired by neural synchronization, which is the phenomenon of spatially displaced neural populations firing in sync across time.

Accumulation within this model depends on the extent to which the probe and composite vector are in sync with one another over time. Synchronization is accomplished by accumulating positive information about a probe (non-zero elements in the probe vector) and 'leaking' negative information (zero elements in the probe vector), within the composite. Leakage of information was proposed by Usher and McClelland (2001) to be an essential property in decision processes, due to the variance in RT data. Over processing iterations, leakage causes the composite to become more synchronized with the probe. The efficiency of this process is determined by how much probe information is contained within the composite, and the corresponding decision that is made is determined by two measures of this efficiency. Hence, the process essentially sharpens attention within the composite to the relevant dimensions within the probe, while irrelevant dimensions are dampened.

There are two components in the process of synchronizing a probe with memory: *sharpening* (amplifying probe information in the composite) and *leakage* (removing contradictory information from the composite). Sharpening was proposed by Norman and O'Reilly (2003) to be an important aspect of recognition memory, in order to create a better representation of a stimulus in memory. Fig. 1 contains a simple diagram of how this process operates. The figure demonstrates that where the probe vector is non-zero, the composite vector is increased in magnitude (sharpening). However, where the probe is zero (contains no semantic information) the composite vector is reduced in magnitude (leakage). Across a number of iterations, the composite becomes more similar to the probe whether or not the probe is contained in memory, and the efficiency of the synchronization process determines what decision is made.

The sharpening process operates by adding probe information into the composite. The amount of probe information that is added into the composite is determined by the similarity between the probe and memory, constrained by a free parameter to control the magnitude of sharpening. This amount of sharpening is determined by taking the cosine between the probe and the memory vector and dividing by the current iteration (cf. Mewhort & Johns, 2005). Hence, even though the cosine increases across iterations due to the synchronization process, the amount of increase is constrained both by the cur-

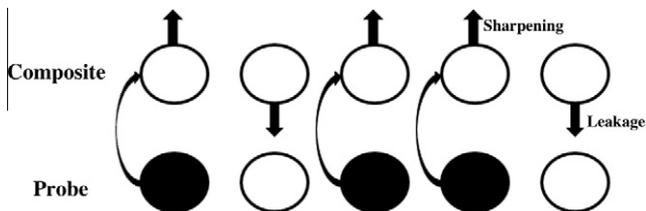


Fig. 1. An illustration of the synchronization process: probe information is iteratively added into the composite (sharpening) as contradictory information is lost (leakage). Filled and empty circles represent non-zero and zero elements, respectively, in the probe's vector representation.

rent level of synchronization and time. The process produces more changes at earlier iterations if the probe is similar to the composite, and allows for the accumulation of more contradictory information if the probe did not occur in the study list. The sharpening parameter (α) constrains the total amount of information that is added into the memory vector, and controls the relative importance of the sharpening process in synchronization. Formally, this process works as follows:

$$(\mathbf{P}_i > 0)\mathbf{M}_{k,i} = \mathbf{M}_{k-1,i} + \left(\mathbf{P}_i * \frac{\cos(\mathbf{M}_{k-1}, \mathbf{P})}{k} * \alpha \right) \quad i = 1, \dots, d \quad (2)$$

where \mathbf{M} is the current memory vector, \mathbf{P} is the probe vector, k is the current iteration, d is vector dimensionality, and α is the sharpening parameter. This operation essentially increases attention to relevant (non-zero) locations of the probe vector in the composite, according to the similarity of the probe and composite, and constrained by the sharpening parameter.

The second component of synchronization (leakage) iteratively reduces the non-defining portions of the probe from the composite (i.e., elements that are zero in the probe vector). This is accomplished by multiplying the memory vector by a free parameter representing contradictory information, which decreases the magnitude of those locations within the composite. Increasing the leakage parameter results in the retention of more composite information, while decreasing the parameter results in greater leakage of composite information. Leakage can be considered to occur when a specific node is not activated by a feedforward connection as a result of the location being zero within the probe vector. Formally, leakage is defined as:

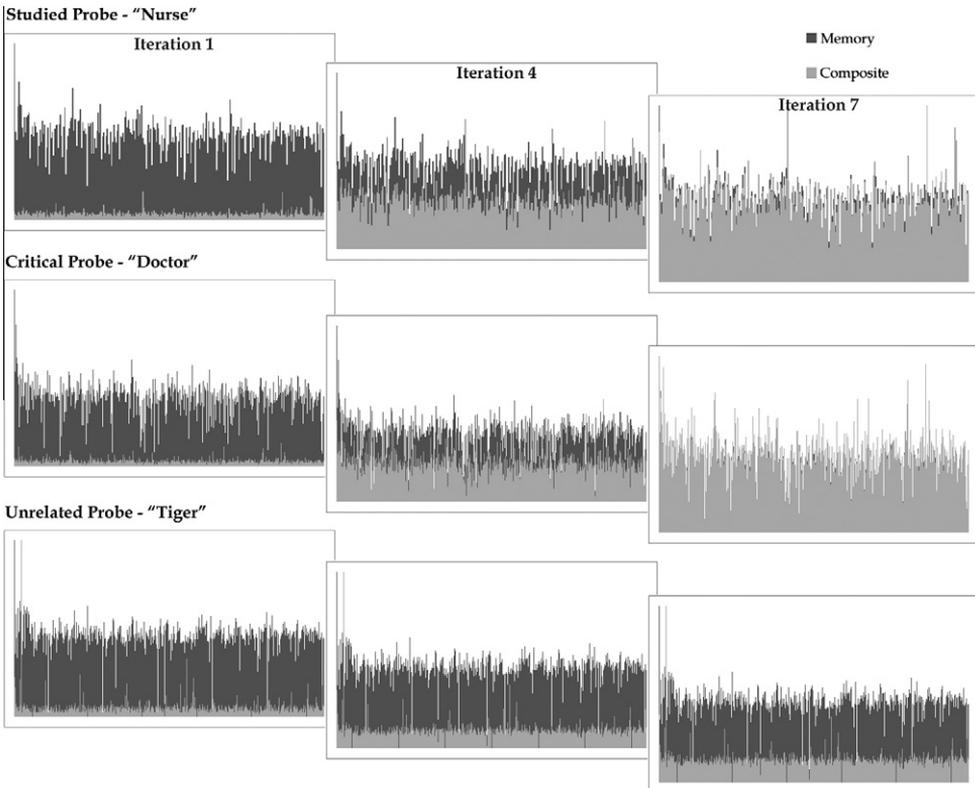


Fig. 2. An example of the synchronization process across iterations for different probe types. When there is a significant amount of probe information contained in the composite (the studied and critical probe) the word is synchronized efficiently, compared to an unstudied probe.

$$(\mathbf{P}_i = 0)\mathbf{M}_{k,i} = \mathbf{M}_{k-1,i} * \delta \quad i = 1, \dots, d \quad (3)$$

where again \mathbf{M} and \mathbf{P} are the memory and probe vectors, respectively, k is the current iteration, and δ is the leakage parameter ($0 \leq \delta \leq 1$). This equation describes how the magnitude of the composite is reduced where the probe is zero, constrained by the leakage parameter.

Together the processes of sharpening and leakage drive the synchronization of the probe with the composite, like trying to fit a puzzle piece in a slot. The efficiency of this process depends on how much probe information is contained within the composite. To visualize the synchronization process, Fig. 2 plots the non-zero locations of a probe within the composite at three time points (1, 4, and 7 iterations) for three different probe types (studied, critical item, and unrelated). As Fig. 2 demonstrates, when a probe item is studied or when a studied list contains a number of semantic associates to an item, those items are synchronized much more efficiently than when a probe is unstudied and unrelated to the studied items. The synchronization process will in turn allow information about whether the word occurred or not to be accumulated, enabling a recognition decision to be made.

2.4. Decision criteria

The RSS decision mechanism is based on a race between different information sources: *Old* responses are based on the similarity of the probe to the memory vector, while *New* responses are based on the amount of contradictory information that the probe did not occur in the study list. Similarity is not an explicit accumulation, but instead represents the current synchronization level between the probe and composite. Functionally the process resembles an accumulator as the amount of synchronization will increase across iterations. Contradictory information will be assessed with an explicit accumulation process, and operates by computing an absolute difference value, and adding this value into an overall accumulator value. A decision is made according to which accumulator reaches a decision first. Hence, *Old* decisions are based on the current similarity of the probe to memory (which increases over iterations), and *New* decisions are based on the accumulated contradictory information over iterations.

Similarity is computed each iteration as the cosine between the memory and probe vector. The cosine between two vectors is simply the dot product of the unit-length normalized vectors:

$$Sim = \frac{\mathbf{M} \cdot \mathbf{P}}{\sqrt{\mathbf{M}^2} * \sqrt{\mathbf{P}^2}} \quad (4)$$

If the similarity value exceeds a criterion, the probe is accepted at that iteration and an *Old* response is made. Hence, similarity is a measure of synchronization between probe and composite, functionally resembling an accumulation process.

The amount of contradictory information is assessed by measuring the difference in the pattern of the probe and the memory vector. This is accomplished by computing the absolute difference between the defining portions of the probe and the corresponding locations within the memory vector, and dividing this summation by the magnitude of the probe. Only the defining portions of the probe are used in the calculation for the same reason that only feature matches are used in Shiffrin and Steyvers' (1997) REM model: extra-item information does not provide information about whether or not an item occurred on a list; it simply demonstrates that other items occurred in the study list. Formally, this contradictory count is computed as:

$$Cont = \sum_{i=1}^d (\mathbf{P}_i > 0) \left| \frac{\mathbf{P}_i}{\sum_{j=1}^d \mathbf{P}_j} - \frac{\mathbf{M}_i}{\sum_{j=1}^d \mathbf{M}_j} \right| \quad (5)$$

This returns a real value between 0 and 1 with 0 indicating that all of the probe information is contained in memory, and 1 indicating that none of the probe information is contained within memory. Because the amount of contradictory information will decrease across iterations (due to the synchronization process), the amount of contradictory information is accumulated across iterations. If the accumulated contradictory information exceeds a criterion, the probe is rejected and a *New* response is made. If the word was in the studied list, a lower contradictory value would likely be observed,

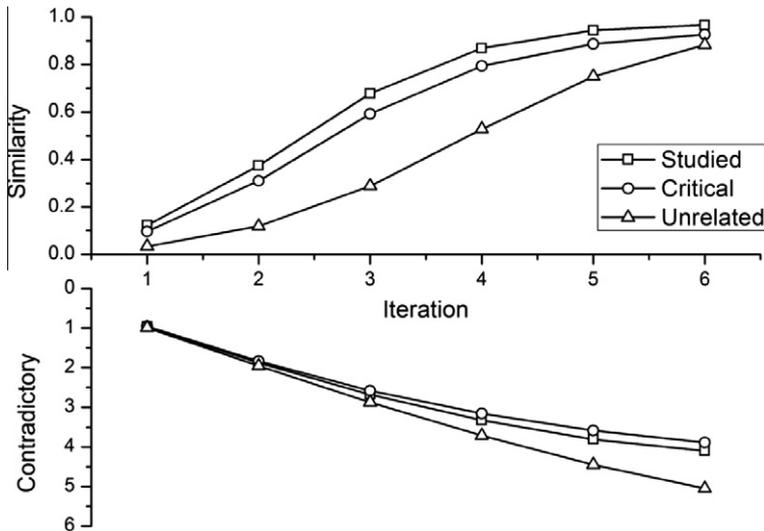


Fig. 3. The accumulation of similarity and contradictory information in the RSS model for the different probe types.

whereas if the word was not in the study list a higher contradictory value would be observed. Contradiction is also closely tied to the synchronization process: If the probe word is not synchronized efficiently with the composite representation a greater amount of contradictory information will be accumulated.

Fig. 3 demonstrates the accumulation of similarity and contradictory information for different probe types across time steps. Studied probes accumulate more similarity information than both critical and unrelated items. However, critical items accumulate more similarity information than unrelated items. In terms of contradictory information, studied and critical probes accumulate approximately the same amount, while unrelated probes accumulate a greater amount than both, enabling these to be rejected at a higher rate. The pattern suggested by this demonstration is unpacked in detail in the following simulations of behavioral data.

2.5. Summary of model parameters

There are five parameters in the RSS model: (1) similarity criterion, (2) contradictory criterion, (3) sharpening parameter (α), (4) leakage parameter (δ), and (5) context noise parameter (σ). This is comparable to other models of recognition memory, such as the BCDMEM model of Dennis and Humphreys (2001) and the REM model of Shiffrin and Steyvers (1997). The RSS model is also considerably more constrained than other models in that it uses structured semantic representations learned from a text corpus.

In the following simulations, the decision criteria are fixed while the other three parameters are fit for standard and false recognition studies. Different sets of synchronization parameters are used to model standard and false recognition because the DRM paradigm encourages a greater reliance on similarity of the probe to memory (more sharpening, less leakage), while in the standard recognition simulations the structural properties of the probe's representation is utilized to a greater degree (less sharpening, more leakage). The noise parameter is also manipulated as there are some methodological differences between standard and false recognition paradigms.

The processing shift between standard and false recognition is grounded partly in the claims of FTT. FTT proposes that different types of traces are used during standard and false recognition. Specifically, FTT proposes that during standard recognition a memory process utilizes verbatim traces to drive recognition and recall, which essentially encode the surface traits of items studied. However, during false

recognition, gist traces are used, and this switch is due to the greater level of semantic similarity of a probe word to list items. A shift in information sources during recognition is supported by experiments manipulating instructions, which influence the type of information subjects focus on during test (e.g., semantics vs. surface forms: Brainerd, Reyna, & Mojardin, 1999; Brainerd et al., 2001).

Although the RSS model does not store different types of traces, there is a processing difference in how it deals with standard and false recognition results. Specifically, during false recognition the level of similarity between the probe and the composite is more important during synchronization (increase in sharpening parameter), while the structural properties of memory become less important (increase in leakage parameter, which causes less non-probe information to be lost). However, during standard recognition similarity becomes less important (decrease in sharpening parameter), mainly due to semantic similarity becoming less diagnostic in a list of random words, and the structural properties of memory become more important (decrease in leakage parameter, which causes more non-probe information to be lost). This allows for an analogue to some of the claims of FFT and also to simulate both standard and false recognition results within the same computational framework.

3. Part 1: Standard recognition simulations

Before proceeding to apply the RSS model to false recognition effects, we first demonstrate that it naturally produces classic effects from the standard recognition memory literature. In this section, the RSS model is applied to three recognition memory effects that have proven challenging for classic global memory models: (1) the mirror effect of frequency (Glanzer & Adams, 1990), (2) the null list strength effect (Ratcliff, Clark, & Shiffrin, 1990), and (3) the null list length effect (Dennis, Lee, & Kinnel, 2008). While the mirror effect and null list strength effects are readily captured by a Bayesian global memory model (REM; Shiffrin & Steyvers, 1997), the null list length finding is problematic even for REM (Dennis et al., 2008), but can be explained by context-noise models (Dennis & Humphreys, 2001). Because the RSS model contains aspects of both item and context noise (as suggested by Criss & Shiffrin, 2004), it is equipped to account for null length and strength effects. Additionally, RSS may be adapted to produce ROC curves, an increasingly important pattern in the study of episodic memory. Capturing a diverse set of results is intended to demonstrate that the RSS framework is a powerful one, and can explain contemporary benchmarks in standard recognition paradigms before moving onto false recognition.

The leakage and sharpening parameters will be allowed to vary between standard and DRM paradigms. As discussed previously, the reason for this parameter change is that subjects are able to shift the type of information that they use during recognition depending on the paradigm (Brainerd et al., 1999; Brainerd, Reyna, & Forrest, 2002), a fundamental claim of FFT. The processing shift is due to gist information being more diagnostic in a DRM paradigm when lists contain words that are semantically related, but gist is an inefficient strategy when random words are used in a standard list learning paradigm. The parameter shift in RSS embodies this shift in processing strategy core to FFT.

The parameters for standard recognition rely more heavily on the leakage mechanism in synchronization rather than semantic similarity (i.e., a greater reliance on the structural properties of the probe and memory representation). To produce this behavior, the sharpening parameter was fixed at 0.15. The leakage parameter was set at 0.28—hence, across iterations the attention to non-probe information in memory is reduced. The context noise parameter was set at 0.01. The similarity criterion was set at 0.93, while the contradictory criterion was set at 4.25 (these criteria remain constant across both the standard and false recognition simulations).

3.1. Simulation 1.1: The mirror effect of frequency

A classic effect in recognition memory is the mirror effect of frequency (Glanzer & Adams, 1990): low frequency words have a higher hit rate and a lower false alarm rate than high frequency words. The mirror effect is difficult to account for with pure similarity models that base recognition judgments on a single dimension of familiarity, but is one of the cornerstones of Bayesian models of recognition memory (such as REM and BCDMEM). In similarity-based models of recognition (e.g.,

MINERVA 2 or TODAM), high-frequency words will appear to be more similar to the contents of memory because they contain more features in their representation, which increases their likelihood of matching even unrelated words. Increased similarity for high-frequency words produces both an increased hit rate and an increased false alarm rate, which is inconsistent with the behavioral data. Although the RSS model does rely on similarity in the synchronization process, it does simultaneously consider contradictory information, which allows the model to produce differential responses to frequency manipulations between words that were and were not studied.

To model the mirror effect in RSS, study lists of 20 high frequency words and 20 low frequency words were generated. These lists were created by sampling from a pool of 1000 high-frequency and 1000 low-frequency words from the MRC Psycholinguistic Database (Coltheart, 1981). The Kucera-Francis log frequency for the LF words was 1.93, and the log frequency for the HF words was 4.94. The model was tested on 1000 randomly created lists sampled from these pools.

For LF words, the model produced a hit rate of 0.88 and a false alarm rate of 0.093, while it produced a hit rate of 0.67 and a false alarm of 0.28 for HF words. This demonstrates that the RSS model naturally displays a mirror effect: LF words have a higher hit rate and lower false alarm rate than HF words. RSS behaves in this manner for three reasons. First, during the encoding process each studied vector is normalized to have unit length, so that each word (regardless of frequency) adds the same amount of information into the composite. Second, due to the contradictory parameter and the organization of LF words (i.e., fewer non-zero locations), a greater amount of contradictory information is leaked at each time step for LF than HF words. This results in a more efficient synchronization process, and an increased hit rate for LF words. The third reason is due to the similarity parameter: HF words are more similar to the composite simply due to the nature of the representation (i.e., more non-zero locations), and so even for non-studied items more of the probe information tends to be added into the composite during synchronization. This produces an increase false alarm rate for HF words, and the mirror effect. This is in some ways related to the explanation proposed by Shiffrin and Steyvers (1997), with LF words having more defining aspects in their representations, leading to a higher hit rate, and HF words having more representational overlap with other words, leading to a higher false alarm rate.

3.2. Simulation 1.2: The strength and list strength effects

The strength effect refers to the finding that slower presentations, or increased repetitions of study items, increase performance (Ratcliff et al., 1990). The list strength effect is the finding that when a list is composed of mixed strong and weak items, the recognition of weak items is not harmed by the presentation of strong items (Ratcliff et al., 1990). The null effect is unexpected because, according to global models, the presence of strong items should harm the recognition of weak items.

Strength is simulated with an extra encoding strength parameter: weak items are encoded with a strength of 0.4, while strong items are encoded with a strength of 1. All the other parameters were kept constant with the other simulations reported here. Three different list types of size 32 were created: (1) pure weak, (2) pure strong 1, and (3) mixed – half of the items are multiplied with a weak encoding strength and half with a strong encoding strength. All list items were sampled from the Toronto word pool (Friendly, Franklin, Hoffman, & Rubin, 1982).

Fig. 4 displays the results of this simulation. The pure strong items had a higher sensitivity than the pure weak items (the strength effect). In addition, for mixed lists adding strong items into the list did not decrease performance levels for weak items (the list strength effect). The reason that RSS accounts for the strength effect is straightforward: A stronger item is better represented within the composite vector compared with weak items. The stronger representation increases the probability of the word being recognized due to increased similarity, and in turn increases the efficiency of synchronization. Also, in the pure weak condition there is a greater proportion of random noise within the composite, which increases the likelihood of a false alarm. This leads to better performance for strong lists vs. weak lists.

RSS produces the list strength effect due to the size and sparsity of the model's vectors, which represent their natural co-occurrences in semantic contexts. As items are added into the composite with differential strength, a stronger item does not affect the representation of a weaker represented item.

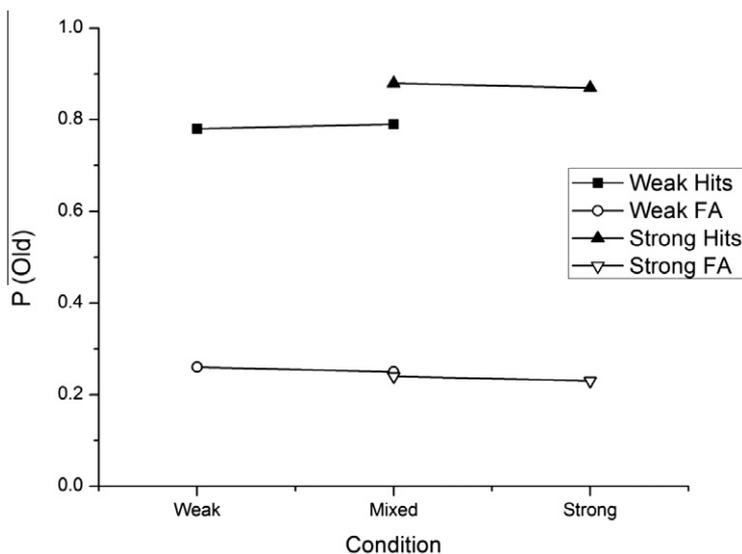


Fig. 4. RSS simulation of the strength and null strength effects of Ratcliff et al. (1990). The strength effect refers to the finding that strong items are better recognized than weak items, while the null list strength effect refers to the finding that the recognition of weak items are not impaired by the presence of strong items.

Because the vectors are sparse and the list is composed of random words, the item noise overlap is limited and so only the extra-list context noise affects the recognition of items. Due to context noise being held constant across different list types, there is no difference in recognition rates, similar to the way the BCDMEM model of Dennis and Humphreys (2001) explains this result. Shiffrin, Clark, and Ratcliff (1990) have used this result as justification for separate storage models of memory, in which each studied item is stored in a separate location, as opposed to composite models. However, the present simulation shows that a composite representation is quite able to account for the effect, if it utilizes a sparse representation scheme.

3.3. Simulation 1.3: Null list length effect

Recent work by Simon Dennis and colleagues has shed light on the nature of recognition through analysis of the list length effect in recognition memory (Dennis & Chapman, 2010; Dennis & Humphreys, 2001; Dennis et al., 2008; Kinnell & Dennis, 2011). It was initially believed that the study of longer lists leads to a reduction in performance due to an increase in the amount of item noise present in memory (Murnane & Shiffrin, 1991). However, Dennis and Humphreys (2001) noted that list length is confounded with retention interval. In shorter lists, the amount of time that subjects have to retain the study list information is much shorter than for longer lists. Dennis and Humphreys (2001) and Dennis et al. (2008) reran list-length experiments controlling for retention intervals and found a null-list length effect—there was no performance decrease with the study of longer lists. This effect has been replicated in a second set of experiments, where the authors concluded that controlling for attention is the most important aspect in eliminating potential confounds (Kinnell & Dennis, 2011).

To simulate the null list length effect within RSS, lists of size 20 and 80 were created by randomly sampling from the Toronto word pool, and the number of hits and false alarms to the different list sizes were recorded across 1,000 simulated trials. Because the retention interval was controlled in these studies, the context noise parameter was kept constant at 0.02. For the 20-item lists, the model produced a hit rate of 0.84 and a false alarm rate of 0.25, while for the 80-item lists it produced a hit rate of 0.85 and a false alarm rate of 0.28, thus showing a null list length effect.

The reason that RSS is able to account for the null list length effect is due to how noise is defined in the model. Although there is item-level noise in the representation, the probability of an element overlap with another random word is quite low, due to the sparsity of the representations and the use of random words, which leads to a reduced amount of item-level overlap. Hence, the main noise factor in lists composed of random words is extra-list context noise, which is kept constant across the two list sizes and results in equal performance. However, this situation does not exist for lists composed of semantically related items, which will be explored in the false recognition experiments.

3.4. Simulation 1.4: ROC curves

A standard method of analyzing recognition performance is with receiver operating characteristics (ROC; for a review, see [Yonelinas & Parks, 2007](#)). ROC curves are simply a function relating hit rate and false alarm rate across some manipulation of response criterion. While there are a variety of methods used to manipulate response criterion, the most common is with confidence ratings. Typically, subjects are presented with a list of items to study, and at test discriminate items by rating their confidence that the item is old on a discrete scale. ROC curves are examined by plotting the cumulative hit and false alarm rating pair as a function of confidence. In addition to being a standard benchmark to be explained by recognition models, ROCs are of interest to the study of false memory because subjects tend to be just as confident that critical lures were on the list as studied items ([McDermott & Roediger, 1998](#)).

Here we keep the test of ROCs produced by RSS simple, borrowing the idea of accumulation of evidence to a fixed criterion from [Pleskac and Busemeyer \(2010\)](#). Pleskac and Busemeyer demonstrated how a diffusion model could account for confidence ratings by accumulating evidence up to a fixed point and simulating confidence as the relative location of the value in the distribution of possible evidence values. Another suggestion from [Van Zandt \(2000\)](#) is to use a mixture of familiarity and contradictory information. While Van Zandt's suggestion is possible in RSS, the similarity and contradictory information in the model are on different scales, which would require the addition of scaling parameters; hence, we keep the ROC simulation simple here and based only on similarity.

Following [Pleskac and Busemeyer \(2010\)](#), we simulate confidence in RSS by synchronizing the probe for a fixed number of iterations, and the ending similarity value is used to generate a confidence rating based on its relative position in the distribution of values produced. To generate confidence ratings, bins of values with 0.01 intervals were constructed, and a confidence value was determined based on which sextile the value fell into (i.e., 1–6). A rating greater than three would correspond to a tendency to respond 'old' to the item.

To test the ROCs produced by this process applied to the RSS model, we simulate the [Egan's classic \(1958\)](#) memory strength result. In this study, strong and weak items were presented on a study list, and ROC curves were computed for the two item types. Egan found inverted U-shaped curves for both item types, with weaker items being less sensitive than strong items, but parallel curves. We simulated this using a total list length of 80, with half of the items being strong items and half being weak items (using the same strength manipulation as in simulation 1.2).

Confidence ratings were assessed for both old and new items across a 1000 simulated trials, with the same parameter values as the above simulations. The resulting ROC curves are displayed in [Fig. 5](#) (with the straight diagonal representing chance performance). This figure demonstrates that the prototypical concave ROC lines are found. In addition, the model produces reduced sensitivity for the weaker items, and symmetric curves between weak and strong. After z-transformation, the high and low strength items have a slope of 0.84 and 0.88 respectively, slightly above normal but within an acceptable range ([Ratcliff, McKoon, & Tindal, 1994](#)). This simulation is intended simply as an existence proof that the RSS framework is capable of generating ROC data. Confidence ratings have also played a central role in the examination of false memory, and the process described here to generate confidence will also be applied to false recognition data in Simulation 1.4 and Simulation 2.4.

3.5. Discussion

These four simulations demonstrate that the RSS model is capable of accounting for contemporary results considered cornerstones of recognition memory performance. The model is not simply a

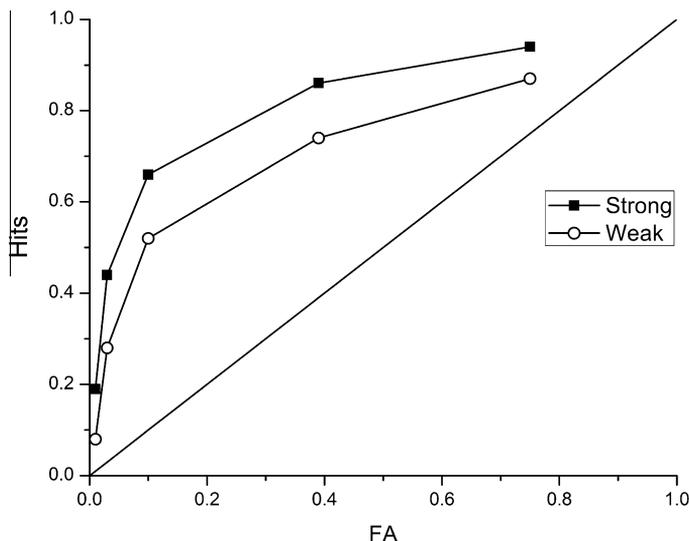


Fig. 5. ROC curve analysis of confidence ratings from the RSS model. The diagonal line represents the chance. The model performs well above chance on both strong and weak studied items, and the strong and weak curves are symmetric, similar to Egan (1958).

simulation of false memory effects, but is also able to explain difficult standard recognition results. However, the main aspect of recognition memory that RSS aims to shed light on is that of false recognition. This is because the RSS integrates a plausible semantic representation type with a processing mechanism, which is unique to modeling work within the DRM paradigm. Since false recognition is dependent on semantic information being contained within a word's representations, we next demonstrate that the RSS model is capable of accounting for a variety of false memory effects as well.

4. Part 2: False recognition simulations

In this section, the RSS model is applied to ten key findings from the false recognition literature. The first cluster of simulations is confirmatory, testing the model's ability to account for general findings of false recognition in the DRM paradigm, its ability to make item-specific predictions for critical lures, and to simulate high confidence in false memories. The second cluster of simulations is intended to be theory differentiating, testing theoretical predictions from the literature in terms of which sources of information elicit false memories, and testing predictions made by FTT instantiated as parameter manipulations in RSS.

The RSS model is a promising candidate to account for false recognition because its synchronization mechanism depends on the amount of semantic information about a probe contained in memory. When a study list contains a number of semantic associates to a specific critical word, its composite vector will have overlapping variance with the word's co-occurrence representation, leading to a higher similarity value and a more efficient synchronization process. Hence, even though a critical lure was not in the study list, it may still have a high probability of being accepted. Additionally, the use of a composite representation allows for the formation of a memory representation that is similar to the use of gist traces, a concept that is heavily emphasized by FTT. From this perspective, the task of recognition involves a process that determines if the probe word's semantic representation is coherent with what was encoded in the study list.

A different parameter set was used to simulate false recognition data than was used in the standard recognition simulations (only the processing parameters were changed; the decision criteria remained constant). Specifically, the similarity parameter was increased to 0.99, making the semantic similarity

between the probe and composite more salient in the synchronization process. The contradictory parameter was increased to 0.55, indicating that less contradictory information is leaked from the composite (compared with the standard recognition simulations).

The change in parameters puts the locus of the synchronization on semantic similarity, and less so on the structural properties of the memory store. Again, this parameter shift is meant to mimic claims of FTT, where more emphasis is placed on semantic information during false recognition experiments (Brainerd et al., 1999, 2002). The context noise parameter was reduced to 0.001, primarily due to the fact that in most false recognition studies there is only a single study session given to subjects, which reduces the amount of extra-list noise. In contrast, many standard recognition experiments require participants to study multiple lists within an experimental context, or employ distractor tasks that also increase context noise. Furthermore, in many false recognition studies, subjects are given a free recall task before the recognition test, which may serve to sharpen the representation of words within memory, and hence reduce noise.

4.1. Simulation 2.1: Levels of false recognition

We first test whether RSS produces similar levels of false recognition to those seen in behavioral data. Three different sets of DRM lists will be simulated: (1) the original DRM lists from Roediger and McDermott's (1995) classic study, (2) the extended DRM list set from Stadler et al. (1999), and (3) the more variable lists of Gallo and Roediger (2002). For a single trial, ten DRM lists were randomly selected, and all of the items in a list were added into the study list. The average hit rate for the studied items and the average false alarm rate for critical words were recorded across 1000 simulated trials. To test levels of false recognition to unrelated items, five words were randomly selected from the Toronto word pool (Friendly et al., 1982) and tested in each simulated trial.

Fig. 6 displays the levels of recognition for studied, critical, and unrelated words produced by RSS and the data from each of the above studies. As the figure shows, the model produces a very good approximation to the behavioral data across the different word types [$r^2 = 0.95$, $p < 0.001$]. The only systematic difference is that the model produces a slightly greater level of false recognition to unrelated items than is observed in the data. However, in these behavioral experiments recall precedes recognition, which artificially decreases unrelated recognition levels. The simulation demonstrates that the RSS model is susceptible to the same type of memory illusions as humans.

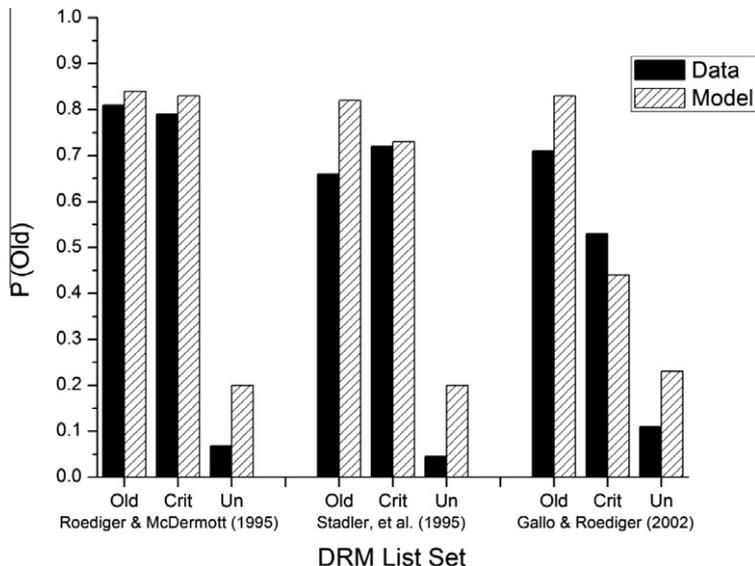


Fig. 6. Levels of false recognition for the RSS model and different DRM list sets.

False recognition occurs in RSS because the model synchronizes the critical lure trace efficiently due to the memory vector containing a large amount of semantic information related to the word. The increased efficiency of synchronization reflects the sharpening process, and also reduces the amount of contradictory information accumulated, leading to an increased probability that critical lures are falsely recognized. However, as Gallo and Roediger (2002) have shown, there is considerable variability in the levels of false recognition elicited by the different DRM lists. One advantage of integrating a semantic representation with a process mechanism is that it allows the model to produce item-level predictions.

4.2. Simulation 2.2: Item-level analysis of false recognition

Stadler et al. (1999) and Gallo and Roediger (2002) have both published the levels of false recognition across their DRM lists (the probability that a given list elicits false recognition of a critical lure). As both of these studies show, there is considerable variability in the levels of false recognition elicited by different DRM lists. To ensure that the model is quantitatively producing false recognition effects in a fashion similar to that of humans, we computed the correlation in levels of false recognition between the model and the behavioral data. This test ensures that the semantic representation and processing mechanism are interacting to generate levels of false recognition in a manner consistent with experimental data.

Levels of false recognition were taken from Stadler et al. (1999) and Gallo and Roediger (2002). Again, ten DRM lists were added to form a single study list. The level of false recognition for each critical word was recorded across 1000 simulated trials. In addition, the cosine between the critical word vector and the composite vector was computed for each critical word to explore how the similarity structure in memory is uniquely contributing to produce false recognition. This allows us to test the respective contributions of the memory structure and the process in producing false recognition. Across the 56 lists, there was a significant correlation between the model's predictions and the human data, $r = 0.41$, $p < 0.001$. This is a comparable level to the best single predictor of false recognition rate, mean backward association strength, demonstrating that the model is as effective as behavioral measures at accounting for variance in rates of false recognition.

To determine the contribution that memory structure alone plays in producing false memories, we computed the average cosine between each critical word and the composite vector that contained its study list. The correlation between the average cosine for the different critical lures and levels of false recognition was $r = 0.29$, $p < 0.05$ across the 56 critical words. When the cosine is controlled for in a partial correlation, a significant correlation of $r = 0.36$, $p < 0.01$ is still found between the levels of the RSS model and the false recognition levels. However, when the levels of false recognition from the RSS model are controlled for, a non-significant correlation of $r = -0.07$ is observed between the cosine and levels of false recognition. The pattern demonstrates that using a semantic representation of words that has sufficient power alone to predict item-level false recognition, combined with a simple processing mechanism that is designed to exploit the word's structure, a better fit to the data can be found than the structure or process alone can accomplish. Hence, it is the interaction between the structure of memory and the process that produces the superior fit to the data, not structure or process alone.

Another important aspect of the model is that it does not completely depend on the representation that has been used so far. Jones et al. (2012) use a similar model to simulate word recognition latencies, but with a more sophisticated sparse contextual representation in which each context was weighted by how much unique information it provided for that word. The weighted representation produced a better fit to lexical decision and naming times compared to other simple sparse representation types (Jones et al.), and has also been shown to provide a better fit to semantic distance norms (Jones, Johns, & Recchia, 2012). We supplanted RSS's standard sparse document occurrence representation with the more sophisticated representation type of Jones et al., and reran the item-level analyses to false recognition norms. Again, a strong correlation of $r = 0.5$, $p < 0.001$ was observed. This demonstrates that the processing mechanism used by RSS is flexible in the representation type that it utilizes. A systematic analysis of different representation types is beyond the scope of this paper.

However, many predictions of the model do depend the process mechanism operating on a sparse representational format.

This set of simulations provides quantitative evidence that the RSS model produces false recognition in a manner similar to human subjects, and can make item-specific predictions. To test that it is actually semantics driving false recognition levels, and not some other variable (i.e., frequency), we next simulated a result by [Robinson and Roediger \(1997\)](#) demonstrating that as the number of semantic associates to a critical lure is increased, levels of false recognition also increase.

4.3. Simulation 2.3: Effect of the number of associates on false recognition

[Robinson and Roediger \(1997\)](#) found that as the number of associates to a critical word that are contained within a study list is increased, a systematic increase in false recognition rates to that critical item is also observed. We expect a similar pattern with the RSS model under the same conditions because an increased number of semantic associates studied should produce a corresponding increase in the ease with which the critical lure is synchronized, in turn producing increased false alarms to these items.

The lists used were the combined list set of [Stadler et al. \(1999\)](#) and [Gallo and Roediger \(2002\)](#). On each simulated trial, five different DRM lists were selected and 3, 6, 9, 12, or 15 items in the study list were randomly selected and added into the study list. As in the previous simulation, 1000 trials were simulated, and the levels of false recognition to the critical lures at each number of associates, as well as the hit rates for the studied items, were recorded across trials. [Fig. 7](#) displays hit rate and the false alarm rate for critical words, for both the RSS model and the data from the [Robinson and Roediger \(1997\)](#) study. As the figure indicates, the model produces an excellent fit [$r^2 = 0.98$, $p < 0.001$] to the increase in false recognition as a function of the number of studied associates. It also predicts true recognition rates very similar to those seen in [Robinson and Roediger \(1997\)](#), and are not greatly impacted by the number of associates contained in the study lists, consistent with the behavioral data.

This simulation demonstrates that the high levels of false recognition produced by the RSS model primarily reflect the increased amount of semantic information contained within a study list's episodic representation. Hence, it appears to be the level of semantic association between words that

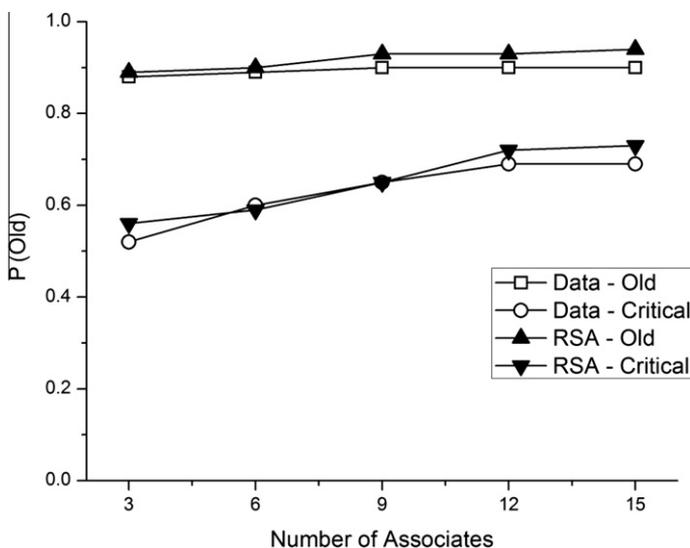


Fig. 7. RSS simulation of the effect of number of associates contained in a study on the levels of false recognition (data from [Robinson & Roediger, 1997](#)).

drives false recognition rates, rather than another variable potentially contained within the representation (such as frequency).

4.4. *Simulation 2.4: Confidence judgments*

Subjects in false memory experiments not only make incorrect decisions about a critical lure, they do so with a high level of confidence. In simulation 1.4 we demonstrated that the model was capable of simulating confidence ratings; hence, it is natural to extend the model's simulation of confidence with false recognition as well. Confidence in false recognition judgments is typically demonstrated with a remember/know test, in which subjects are asked whether they specifically remember a word's occurrence, or simply knew that the word had occurred (Tulving, 1985). A one-dimensional explanation of remember/know would simply assume that remember judgments are of higher confidence (e.g., Hirshman & Master, 1997). However, there is considerable evidence to suggest that remember and know judgments may be based on distinct processes (e.g., Yonelinas, 2002) or dimensions (Rotello, Macmillan, & Reeder, 2004).

Research using the remember/know paradigm has consistently found that subjects rate critical lures to be "remembered" as often as they do studied items (Roediger & McDermott, 1995; Seamon, Luo, Schwartz, et al., 2002; Seamon, Lee, Toner, et al., 2002), and the pattern has also been observed in confidence judgments (e.g. McDermott & Roediger, 1998). Because remember judgments are generally thought to require a conscious recollection process (Mandler, 1991), which would require additional assumptions to implement in RSS, we focus here on the finding that the confidence ratings assigned to critical lures are equivalent to studied items.

We simulated confidence ratings from RSS using the same processes described in Section 1.4 to generate ROC curves. The lists from Roediger and McDermott (1995) were added into a single study list in the model. The average confidence rating generated by the model to studied, critical, and unrelated items was recorded over 1000 simulated trials. Studied items had an average confidence rating of 5.13, critical items had an average confidence rating of 4.67, and unrelated items had a confidence rating of 1.55. These results show that the confidence rating assigned by the model to critical lures was similar to that of studied items. In contrast, the confidence assigned to new items was much lower than either of the other two types. Although it is beyond the current instantiation of RSS to account for more complex behavior, such as remember/know judgments, this simulation demonstrates that in addition to producing false alarms to critical lures, it predicts a degree of confidence in the response comparable to old items.

This first cluster of false memory simulations has demonstrated that the RSS model is able to account for challenging results from the false recognition literature in tandem with results from the standard recognition memory literature. The next cluster of simulations applies RSS to theory-differentiating effects from the false memory literature, and explores the explanations for the effects that are suggested by the parameters and mechanisms in the model.

4.5. *Simulation 2.5: Shifting criterion or shifting distributions?*

We have demonstrated that the RSS model is capable of accounting for a range of false recognition data. However, the role played by the decision process in explaining these data has not been tested. An experiment by Miller and Wolford (1999) provides a coherent test case for the RSS decision process. Miller and Wolford conducted a DRM experiment in which the critical word was either contained in the study list or it was used as a lure. They found that when the critical item was contained in the study list it was recognized at a significantly higher rate than when it is not in the list. Based on a signal detection analysis of the resulting data, Miller and Wolford (1999) proposed that in the DRM paradigm subjects are not actually falsely remembering anything; instead, they are simply shifting their decision criterion. The authors suggest that this shift occurs because the subjects realize that the critical word closely matches the theme of the list, which caused them to relax their criterion.

There is considerable evidence that a criterion shift is not what is occurring during false recognition. For instance, when subjects are given explicit instructions not to make any errors (i.e. under conditions where subject's criterion should be increased), there is still a robust false recognition effect

(Gallo, Roberts, & Seamon, 1997; McDermott & Roediger, 1998). Miller, Guerin, and Wolford (2011) recently clarified their position, by suggesting that there are two criteria at play during a recognition process: a more liberal criterion for words that match the gist of a study list, and a more conservative one for all other words. Miller et al. demonstrated that when warned about this underlying process, subjects were able to reduce their rates of false recognition, though not eliminate them. This work strongly suggests that strategic processing occurs during false memory experiments.

As proposed by Wixted and Stretch (2000 and acknowledged by Miller and Wolford (1999)), the data reported could also have been explained by shifts in the evidence distributions; that is, the similarity distribution for the critical item when it is contained in the study list is shifted up. The shift is exactly the pattern that the RSS model predicts: if the critical word is included in the study list, more positive information about it is accumulated due to both its item information being encoded and also that of its associates. The situation is similar to including the prototype as an exemplar in a schema abstraction task (Posner & Keele, 1968). This structure should increase the efficiency of the synchronization process, leading to an increased probability of accepting the probe. To test this hypothesis, we simulated the results of Miller and Wolford (1999) using RSS.

Each study list consisted of four DRM lists from Stadler et al. (1999). However, in two of the lists, one item (called the related lure) was taken out of the list and replaced with the critical word. The choice probability for the critical and related words was assessed when presented and not presented. Fig. 8 displays the results of the simulation for the critical lures and related lures, for both the model and the data from Miller and Wolford (1999). As the figure indicates, the model accurately predicts the level of false recognition seen when both the critical and related lure are presented vs. when they are not presented, in absence of a criterion shift. Specifically the level of false recognition for the critical word is significantly higher when the word is presented in the study list. This simulation corroborates those in the previous sections, suggesting that it is the amount of semantic information about a word that is the driving force behind false recognition, and not a change in decision strategy. The result is consistent with a shift in the similarity distribution for the critical word—when it is included in the study list there is more semantic information about that word within the trace, leading to a higher similarity value and increased ease of synchronization.

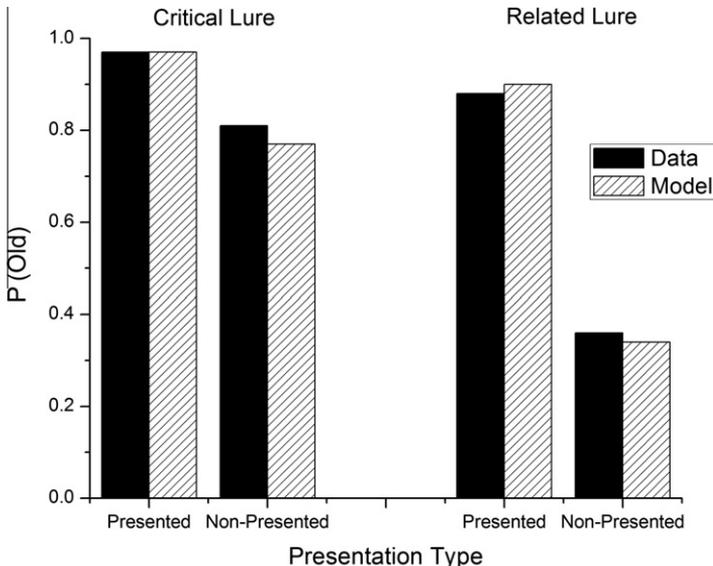


Fig. 8. RSS simulation of the results from Miller and Wolford (1999). The model suggests that this phenomenon is not indicative of a criteria shift but, rather, is produced by an increased amount of semantic information when a critical word is contained within a study list.

4.6. Simulation 2.6: Thematic vs. associative information

A key distinction between spreading activation theories of false recognition and FTT is the importance of theme. FTT assumes that exposure to a number of semantically interrelated items causes a gist trace to be formed of those items. In contrast, spreading activation theories assume that it is simply the associative connectivity between the studied and critical lures that produces false recognition: As more associates of an item are experienced it becomes more likely that critical lures will be implicitly generated, resulting in confusion at test. To examine whether thematic information is necessary for false recognition, Hutchinson and Balota (2005) created a set of homograph DRM lists in which half of the words were related to one of the meanings of the critical word and the other half was related to a different meaning. Mean backward association strength was controlled across all lists. Hutchinson and Balota found equivalent levels of false recognition for both homograph and standard DRM lists. The result suggests that it is not only gist extraction that is at play in producing false recognition, but that pure association among words may also be important.

The 18 DRM lists and the 12 homograph lists described in Hutchinson and Balota (2005) were used in this simulation. A study list was created out of 6 different random lists, composed of 12 items each. The probability of accepting the critical lure and studied items was assessed for both DRM and homograph lists; the results are illustrated in Fig. 9. Again, a close approximation between the levels of false recognition for the data and the model was observed. The experiment and simulation both indicate that false recognition is not completely driven by a thematic representation of a context, but instead is due to the amount of distributional information about a word in memory. Although FTT seems to entail a sophisticated gist extraction technique, this simulation with RSS suggests that this may not be necessary all of the time. However, some experiments have found the generation of gist traces to be very important, and this issue will be examined in the next simulation.

4.7. Simulation 2.7: Situational knowledge

Although the results of Hutchinson and Balota (2005) suggest that associative information may be the predominant factor in false recognition, this has been challenged on a number of grounds. One recent example is given by Cann, McRae, and Katz (2011), in which they tested how well DRM lists that describe a specific situation are able to elicit false memories. For example, the situation list for *farm*

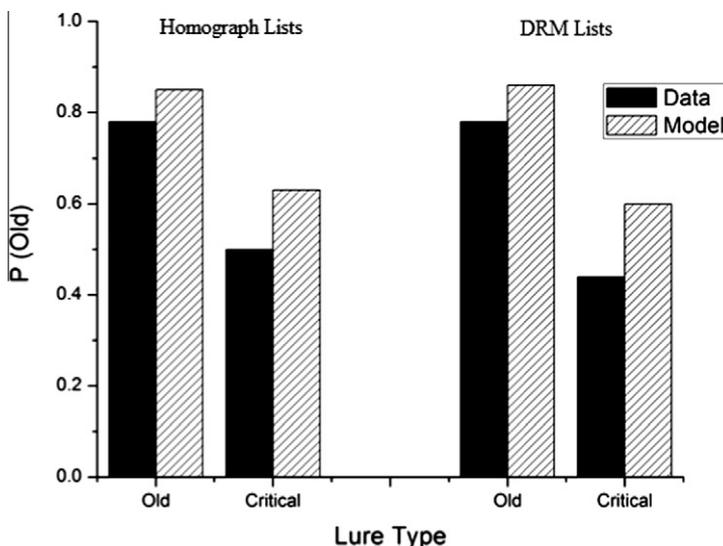


Fig. 9. RSS simulation of the homograph and standard list types from Hutchinson and Balota (2005).

consisted of words such as *barn*, *cow*, and *tractor*. However, key to the design of these “situation lists” was that they all had very low average backward association strength. Hence, false memories to these lists could not be produced by pure association (although see [McRae & Jones, 2012](#), for a discussion of “association” vs. “association norms”). Rather, the authors argued that such lists led to a strong gist formation (consistent with the proposal of FTT), reflecting the common situational features of the words in the list. Cann et al. found high levels of false memory for both recall and recognition to the situation lists, suggesting that strong gist formation was indeed occurring. As previously discussed, it has been proposed that the encoding and processing of RSS has similarities to FTT, which makes this result an interesting test case to simulate, especially given that the previous simulation was able to account for a result based on pure association. We used the same situation and DRM lists used in Cann et al. Experiment 4 (the only experiment which used recognition), in a simulation using RSS. The DRM lists in this experiment consisted of strong, medium, and low situational relatedness groups. Cann et al. found that the situation lists elicited similar levels of false recognition as the strong DRM lists. To simulate their result, all DRM lists were added into a single study list in RSS.

The results of this simulation are displayed in [Fig. 10](#). The RSS model produced an excellent fit to the data, suggesting that the encoding assumptions are not capitalizing on mere associations between words (as was demonstrated in simulation 2.5), but the model is able to form a gist trace of what words on the list are referring to. This pattern reflects the model’s flexibility in terms of the type of information contained within its co-occurrence representation—it is not storing simple associative or semantic information, but a mix of the two, as both this simulation and the previous one demonstrate. However, it is worth noting that both the raw co-occurrence representation used by RSS and those used by many other semantic space models give quite a poor fit to free association norms on their own (although some do well; see [Griffiths et al., 2007](#)), suggesting that it may be fallacious to directly equate association strength and co-occurrence (see [Jones, Gruenenfelder, & Recchia, 2011](#)). These simulations lead to the question of what type of information is *associative* and what is *semantic*, a distinction that has recently been questioned ([McRae, Khalkali, & Hare, 2011](#)). These two simulations further support the notion that this may be a false dichotomy, as a simple co-occurrence representation contains sufficient information to account for false recognition experiments based on both types of information.

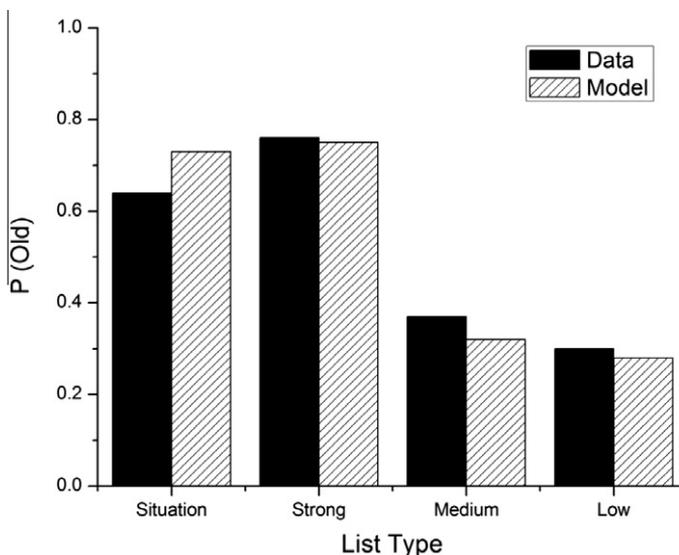


Fig. 10. RSS simulation of the situation knowledge lists from [Cann et al. \(2011\)](#).

4.8. Simulation 2.8: Categorical false recognition

Similar to the importance of associative and thematic information in false recognition, a consistent finding in recognition memory (related to the DRM paradigm) is that as the number of studied words from a specific category is increased, the recognition rates to both the studied exemplars and also the unstudied prototype word increases as well (Arndt & Hirshman, 1998; Dewhurst & Anderson, 1999; Shiffrin, Huber, & Marinelli, 1994; Dennis & Chapman, 2010). So far we have tested the RSS model primarily on associative/semantic lists, and the point of this simulation is to determine if it can also be used to simulate false recognition based upon taxonomic relations among words. Although the generality of categorical false recognition has been questioned (Maguire, Humphreys, Dennis, & Lee, 2010), it still serves as a useful test of RSS's ability to simulate false recognition across many different types of semantic relations.

We used 21 categories that each had a single word category label from the Van Overschelde, Rawson, and Dunlosky (2004) norms. For each of these categories, the top eight members were used as exemplars, and the label as a prototype. The method of testing this model was similar to the methods of Dewhurst and Anderson (1999) and of Hintzman (1986) who varied number of category members across study lists to explore recognition rates across the different category lengths. Specifically, category size was manipulated by adding 1, 4, or 8 category members into the list, with 4 categories being randomly selected (without replacement) for each list size. Hence, a total of 12 prototypes were tested on each trial. The recognition rates to both studied exemplars and unstudied prototypes were recorded across 1000 simulated trials. Based on past experiments (e.g. Hintzman; Dewhurst & Anderson), we expected an increase in recognition rates for exemplars and prototypes, with the increase for prototypes occurring at a steeper rate.

The results of this simulation are displayed in Fig. 11. Recognition rates to both studied exemplars and unstudied prototypes increased as a function of category length. However, the rate of increase was steeper for prototypes, consistent with previously reported data in schema abstraction tasks. This is an important result for RSS, as well as for models based on co-occurrence learning in general, because it shows that it is able to account for studies using categorical relationships among words, and not

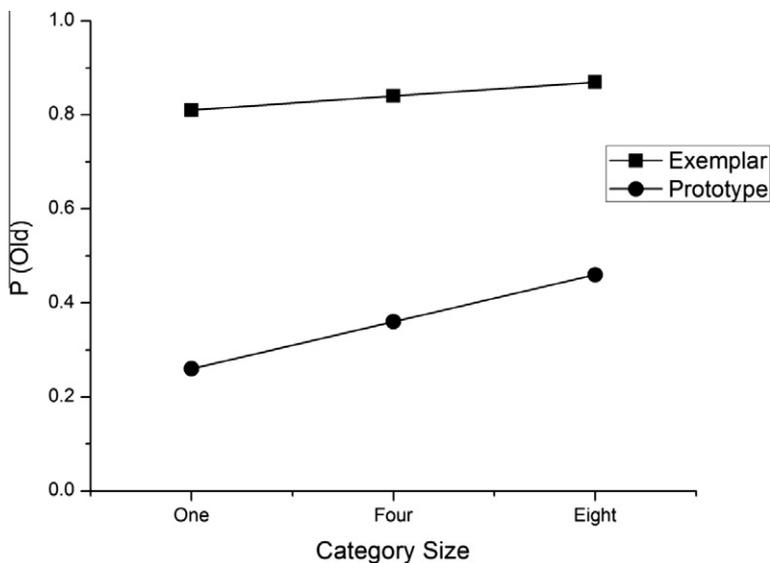


Fig. 11. RSS simulation of categorical false recognition, similar to the result of Hintzman (1986) and Dewhurst and Anderson (1999). Probability of endorsing the prototype increases as a function of items stored at a steeper rate than it does for exemplars.

simply associative or semantic relations. Furthermore, along with simulations 2.6 and 2.7, the current simulation demonstrates that the RSS model is able to account for a variety of different types of false recognition experiments organized around different types of semantic relations, and is not limited to those based on the original DRM lists.

4.9. Simulation 2.9: Retention Intervals and false memories

The previous simulations have demonstrated that the RSS model is capable of accounting for a variety of experimental manipulations that produce false recognition. However, the model's connection to current conceptual theories of false recognition has not yet been demonstrated. Because the RSS model contains many similarities to the proposals of FTT, it is worth testing whether the predictions made by FTT are borne out by the RSS model. This will allow for a stronger connection between FTT and the RSS model to be established. A common finding in false memory research is that false memories are actually more persistent than true memories and, after a suitable retention interval, levels of false recognition tend to exceed those of true recognition (Brainerd, Reyna, & Brandse, 1995; Seamon, Luo, Kopecky, et al., 2002; Thapar & McDermott, 2001; Toglia, Neuschatz, & Goodwin, 1999), even with retention intervals of up to a month (Toglia et al., 1999). This result is predicted by FTT due to gist traces being more stable than verbatim traces (Brainerd & Reyna, 2002).

The RSS model proposes that this verbatim/gist processing difference emerges through differential processing of a common memory store during the synchronization process. To simulate the effect of retrieval interval on false memories in a manner consistent with the proposals of FTT, the synchronization process in RSS should be more dependent on semantic information. This behavior was simulated by increasing the leakage parameter (which reduces the magnitude of verbatim processing) to a value of 0.6. Additionally, as we are simulating a large retention interval, a decay parameter (similar to the strength manipulations used above) of 0.25 was used to reduce the resolution of the memory trace, and the context noise parameter was increased to 0.01, to simulate extraneous noise reducing the resolution of the memory trace. All other parameters were kept constant.

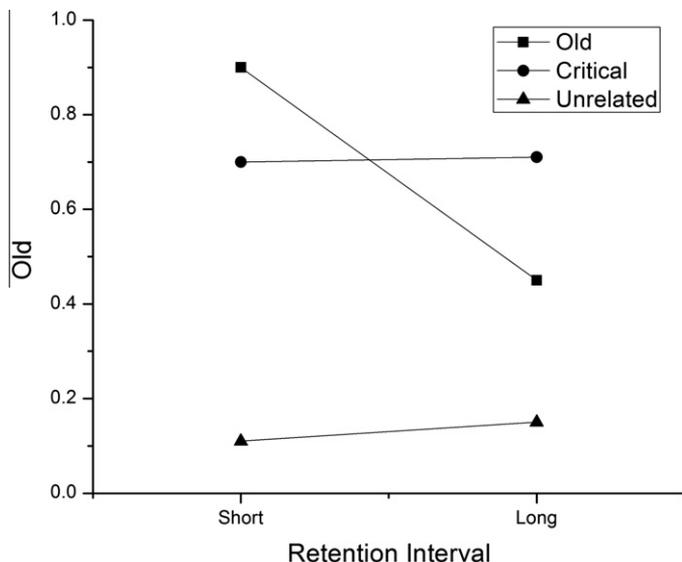


Fig. 12. RSS simulation of the effect of retention interval on false recognition. Long retention intervals were simulated by increasing the amount of context noise contained in the memory vector, and also by increasing the reliance of the synchronization process on semantic information, coherent with the proposals of FTT. Short retention intervals were simulated with the standard set of parameters for false recognition.

The results of this simulation are displayed in Fig. 12 (“short” test lag is the original set of parameters), demonstrating the two central characteristics of these experiments: (1) a sizeable decrease in the hit rate for studied items and (2) the level of false memories is stable. This pattern has been observed in human data across several studies, and demonstrates the connection between RSS and FTT. As FTT proposes, gist-based processing is a more stable form of memory, and this can be captured in the RSS model with a parameter shift emphasizing the role of semantic information in the synchronization process and an increase in the levels of extra-list context noise.

4.10. Simulation 2.10: Developmental increases in false memory

A second hypothesis of FTT is that the use of gist-based processing should increase across development, as the ability to form gist traces develops. This leads to the prediction that certain types of false memory should increase across development, a counterintuitive idea as it had been proposed that children are more susceptible to false memories due to an increase in suggestibility (Ceci & Bruck, 1993). However an increase in gist-based false memories has been observed in multiple studies (for a review, see Brainerd, Reyna, & Ceci, 2008). Clearly, the current version of RSS is not a model of development, but simple manipulations in the size of the corpus used for training and a change in processing parameters can illustrate whether it is in principle able to account for this phenomenon, and can shed light on some the underlying processes changing during development.

Brainerd et al. (2002) tested the levels of false recognition produced by children and young adults in the DRM paradigm. They found that young children (age 5) were significantly less susceptible to false recognition than adults, both for lists that elicited high and low levels of DRM false recognition. We simulated this study both by manipulating the size of the corpus from which the co-occurrence representations were created (to simulate differences in experience between children and adults), and manipulation in parameters (to simulate the developing strategy of semantic “gist” processing). For children, we simply used the first 10,000 documents in the TASA corpus for their lexical representations (compared to the full 37,600 documents for the adults). To simulate reduced gist-based

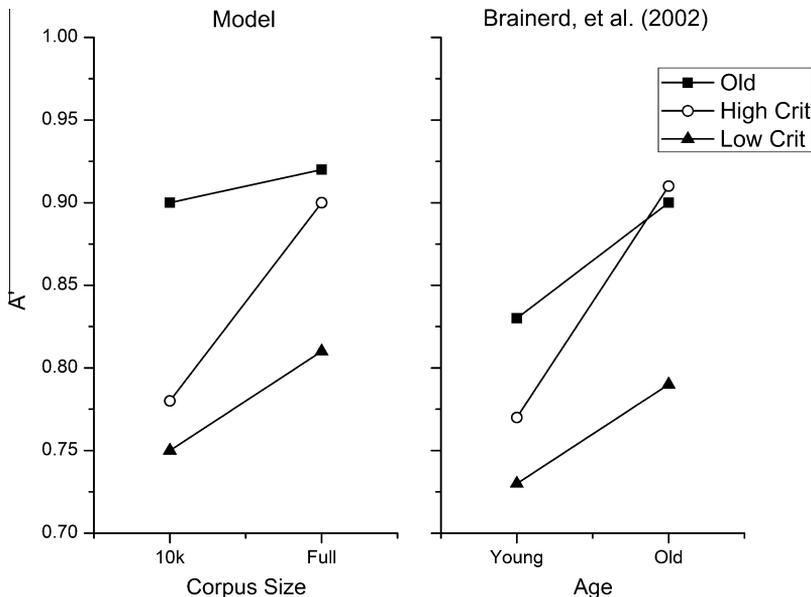


Fig. 13. RSS simulation of the developmental increase in false alarms from Brainerd et al. (2002). Behavior from younger subjects was simulated both by reducing the size of the training corpus, and by shifting the processing parameters to reduce the reliance on semantic information in synchronization. Behavior from adults was simulated using the original parameter set.

processing in children, as FTT proposes is occurring at early stages of development, the importance of semantic information in the synchronization process was reduced both by decreasing the sharpening parameter (to 0.69; making similarity less important), and decreasing the leakage parameter (to 0.34; making structural characteristics more important). Additionally, Brainerd et al. (2002) found a sizeable increase in false alarm rate to unrelated items, suggesting a more liberal criterion is used by the children, so the similarity criterion in RSS was decreased to 0.91. For the adult group, we used the same parameter set used in all the previous false-recognition simulations.

To ensure that differences in the amount of random noise due to the dimensionality of the vectors was not affecting the results, the context noise parameter was reduced to a small 0.0001 for both groups, putting the onus on the actual processing and representation differences. Brainerd et al. (2002) used only a limited number of lists (8 for each condition), but to ensure that any result is not due to the use of a small number of lists this was extended to include all lists from Stadler et al. (1999) and Gallo and Roediger (2002). High lists were lists that elicited a false recognition response 60% of the time or greater, while low lists were lower than 60%. This split produced 26 high and 29 low lists.

Following Brainerd et al. (2002) we analyzed A' in the simulation results (a measure of the discriminability of a stimulus; Pollack & Norman, 1964). Although there are known issues with A' as a measure of discriminability (Rotello, Masson, & Verde, 2008), it still allows a coarse evaluation of whether RSS is performing in a manner that is approximately similar to children. Fig. 13 displays the results of the simulation, and the corresponding data from Brainerd et al. (2002). The changes in sensitivity to false recognition produced by RSS mimic the patterns seen in development. This pattern is naturally produced by shifting parameters, in a principled manner guided by FTT, to make semantic information less important in the synchronization process for children (reducing gist-based processing) and reducing the sensitivity to false recognition. Hence, manipulating parameters in RSS consistent with the informal predictions of FTT produces simulated behavior very coherent with the human data.

4.11. Discussion

This set of simulations demonstrates that RSS provides a formal framework to explain a wide variety of false recognition effects. Together with the results of the standard recognition simulations from Section 2.1, the false recognition simulations lend further evidence that a recognition memory system based on the efficiency of the synchronization between a probe and studied context is a plausible cognitive account of recognition across multiple paradigms. It also shows the advantages of integrating a semantic representation of words with a process model of recognition. Using a realistically structured representation makes fewer assumptions about memory structure (Johns & Jones, 2010), and also increases the plausibility of all of the integrated systems. Finally, the RSS model shows a strong coherence with FTT, as parameter manipulations in RSS informed by FTT in both retention interval and development give an excellent account of the behavioral data.

5. General discussion

We have described a new model of recognition memory, the Recognition through Semantic Synchronization (RSS) model. The two core components that differentiate the RSS model from other accounts are its representation and its synchronization mechanism. The lexical representation of a word is based on a corpus-based distributional vector, allowing the model to make item-specific predictions. The process mechanism is based on the concepts of neural synchronization and information accumulation. The model makes an old/new decision for a test word by attempting to synchronize the probe and memory vectors (analogous to trying to fit a puzzle piece into a space). The decision is based on a race between two sources of information: the amount of synchronization achieved (for old decisions), and the accumulated difference between the probe and composite (for new decisions) over discrete time steps. The information source that exceeds its criterion first is the corresponding decision made.

5.1. Relation to fuzzy trace theory

The RSS model was inspired by some of the key concepts that define FTT. One similarity between RSS and FTT is that both theories propose that ‘gist’ traces of events are stored in memory—traces that capture the meaning of an episode, without specific perceptual features (Brainerd & Reyna, 2002). RSS encodes a composite ‘gist’ vector of all the words that occur in a specific study list, and this vector represents the average meaning of the study list. Another similarity between FTT and RSS is the processing dichotomy each posits for standard and false recognition. FTT proposes that standard recognition is based on stored verbatim traces of studied items, while false recognition is dependent on gist traces containing semantic information. In a similar fashion, RSS proposes a processing shift between standard and false recognition (although the same representation is used for both). In standard recognition there is a shift in processing to focus more strongly on the structural properties of the representation, rather than semantic similarity. The shift is due to the unreliability of semantic similarity when all of the words are random and have no semantic relation to one another. However, when processing probes in a false recognition setting, semantic similarity is used to a greater extent in the synchronization process due to the increase of semantic coherence within the study list.

Many of the simulations presented also serve to inform aspects of FTT. For instance, FTT entails rather sophisticated mechanisms to construct gist traces. However, as demonstrated in simulations 2.6 and 2.7, the use of a simple co-occurrence representation was able to capture results from both associative and thematic based lists. Thus, composite vectors of studied words may be sufficient to account for false memory effects, and not necessarily more complicated representational schemes. Also, as demonstrated in simulations 2.9 and 2.10, the predictions made by FTT regarding differences in processing under specific experimental conditions can be accounted for by plausible changes in the parameters of the model, strengthening the connection between RSS and FTT.

5.2. Relation to source monitoring

The relation between RSS and the source monitoring framework is less obvious. Source monitoring assumes that false memories occur because when one studies a list of words semantically related to a critical word, the critical word is often accidentally generated. Accidental generation in turn leads to confusion at testing as to whether the word was studied or not. The source monitoring framework has been used as an explanation for a considerable array of results within false memory (Lindsay & Johnson, 2000), and this type of mechanism may also be integrated into the RSS framework. In an earlier version of RSS, Johns and Jones (2009a, 2009b) proposed a version that could be applied to false recall and false recognition (where recognition is a generate-recognize process on top of recall). Recall in the model was accomplished by constructing a recall search set based on the full gist trace by activating each trace in memory relative to its similarity to the studied context. The search set was constructed by selecting all of the words in the lexicon that exceeded a similarity recall criterion; however, there is no reason why such an activation process could not be continuous, similar to the proposals of spreading activation theories. As each new word is studied, words in the lexicon would be activated according to their semantic similarity to the current word. If a word’s activation level exceeds a certain threshold, then the word would be generated and added into the gist trace, yielding source confusion at test about whether that word was actually studied.

Another issue for the model is how item-specific source information could be encoded and retrieved. Numerous studies have demonstrated that subjects tend to attribute the same source information (e.g. voice, font, etc.) to a critical word as that of its studied associates (Arndt, 2006, 2010; Hicks & Hancock, 2002; Roediger, McDermott, Pisoni, & Gallo, 2004). RSS is currently unable to address this issue because it is lacking a representation of the experimental manipulations of source information. However, fusing RSS with the mechanisms of recent temporal context models (TCM; Howard & Kahana, 2002; Sederberg et al., 2008) holds promise, particularly TCM’s use of Hebbian learning to encode temporal ordering. Preliminary work using a similar process in RSS to associate specific words with source information has been quite successful (Johns & Jones, 2012b). A Hebbian learning layer between the semantic representation of a word and a source representation may be used to learn word-source mappings. During synchronization, source information is then gradually reinstated

across iterations through these learned weights. Because semantic information was used to associate words with their source, critical words would tend to reinstate the same source as those of its studied associates. This type of process could also be used to extend the model to multi-list paradigms (e.g. Humphreys et al., 2003), where each list is associated with a separate source. Another possible integration to achieve source memory is given by the matrix model (Humphreys, Bain, & Ray, 1989), which has proven successful at accounting for this type of behavior previously. This type of integration with source mechanisms is a promising avenue to explore predictions of FTT and source monitoring within the same formal framework.

5.3. Simulating response latency

Because it is partially based on sequential sampling models of response latency, an obvious question for the RSS model is whether it is capable of accounting for latency data in tandem with the choice data modeled here. Latency in RSS would be based on the number of iterations required for the model to reach a decision (cf. Hintzman's, 1986, notion of deblurring). Mapping response iterations to response latency has seen previous success in models of the same architecture (e.g., Mewhort & Johns, 2005; Jamieson & Mewhort, 2009). To demonstrate that RSS is capable of simulating latency data, a simple simulation of the logarithmic increase in reaction time as a function of set size from Burrows and Okada (1975) was conducted. The parameter values from Section 2.2 were used in this simulation with the context noise parameter set to 0, due to Burrows and Okada (1975) using perfectly memorized lists. Fig. 14 displays the results of this simulation: the number of iterations that RSS takes to make a decision is a logarithmic function of the set size, equivalent to the results reported by Burrows and Okada. This result suggests that RSS is at least capable of accounting for some response latency results, but a more thorough analysis will need to await future work (including latency distributions).

5.4. Simulating recall in RSS

A model of false recall, based on the SAM model (Shiffrin & Raaijmakers, 1981), has been recently been proposed by Kimball, Smith, and Kahana (2007). Their fSAM model proposes that studied words activate their semantic associates in memory through rehearsal in a short-term memory store, and at

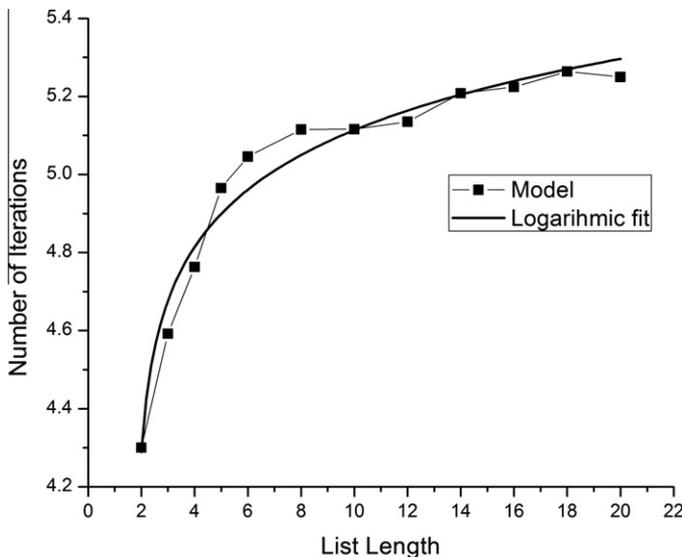


Fig. 14. RSS simulation of Burrows and Okada (1975) finding of a logarithmic increase in response latency as a function of number of studied items.

retrieval words with a stronger activation to the episodic context are recalled at a higher rate. In fSAM the associations between words are taken either from a word association space created with human free association norms (Steyvers, Shiffrin, & Nelson, 2004), or are hand-coded to give the necessary association values. A primary distinction between fSAM and RSS is that the representation used by RSS is based on the word's linguistic distribution in the environment, whereas in fSAM it is based on behavioral data. In addition, the behavior of RSS depends on a sparse contextual representation.

As mentioned earlier, preliminary work has explored fusing the RSS model with a simple recall process (Johns & Jones, 2009b). The recall model has the same representational assumptions described here (e.g. a composite vector is used as a list memory trace). To recall items, a semantic search process is utilized to retrieve the most similar words to the composite, and the recognition process described here (with a parameter shift) is utilized as a decision mechanism. This model is capable of simulating levels of false recall, produces good item-level fits to the levels of false recall for different DRM lists, and can successfully model the rise in false recall as a function of number of studied associates, among other effects (Johns & Jones, 2009b). However, this work is still in its preliminary stages and more research is required to determine its plausibility as a model of recall.

As discussed previously, an enticing integration would be to use the decision and representation assumptions of the RSS model in combination with the temporal encoding mechanisms of the TCM framework (Howard & Kahana, 2002; Sederberg et al., 2008). This would enable a sounder mechanism of recall—by using the current word as cue to retrieve items that occurred within a similar temporal context. The integration is feasible due to the composite storage assumption common to both RSS and TCM, although they do have different representation assumptions.

5.5. Limitations

As with any formal model, there are empirical results that RSS is not able to account for in its current form. For instance, the model is not equipped to explain the effects of repeating a DRM list multiple times. In a study by Seamon et al. (2002) DRM lists were repeated 1, 5, or 10 times. The authors reported an increase in false alarm rates from 1 to 5 repetitions, but a decrease from 5 to 10 repetitions. When this result is simulated with the RSS model, a large increase in false recognition is seen with critical lures from 1 to 5 repetitions, and a smaller increase is seen in false recognition rates from 5 to 10 repetitions. Brainerd et al. (2001) interpret the effect of repetition in terms of FTT by suggesting that repetition gives rise to a recollection process that examines verbatim traces, instead of a familiarity process based on a gist trace. By their account, it makes sense that the RSS (a single-process, familiarity-based model) cannot account for this result. However, it is possible that the RSS might account for repetition if it were given more sophisticated encoding assumptions or a recollective process.

There are other results that RSS cannot currently capture, such as the effects of levels of processing (Thapar & McDermott, 2001), and these shed light on the limitations of formalizing a problem to produce quantitative predictions (at the expense of flexibility). However, this does not entail a dismissal of RSS as a model, but instead should spur future work to determine what might be necessary within its formal framework to generate these behavioral patterns. One of the attractive features of the RSS model is that it is very simple and can be modified without increasing the complexity of the model to a point where it becomes cognitively implausible. It is also attractive because it is capable of simulating various behavioral variables (choice probability, confidence, response latency, etc.). This allows the model to be tested within a number of different paradigms to determine limitations and to suggest future modifications.

6. Conclusion

Nosofsky (1991) demonstrated that the seemingly random relation between classification and recognition performance (to the same stimuli) could be clearly understood under a formal model as a shift in cognitive process parameters. Even though the linear correlation between performance on the two tasks was low, the correlation of predictions under his General Context Model was essentially perfect: "Under the guidance of a formal model, . . . a unified account of these processes is achieved" (p. 9). We make the same point here by using a realistic semantic representation. Standard and false

recognition, although often studied separately, can be understood as changes in process parameters under a single model using a common structural representation for words. In addition, the integration of structural representation and process model is essential to simulate the behavior. The combination of realistic processing mechanisms and plausible representations has long been a goal in cognitive modeling (Estes, 1975), and RSS was created with this goal in mind.

To advance our formal understanding of the cognitive processes, it is necessary to continue to evolve the types of mechanisms proposed. The RSS model takes a step in this direction by integrating a realistic semantic representation (learned from the language environment), and a plausible processing mechanism based on the cortical communication method of neural synchronization together with the widely used decision process of information accumulation. The model successfully accounted for a wide variety of results from both standard and false recognition, suggesting that by using realistic representations in combination with plausible processing mechanisms, better theories of human cognition can be constructed.

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