

Retrieving Information From Memory: Spreading-Activation Theories Versus Compound-Cue Theories

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McNamara (1992a) attacked compound-cue theories on a number of grounds. Using free association as a measure of distance between concepts in memory, he argued that compound-cue theories cannot explain mediated priming effects. The authors show that free-association production probabilities do not accurately predict priming effects, either directly or in the context of current spreading-activation models, and so remove the basis for McNamara's criticism. McNamara also claimed that compound-cue theories cannot account for the sequential effects of items that precede a target on responses to the target, but the authors show that sequential effects are consistent with compound-cue models if the target item is weighted more heavily than preceding items in the calculation of familiarity that determines response time and accuracy for the target. It is concluded that, although compound-cue and spreading-activation theories are both consistent with available data, the compound-cue theory, having less freedom, has passed more stringent tests.

Ratcliff and McKoon (1988) and Doshier and Rosedale (1989) proposed that information is accessed in memory by a process that combines the multiple cues present in the retrieval environment into a compound cue. In a critique of compound-cue models, McNamara (1992a) addressed a large number of issues, contrasting compound-cue models with their main competitors, spreading-activation models, and concluded that compound-cue models, could do little more than "explain (experimental) results by questioning the methods or appealing to ad hoc processes" (p. 658). In this reply to McNamara's article, we respond to his main criticisms, and we reiterate our 1988 claim that compound-cue models provide an alternative view that can be used to generate empirical investigations of retrieval that would not be suggested by spreading-activation models.

Spreading-activation and compound-cue theories have the important function of explaining how the processes of memory retrieval focus on subsets of information in long-term memory. In the two theories, focusing is accomplished by quite different mechanisms. For the tasks discussed in this article, lexical decision and recognition, spreading-activation theories propose that

all the action in retrieval processing takes place in temporary changes to long-term memory: When an item is presented to the system, activation spreads from the representation of that item in long-term memory to other nearby items in long-term memory. In compound-cue theories, all the action takes place in short-term memory. Items presented to the retrieval system are assumed to join together into compounds in short-term memory. A compound is matched against information in long-term memory by a global and passive matching process. In spreading-activation models, the result of retrieval processing is increased activation in long-term memory of items related to the input item. In compound-cue models, the result of retrieval processing is a value indicating the familiarity of the cue compound to all the items in long-term memory. The two different sets of assumptions about retrieval offer two different ways to think about processing, about what experiments are interesting to perform, and about how to interpret data. In this way, each kind of theory is valuable to the other.

"Mediated" Priming?

In spreading-activation models, items in memory vary in the number of links between them. Items connected by one or even two mediators should prime each other in tasks such as lexical decision because presentation of the prime word sends activation spreading to the target word, so that the target is already activated in advance of its actual presentation. In contrast, distance between items in terms of number of links is not meaningful for compound-cue theories. In the search of associative memory (SAM) model, for example (Gillund & Shiffrin, 1984), priming occurs when the strength value of the prime matched against some word(s) in memory is high and the strength value of the target matched against the same word(s) is also high. Thus, compound-cue models predict priming only for items that are directly related by high strength values (or, in SAM, related by at most one other item with high strength values to both prime and target), but spreading-activation models predict priming for items separated by multiple links. Because of these

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This research was supported by National Institute of Mental Health Grants HD MH44640 and MH00871 to Roger Ratcliff and National Science Foundation (NSF) Grant 85-16350, National Institute of Deafness and Other Communicative Disorders Grant R01-DC01240, and Air Force Office of Scientific Research Grant 90-0246 (jointly funded by NSF) to Gail McKoon.

We thank Tim McNamara for providing his free-association data to us and for extensive discussions, which we hope have resulted in agreement on the points of agreement and disagreement in this debate. It should be noted that space limitations prohibited a point-by-point rebuttal to McNamara (1992b), so we have restricted this discussion to the most important arguments.

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contradictory predictions, mediated priming has become a critical focus of the debate about the relative merits of spreading-activation theories and compound-cue theories.

The key issue in this debate is how the distance between two concepts in memory should be measured. McNamara (1992a) argued that the best available measure of distance is free-association production probability (p. 652) and used this measure to account for priming effects that he claimed "pose difficulties to non-spreading-activation (compound cue) theories" (p. 653). Specifically, he claimed on the basis of free-association data that there exist pairs of words that prime each other but are not directly related, in contradiction to compound-cue models. However, the claim is wrong: Free-association production probability is not an accurate measure of distance for predicting priming effects. First, there exist pairs of words that prime each other even though connections between them are not produced in free association. For example, Fischler (1977), McKoon and Ratcliff (1994, unpublished data using a short stimulus onset asynchrony [SOA], following Shelton & Martin, 1992), McKoon and Ratcliff (1992), and Seidenberg, Waters, Sanders, and Langer (1984) have all shown priming for pairs of words that are not associated according to free-association production measures. Second, even when free association does produce connections between words, the production probabilities do not correctly predict priming effects, as we demonstrate in the next section. Thus, free association is not a veridical measure of distance in memory, and so priming effects should be explained using other measures such as co-occurrence statistics or relatedness judgments that are consistent with compound-cue theories (McKoon & Ratcliff, 1992).¹

Free-Association Production Probabilities Do Not Accurately Predict Priming Effects

To present these issues, we (like McNamara, 1992a) center our discussion around two sets of pairs of words, one set from Balota and Lorch (1986) and McNamara and Altarriba (1988), the MA set (named for McNamara and Altarriba), and the other set from McKoon and Ratcliff (1992), the MR set (for McKoon and Ratcliff). McKoon and Ratcliff (1992) found that the two sets of pairs gave priming effects of about the same size (14 and 13 ms). Primes and targets of the MA set were intended to be words connected by mediators: *flower-thorn* is an example. Primes and targets of the MR set were originally intended to be words that were not connected by any mediator produced in free association: *flower-root* is an example. However, McNamara (1992a) claimed that both sets of primes and targets did have mediators, and that the equivalent priming effects between the prime and target words of these pairs were predicted by equivalent probabilities that the primes and targets were linked through free associations. He used this to support his contention that free association is the best available measure of distance between concepts in memory.

To obtain chains of mediating concepts by which primes and targets could be linked, McNamara (1992a, Table 1, 1992b) used what has been termed the *continued-association* procedure (Postman & Keppel, 1970), asking subjects to generate multiple free associates (e.g., as many as they could in 1 min) to each prime word, target word, and potential mediating word.

However, for measuring associative distances among concepts in memory, the continued-association procedure is problematic. In the earlier literature about free associations (Postman & Keppel, 1970, and precursors), it was generally accepted that this procedure allowed each next response generated from a single stimulus to be determined not only by the initial stimulus but also by the prior response or any of the other previously produced responses (see recent discussion by Nelson, Schreiber, & McEvoy, 1992). Moreover, the probabilities produced for a given stimulus by the continued procedure sum to more than 1 and so cannot be considered associative strengths for the purpose of modeling a network in which the total proportion of activation spreading from one node to each of its directly connected nodes must not sum to more than 1.0 (cf. ACT*, Anderson, 1983). The standard free-association method for obtaining association strengths (avoiding the problems with the continued procedure, Postman & Keppel, 1970) is to ask subjects to give only a single response for each stimulus. We collected data with this procedure, asking subjects to generate free associates to all of the primes, potential mediators (from McNamara, 1992a), and targets for both the MA and the MR pairs. For the MA pairs, the prime and target are supposed to be linked by one mediating concept, a two-step chain. For some of the MR pairs, McNamara also proposed a two-step chain, and for others a three-step chain. For both kinds of chains, Figure 1 shows the data we obtained; the mean first production probabilities for the directions are indicated by the arrows.

The important result is that the average probabilities for the two- and three-step MR chains are considerably lower than the average probabilities for the MA chains, contrary to McNamara's claims that the two kinds of pairs are equivalent. For example, for the two-step chains, the probability that a mediator is produced in response to its prime is 0.192 for the MA pairs, but only 0.053 for the MR pairs. For a very simple spreading-activation model, it might be assumed that when a prime is presented, some proportion of activation spreads from prime to mediator (p) and some proportion spreads from mediator to target (q), so that the activation passed from prime to target is pq . Using the production probabilities for each link to determine p and q and then multiplying along the links gives an activation value on a target of 0.0219 for the MA targets (0.192×0.114), but only 0.0025 for the MR two-step targets and only 0.0007 for the MR three-step targets (values from Figure 1). Over all the targets, the weighted mean value of activation for the MR targets (0.00175) is 13 times less than for the MA targets. Clearly, these values in this simple model cannot predict equivalent priming effects for the MA and MR pairs.

¹ McNamara (1992a) suggested that an experiment by Ratcliff and McKoon (1978) provides evidence against co-occurrence as a predictor of priming. Ratcliff and McKoon measured the amount of priming due to temporal contiguity, that is, the nearness of words to each other in a sentence. They found that the amount of priming due to temporal contiguity was less than that due to propositional distance. McNamara (1992a) identified co-occurrence as being necessarily closely related to temporal contiguity and less related to propositional distance. However, co-occurrence as presently defined includes propositional, temporal, and even between-sentence effects, and so Ratcliff and McKoon's results currently have no implications for the use of co-occurrence measures.

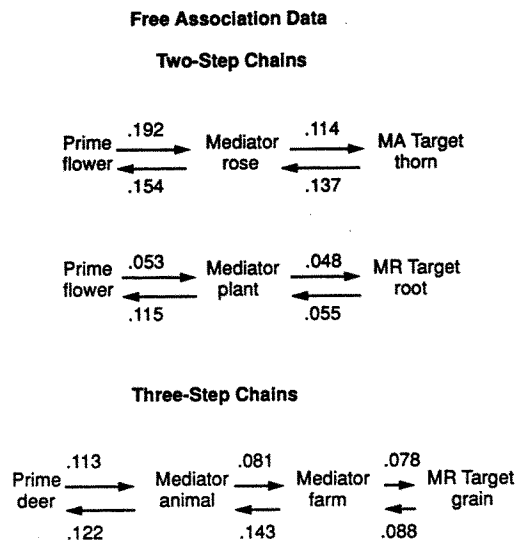


Figure 1. Free-association production probabilities (means across subjects and items) from the single-response procedure for the MA (McNamara & Altarriba, 1988) pairs, the MR (McKoon & Ratcliff, 1992, with McNamara's, 1992a, mediators) two-step pairs, and the MR (McKoon & Ratcliff, 1992, with McNamara's, 1992a, mediators) three-step pairs.

The difference between the MA and the MR pairs is even larger when an averaging artifact is taken into consideration. The averages just given were calculated by averaging across items (e.g., averaging all prime-to-mediator links and averaging all mediator-to-target links) and then multiplying the averages to get activation for the target. A more appropriate way to average would be to multiply the probabilities for the chain for each item and then average the resulting values of target activation. This way of averaging is more appropriate, because for the MR pairs it is almost always the case that when the probability for one of the links (prime-to-mediator or mediator-to-target) is high, then that for the other is very low. This second way of averaging increases the difference between the MA and MR pairs. For the MA pairs, multiplying probabilities before averaging gives a value of 0.0162 (cf. 0.0219 above, which is 1.3 times smaller) and for the MR pairs (weighted average) a value of 0.00034 (cf. 0.00175, which is 5 times smaller), giving a ratio of 47:1. The same averaging problem applies to the data McNamara (1992b) collected with the continued-association procedure. Averaging across items first and then multiplying gives a value of activation for the MA targets of 0.114, whereas multiplying links for each item first and then averaging gives a value of 0.104. The difference between the two ways of averaging is larger for the MR pairs: 0.063 versus 0.037 for the two-step pairs and 0.016 versus 0.011 for the three-step pairs. Combining the two-step and three-step pairs (and weighting by the number of each), the ratios of MA to MR activation are 1.1:1 (the value reported by McNamara, 1992b) versus about 4:1 (0.104:0.026). Thus, using the method of averaging that is most appropriate to the spreading-activation model, priming is predicted to be four times larger for the MR pairs than for the MA pairs.²

Modeling Priming Effects With an Explicit Spreading-Activation Model

To develop the argument further, we examined whether an explicit spreading-activation model, ACT* (Anderson, 1983), could jointly accommodate free-association production probabilities and priming effects. In ACT*, activation reverberates among connected concepts, and so the strengths of the links from a prime to its target and the strengths from the target back to the prime both determine the total amount of activation that accrues at the target. ACT* predictions for relative amounts of priming were calculated for a network with a prime, a mediator, and a target along with some other nodes connected to them. Figure 2 shows one mediator for a two-step chain between prime and target; the corresponding network for a three-step chain would have an additional mediator with three other nodes connected to it, for a total of 18 nodes. The sum of the strengths leaving each node is set to 1.0, making the network consistent with the assumptions of ACT* (Anderson, 1983, p. 22).

Connection strengths were derived from the production probabilities in Figure 1 for the MA pairs and the MR (two- and three-step) pairs. Table 1 shows the predicted amounts of activation on the target node after activation has been entered at one or more source nodes and the system has stabilized (see the Appendix for the equations and assumptions used to implement ACT*). We assumed as a baseline against which to measure the predicted amount of priming the case where only the target node was a source of activation, corresponding to the case where the target was presented to the system with an unrelated prime. Given this baseline, we could then predict mediated priming from prime to target, for which we assumed that the prime and target were sources of activation, and direct priming from the mediator to the target, for which we assumed that the mediator and target were sources of activation. Direct priming should always lead to more activation on the target than mediated priming, and this is what the predictions in the table show. For example, for the MA items, the prediction for activation on the target as a result of direct priming is 2.777, up 0.434 from baseline. The prediction for activation on the target as a result of mediated priming is 2.481, up only 0.138 from baseline. Comparing the two amounts of priming, the ratio of direct to mediated is 3.1 (shown in the fifth column of Table 1), consistent with empirical data within typical standard errors (assuming a linear relationship between activation and reaction time, e.g., as in Anderson, 1983). For example, McNamara and Altarriba (1988) found 24 ms of direct priming and 10 ms of mediated priming.

The important results in Table 1 are the ratios of the pre-

² In calculating average association strengths, McNamara (1992b) used both forward and backward association probabilities, simply averaging the two. However, for a model such as ACT*, this would be incorrect: Activation reverberating between prime, mediator, and target would become increasingly smaller as the number of forward and backward traverses across the links multiplied the activation to smaller and smaller values. In fact, the effect of a backward link would have to be multiplied by the square of the corresponding forward link. So to calculate predictions for average activation in ACT*, these reverberations and their effect are taken into account in the formulation of the model.

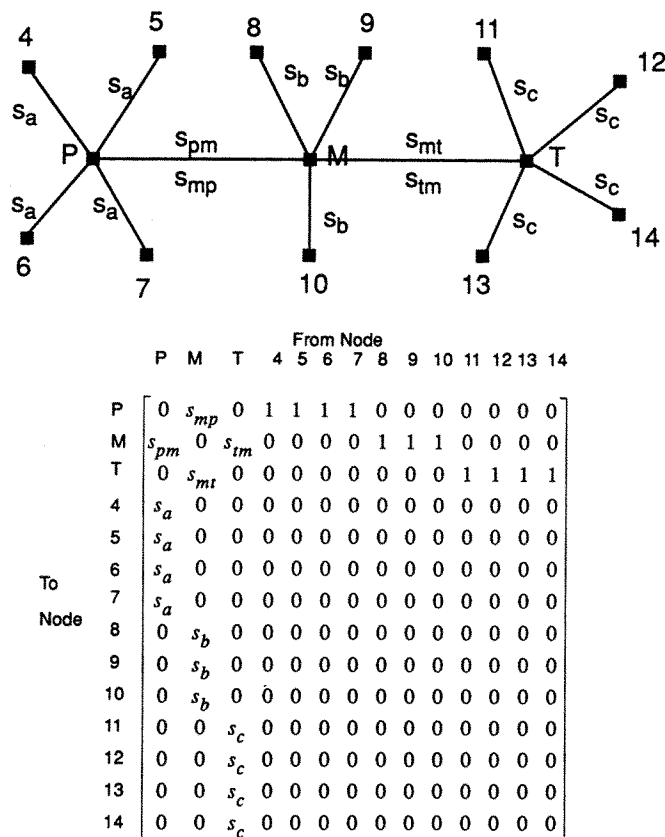


Figure 2. A network for spreading-activation computations for ACT* and a matrix of the strengths of connections between nodes. For ACT*, the weights leaving a node are assumed to sum to 1, so strengths in each column of the matrix sum to 1. P = prime; M = mediator; T = target; s = strength. s_{pm} , s_{mp} , s_{mt} , and s_{tm} are derived from production probabilities (see text). s_a , s_b , and s_c are the strengths from the prime mediator and target, respectively, to other nodes in the network.

dicted priming effects for the MA pairs and the MR pairs. First, the ratio of the direct-priming effect for the MA pairs (empirically, 24 ms) to the mediated-priming effect for the MR pairs (empirically, 14 ms) is predicted to be at least 18.9. Second, the MA mediated-priming effect is predicted to be at least 5.6 times

larger than the MR mediated-priming effect. Empirically, these effects are about the same size (about 14 ms).

The network shown in Figure 2 would not be a completely acceptable representation of a semantic memory network because Nodes 4 through 14 send all of their strength back to the prime, mediator, or target (whichever of these nodes they are connected to). More realistically, each of Nodes 4 through 14 would be expected to be connected to other nodes, and this would mean that the strength on the link from one of these nodes back to the prime, mediator, or target would have to be less than 1.0, because some of the strength leaving these nodes would have to go to their other connected nodes. However, repeating the calculations of target activations with two other nodes connected to each of Nodes 4 through 14 made ACT*'s predictions even worse, with the predicted ratios of priming effects being much larger than those found empirically.

What can be concluded from this discussion? First, reiterating McKoon and Ratcliff's (1992) previous conclusion, free-association production probabilities do not correctly predict priming effects. In this article, we demonstrate this for an explicit model, ACT*. Thus, in the context of current theories and data, free-association data cannot be used to decide whether two items in memory are directly connected, and so, consistent with compound-cue models and alternative measures of strength of connection (e.g., relatedness and co-occurrence), it is reasonable to suppose that all pairs of words that give priming are directly connected with some degree of strength. In consequence, contrary to McNamara's (1992a, p. 653) claims, priming effects and free-association production probabilities do not pose problems for compound-cue models. However, priming effects and free associations do pose problems for spreading-activation models if the models assume that free-association probabilities should predict priming effects.

McNamara (1992a) acknowledged both that there are inherent problems in measuring distances between items in memory and that measures like free association may not be definitive (p. 653). It is important to understand why they are not definitive: It is not the case that free association is "probably" an accurate measure, if we could only get enough subjects to generate enough responses. Instead, as is exemplified by the exercise above with ACT*, free association clearly fails as a predictor of priming. As a result, both spreading-activation and compound-cue models need to provide a theoretical account of processing

Table 1
Predictions From ACT* for MA and MR Pairs

Materials	No. of nodes	Baseline activation	Mediated activation	Direct activation	Ratio of MA direct to mediated	Ratio of MA mediated to mediated
MA	14	2.343	2.481	2.777	3.1	1
MR two-step	14	2.550	2.573	2.766	18.9	5.6
MR three-step	18	2.288	2.302	2.589	31.0	9.1

Note. The ratio of direct to mediated priming and mediated to mediated priming is the ratio of the differences between the condition and baseline. Ratios based on the probabilities from free association (ratios of probabilities or ratios of products of probabilities) are MA mediated to direct, 5.2; MR two-step mediated to MA direct, 44.8; and MR three-step mediated to MA direct, 158.3. MA = McNamara and Altarriba (1988) materials; MR = McKoon and Ratcliff (1992) materials.

in the free-association task, of how free association and priming effects can be related to each other, and of how they can both be related to other variables such as semantic relatedness and co-occurrence frequencies that might be more direct predictors of priming effects (see McKoon & Ratcliff, 1992, for a discussion of these variables).

Sequential Effects

McNamara (1992a, 1992b) argued that sequential (lag) effects among multiple lexical decision tests cannot be explained by compound-cue theories. McNamara began by demonstrating that, for a particular set of experimental procedures, the compound used to retrieve information from memory about a target word must contain the two items preceding the target as well as the target. McNamara demonstrated this by showing facilitation for a target when the related word that preceded it was separated by an intervening word (e.g., facilitation for *nail* in the sequence *hammer, vase, nail*; see similar results in Ratcliff & McKoon, 1978; Ratcliff, Hockley, & McKoon, 1985).³ Then McNamara considered sequences like *hammer, nail, vase*, in which the first, "preprime," word and the second, "prime," word are related to each other but not to the target. Because the compound used to access memory for the target must contain all three items, response time for the target should be facilitated by the relation between the preprime and prime. When such facilitation was not found in his experiments, McNamara concluded that the compound-cue prediction failed. McNamara also considered triples for which the preprime was a nonword and claimed that their inclusion in a compound would diminish the familiarity of the compound sufficiently that the effect of a prime-target relation would be reduced. In other words, facilitation on the target *nail* should be less in the sequence *bame, hammer, nail* than in the sequence *vase, hammer, nail*. Again, when this inhibition was not found in his experiments, McNamara claimed a failure of compound-cue theory.

What is wrong with McNamara's conclusions is that they are based on assumptions about the application of compound-cue theory that are not reasonable, assumptions about the relative weightings of the preprime, prime, and target in the calculation of the total familiarity value for the target. When more reasonable weightings are assumed, compound-cue theory can fit the data quite well. Table 2 shows quantitative predictions for sev-

Table 2
Familiarity of Various Preprime, Prime, and Target Sequences

Weights	Preprime, prime, target					
	UUU	RRU	RUR	URR	XUU	XRR
0.1, 0.2, 0.7	3.58	3.61	3.73	3.90	3.25	3.54
0.14, 0.29, 0.57	3.41	3.47	3.56	3.77	2.96	3.28

Note. UUU means that none of the words are related, RRU means that the preprime and prime are related (e.g., *hammer, nail, veil*, in a sequence), RUR means the preprime and target are related, URR means the prime and target are related, X refers to a nonword; in XUU, the prime and target are not related, and in XRR, they are related.

Table 3
The Retrieval Structure for the Search of Associative Memory Model Used in Modeling Priming Effects

Cue	Target									
	1	2	3	4	5	6	7	8	9	10
1	1	1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
2	1	1	1	0.2	0.2	0.2	0.2	0.2	0.2	0.2
3	0.2	1	1	1	0.2	0.2	0.2	0.2	0.2	0.2
4	0.2	0.2	1	1	1	0.2	0.2	0.2	0.2	0.2
5	0.2	0.2	0.2	1	1	1	0.2	0.2	0.2	0.2
6	0.2	0.2	0.2	0.2	1	1	1	0.2	0.2	0.2
7	0.2	0.2	0.2	0.2	0.2	1	1	1	0.2	0.2
8	0.2	0.2	0.2	0.2	0.2	0.2	1	1	1	0.2
9	0.2	0.2	0.2	0.2	0.2	0.2	0.2	1	1	1
10	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	1	1
11	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
12	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

Note. Cues 11 and 12 are assumed to be nonwords with strengths 0.1, the residual strengths from word cues to other words are assumed to be 0.2, and the strengths of words connected to each other are assumed to be 1. Familiarity is computed from $F(\text{cue } i, \text{cue } j, \text{cue } k) = \sum_l S_{il}^{w1} S_{jl}^{w2} S_{kl}^{w3}$, where S_{il}^{w1} is the strength of cue i to target l with weight $w1$.

eral kinds of sequences generated from a compound-cue model based on SAM (Gillund & Shiffrin, 1984; Ratcliff & McKoon, 1988). The predictions were derived for the simplified memory structure shown in Table 3 (see Ratcliff & McKoon, 1988, Table 1) in which each cue word is related with strength 1.0 to itself in memory, it is related with strength 1.0 to each of two related other words in memory (which are in turn related back to the cue word with strength 1.0), it is related to all other items in memory (and they are related to it) with strength 0.2, and it is related to a nonword with strength 0.1. To determine the familiarity value for the target (see Table 3), the strength values for the preprime, prime, and target cue words are weighted differently, with most weight on strength values for the target because it is the word that actually requires a response, and the weighted strength values are summed over all items in memory.

McNamara used a weighting scheme of 0.5 on the target, 0.3 on the prime, and 0.2 on the preprime. This scheme places a lot of weight on the preprime and prime relative to the target. It means that if the prime and preprime were nonwords and the target a word, equal weight would be given in the decision process to the nonwords (preprime and prime) and the target word; an error rate of roughly 50% on the target word would be expected. We believe that this is not a reasonable choice for a weighting scheme, and others are presented in Table 2. The results show that McNamara's claims depended on the excessive weighting of the prime and preprime.

Table 2 shows familiarity values for two different weighting schemes for several kinds of sequences (see McKoon & Ratcliff,

³ Joordens and Besner (1992) have criticized compound-cue theory because, they claimed, it cannot predict priming effects when an item intervenes between a related prime and target. This is clearly false; Ratcliff and McKoon (1988) showed exactly how compound-cue models predict such effects (as did McNamara, 1992a, 1992b).

Table 4
Predicted Priming Effects

Values	Priming effect: Condition–baseline familiarity					
	URR–UUU	RUR–UUU	RRU–UUU	XUU–UUU	XRR–URR	XRR–XUU
Weights 0.1, 0.2, 0.7	0.32	0.15	0.03	–0.33	–0.36	0.29
Weights 0.14, 0.29, 0.57	0.36	0.15	0.06	–0.45	–0.49	0.32
Reaction time difference (ms)	–26	–14	<i>ns</i>	31	24	–33

Note. Reaction times are from McNamara (1992b). Note that the reaction time and familiarity value differences have opposite signs, because smaller reaction times correspond to higher familiarity values for positive responses. U = unrelated; R = related; X = nonword.

1992, for other schemes) and the resulting predictions for priming effects (in the rightmost columns). The empirical constraints that the predictions must meet are straightforward (from McNamara, 1992b): First, consider the cases for which the preprime is a word. The familiarity value on the target should be lowest when neither preprime nor prime is related to it (baseline = UUU, where U = unrelated) and highest when the prime is related to it (URR, where R = related). McNamara (1992b) obtained a difference between these two conditions of 30 ms. The familiarity value on the target should also be higher than baseline when the preprime is related to it (RUR); McNamara obtained a difference for these two conditions of 14 ms in one experiment and 21 ms in another experiment. Importantly, the familiarity value on the target should not be distinguishably higher than baseline when the preprime and prime are related to each other but not the target (RRU); for these two conditions, McNamara found no significant difference in response times.

With McNamara's weighting scheme (0.2, 0.3, 0.5), the URR priming effect in terms of familiarity value would be 0.30, the RUR priming effect would be 0.19, and the RRU effect would be 0.10. The RRU effect is one third the size of the URR effect, and so should be observable empirically. However, if the weight on the target is increased to 0.7 and the weights on the preprime and prime are decreased accordingly, then the compound-cue model predicts the relative amounts of priming quite accurately, as shown in Table 4. The RRU effect is predicted to be about one tenth the size of the URR effect, and it would be unlikely that this could be detected empirically. The URR effect is 30 ms, and one tenth of that would be only about 3 ms. The other weighting scheme shown in Table 4 also predicts an RRU effect too small to be observed.

When the preprime is a nonword, the compound-cue model also does well. A nonword preprime produces lower values of familiarity, comparing favorably with the slower reaction times observed in McNamara's data for both the XUU condition (where X is a nonword, here preceding an unrelated prime and target) relative to the UUU condition, and the XRR condition (a nonword preceding a related prime and target) relative to the URR condition. In addition, the model predicts that the RR priming effect should be about the same size for nonword preprimes as for word preprimes, in accord with McNamara's data (the 26 and 33 ms priming effects were not significantly different from each other).

The conclusion to be drawn from the results displayed in Table 4 is clear: SAM correctly predicts the relative sizes of the URR, RUR, and RRU priming effects and simultaneously ac-

counts for the effects of a nonword preprime. Thus, contrary to McNamara's claim, the SAM compound-cue model gives an excellent fit to a complicated pattern of data (and may also apply to choice reaction time sequential effects, see McKoon & Ratcliff, 1992), whereas spreading-activation models require the addition of an explicit reaction time model to account for sequential effects.^{4,5}

Naming

Researchers interested in priming effects have often argued that theories designed to explain such effects should link priming in lexical decision with priming in the task of naming a word, because both tasks involve accessing the lexicon and because similar experimental variables have been examined in the two tasks (cf. McNamara, 1992a; Neely, 1991). In contrast, we have argued that priming in lexical decision has a natural affinity with priming in recognition memory (McKoon & Ratcliff, 1979). Our strong inclination is to attempt to generalize research domains in terms of underlying theoretical mechanisms, and in theoretical terms, both lexical decision and recognition require an item to be encoded and compared with memory to produce a binary decision. Naming a word, on the other hand, is a task for which one out of tens of thousands of possible responses must be produced. McNamara (1992a) criticizes compound-cue theories because they fail to explain priming effects in naming, but models that deal with naming

⁴ A third sequential effect that McNamara (1992a) marshals in his critique of compound-cue theories involves sequences of only two items, not three. He points out that compound-cue theories should predict slower response times on a positive target when it is preceded by a negative test item, because the negative item will cause the familiarity of its compound with the target to be low. Sequential effects have been demonstrated in choice reaction time (Remington, 1969; Falmagne, 1965) as mentioned above. McNamara cites two sets of data for which the predicted effect does not hold (LeSueur, 1990; Neely & Durgunoglu, 1985). However, there are other sets of data that do show the predicted effect (cf. Ratcliff, Sheu, & Gronlund, 1992, Experiment 1; McKoon & Ratcliff, 1994) and also sequential effects in choice reaction time (Falmagne, 1965; Remington, 1969).

⁵ McNamara (1992a) also considered sequential effects that involve neutral prime items (a neutral prime is a word like *ready*, presented many times over the course of an experiment). Such effects depend on the mixtures of prime–target SOAs in the experiment; see McKoon and Ratcliff (1994).

and lexical decision could be similarly criticized because they do not deal with recognition memory.

Although we are biased against relating naming and lexical decision through empirical considerations, it may be possible to relate them theoretically by implementing a compound-cue mechanism in models of naming. Memory models in which compound-cue mechanisms have been implemented are parallel processing models. This characteristic suggests Seidenberg and McClelland's (1989) model for lexical decision and naming as a candidate to implement a compounding mechanism. In Seidenberg and McClelland's (1989) model, orthographic and phonological units each form two distinct levels of representation, linked by a hidden layer of units. To model compounding, gradual (stochastic) replacement of one item by the next item (e.g., with an exponential probability of a feature being replaced) would allow the representation at input to be a compound (a combination of features from the current and prior items), and this compound could percolate through the whole network. To produce semantic priming effects, it would be necessary to add an explicit (as yet unimplemented) semantic layer of information. Then the semantic layer could represent semantic feature overlap, so that a compound of related items would produce a better match to memory and faster responses. To assess whether such a marriage of models could account for priming in naming, testing and data fitting would be required, as would development of a representation system for the semantic layer.

Conclusions

McNamara (1992a) claimed that compound-cue theories could not account for mediated priming effects and sequential effects. We demonstrated that compound-cue models could account for these effects by exploring them in the joint context of empirical data and specific models. We also found that the juxtaposition of spreading-activation and compound-cue models suggested new ways to view some empirical phenomena. Our findings can be summarized by the following points.

McNamara (1992a) claimed that some sequential effects are inconsistent with compound-cue models. However, when the familiarity of a sequence was calculated with reasonable weights on the strengths of the different items in the sequence, compound-cue models fit the data quite well.

McNamara (1992a, 1992b) failed in his effort to demonstrate multiple-step priming, because predictions derived from his method of measuring distances between concepts in memory (free-association production probability) are not consistent with observed data.

Neither current spreading-activation models (such as ACT*) nor compound-cue theories can jointly predict free-association production probabilities and priming effects. Variables other than free association, including semantic relatedness and co-occurrence measures, may predict priming effects, but these measures need more investigation, both empirical and theoretical, to relate them to priming.

All words that prime each other may be directly related to each other in memory, and therefore priming effects among them are consistent with compound-cue theories. Because we currently have no empirical method for measuring distance in

semantic memory, words that seem far apart may instead be weakly directly related. A corollary of this point is that any individual word may have literally hundreds of associates, most of which are weakly but directly related. A memory system made up of large numbers of weak but direct associates is consistent with compound-cue models of retrieval and with the intuition that any word can appear in many (perhaps hundreds) of familiar combinations with other words (see McKoon & Ratcliff, 1992).

Free-association data suggest that a word in memory has many other words associated with it. When this is taken into account, the utility of spreading activation as a general retrieval mechanism must be viewed with suspicion. Suppose each word had 20 other words that it activated to a nontrivial degree (see Postman & Keppel, 1970). Then, with three-step priming in a spreading-activation model, $20 \times 20 \times 20 = 8,000$ words would be activated; this is a good proportion of the adult lexicon. Alternatively, if a single word activated 40 other words, then 64,000 words would be activated by three-step priming, about the number of words in the adult lexicon. Note that dampening mechanisms would not help here, because activation is spreading only three links away, well within the range of that purportedly measured in priming procedures. Such rampant spread of activation through memory would severely reduce the utility of the spreading-activation process as a general retrieval mechanism.

Spreading activation has been almost unchallenged as an explanation of priming phenomena. It has remained unchallenged despite the development of parallel processing and feature models that are inconsistent (to various degrees) with it. In particular, models with distributed representations (e.g., Seidenberg & McClelland's, 1989, model) have no way of activation spreading from concept to concept, because concepts are instantiated over the same set of units. The compound-cue model provides a strong candidate for implementing priming within these distributed frameworks. The debate presented in this article contributes to a long overdue examination of spreading activation, and provides additional evidence in support of compound-cue theories as viable alternatives.

References

- Anderson, J. R. (1983). *The architecture of cognition*. Cambridge, MA: Harvard University Press.
- Balota, D. A., & Lorch, R. F. (1986). Depth of automatic spreading activation: Mediated priming effects in pronunciation but not in lexical decision. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 12, 336-345.
- Dosher, B. A., & Rosedale, G. (1989). Integrated retrieval cues as a mechanism for priming in retrieval from memory. *Journal of Experimental Psychology: General*, 2, 191-211.
- Falmagne, J. C. (1965). Stochastic models for choice reaction time with applications to experimental results. *Journal of Mathematical Psychology*, 12, 77-124.
- Fischler, I. (1977). Semantic facilitation without association in a lexical decision task. *Memory & Cognition*, 5, 335-339.
- Gillund, G., & Shiffrin, R. M. (1984). A retrieval model for both recognition and recall. *Psychological Review*, 91, 1-67.
- Joordens, S., & Besner, D. (1992). "Priming" effects that span an intervening unrelated word: Implications for models of memory repre-

- sentation and retrieval. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 18, 483–491.
- LeSueur, L. L. (1990). *On metaphors and associations*. Unpublished doctoral dissertation, Vanderbilt University, Nashville, TN.
- McKoon, G., & Ratcliff, R. (1979). Priming in episodic and semantic memory. *Journal of Verbal Learning and Verbal Behavior*, 18, 463–480.
- McKoon, G., & Ratcliff, R. (1992). Spreading activation versus compound cue accounts of priming: Mediated priming revisited. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 18, 1155–1172.
- McKoon, G., & Ratcliff, R. (1994). *Tests of compound cue theory in lexical decision*. Unpublished manuscript.
- McNamara, T. P. (1992a). Priming and constraints it places on theories of memory and retrieval. *Psychological Review*, 99, 650–662.
- McNamara, T. P. (1992b). Theories of priming: I. Associative distance and lag. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 18, 1173–1190.
- McNamara, T. P., & Altarriba, J. (1988). Depth of spreading activation revisited: Semantic mediated priming occurs in lexical decisions. *Journal of Memory and Language*, 27, 545–559.
- Neely, J. H. (1991). Semantic priming effects in visual word recognition: A selective review of current findings and theories. In D. Besner & G. Humphreys (Eds.), *Basic processes in reading: Visual word recognition*. Hillsdale, NJ: Erlbaum.
- Neely, J. H., & Durgunoglu, A. (1985). Dissociative episodic and semantic priming effects in episodic recognition and lexical decision tasks. *Journal of Memory and Language*, 24, 466–489.
- Nelson, D. L., Schreiber, T. A., & McEvoy, C. L. (1992). Processing implicit and explicit representations. *Psychological Review*, 99, 322–348.
- Postman, L., & Keppel, G. (1970). *Norms of word association*. San Diego, CA: Academic Press.
- Ratcliff, R., Hockley, W. E., & McKoon, G. (1985). Components of activation: Repetition and priming effects in lexical decision and recognition. *Journal of Experimental Psychology: General*, 114, 435–450.
- Ratcliff, R., & McKoon, G. (1978). Priming in item recognition: Evidence for the propositional structure of sentences. *Journal of Verbal Learning and Verbal Behavior*, 17, 403–417.
- Ratcliff, R., & McKoon, G. (1988). A retrieval theory of priming in memory. *Psychological Review*, 95, 385–408.
- Ratcliff, R., Sheu, C.-F., & Gronlund, S. (1992). Testing global memory models using ROC curves. *Psychological Review*, 99, 518–535.
- Remington, R. J. (1969). Analysis of sequential effects in choice reaction times. *Journal of Experimental Psychology*, 82, 250–257.
- Seidenberg, M. S., & McClelland, J. L. (1989). A distributed, developmental model of word recognition and naming. *Psychological Review*, 96, 523–568.
- Seidenberg, M. S., Waters, G. S., Sanders, M., & Langer, P. (1984). Pre- and postlexical loci of contextual effects on word recognition. *Memory & Cognition*, 12, 315–328.
- Shelton, J. R., & Martin, R. C. (1992). How semantic is automatic semantic priming? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 18, 1191–1210.

Appendix

ACT* Implementation

The equations for asymptotic activation (i.e., when the system has settled to a final state) are $0 = pn_i - a_i$ and $n_i = c_i/p + \sum_j r_{ji}a_j$, where a_i is the activation value of the i th node, p is a maintenance factor denoting the amount of activation transmitted to neighboring nodes and which is set to 0.8 here (and usually set to 0.8 by Anderson, 1983), n_i is the total activation to node i , r_{ji} are the link strengths to node i , and c_i is the input activation of node i . These equations appear simpler when converted to matrix form, $\mathbf{A} = \mathbf{C} + p\mathbf{R}\mathbf{A}$, and solving for \mathbf{A} : $\mathbf{A} = (\mathbf{I} - p\mathbf{R})^{-1}\mathbf{C}$, where \mathbf{A} is a vector (or list) of the asymptotic activation values, \mathbf{C} is the vector of input activations, \mathbf{R} is a matrix of connection strengths, and \mathbf{I} is the identity matrix (a matrix with diagonal elements 1 and off diagonal elements 0). Using a system such as Mathematica, predictions for asymptotic activation values can easily be obtained using just six lines of computer code. Our computations assumed c set to 1.0.

It should be noted that ACT* relates link strength to node strength by requiring that link strength $r_{ij} = s_j/\sum_k s_k$, where s_k are all the nodes connected to node i (including s_j). The problem is that for most networks that are relatively interconnected, it is impossible to obtain node

strengths for all the nodes in the network that will satisfy this equation for all link strengths. This can be seen easily with a three-node network and six links all set to different nonzero values, with r_{ij} summing to 1 for the two links leaving node i . In this case, no solution can be found, and in general, unless there are fewer nonzero interconnection or link strengths than nodes, nontrivial solutions are impossible. A specific example is shown in McNamara's mediators (1992b, Appendix C, item 12). The ratio of the node strength of *moon* to *cold* must be 2.71 for the mediator *darkness*, and it must also be 0.58 for the mediator *Neptune*. As this example shows, node strengths cannot be assigned on the basis of link strengths, and so the input activation of a node c_i cannot depend on a value of node strength derived from link strengths, as assumed in ACT*. We have no independent measure of node strength for the items modeled here, so all node strengths were set to 1.

Received June 3, 1992

Revision received April 30, 1993

Accepted July 1, 1993 ■