Title
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Introduction

To understand language, one must first be able to access items in an internal lexicon and retrieve the semantic properties of the token specified graphemically or phonemically. In recent years, a number of different models of this process have been proposed. These include Morton's logogen model (Morton, 1982), Marslen-Wilson and Tyler's interactive model (Marslen-Wilson and Tyler, 1978) and the McClelland and Rumelhart's interactive activation model (McClelland and Rumelhart, 1981).

One aspect of lexical retrieval that has received a great deal of attention recently is the problem of lexical disambiguation. Despite the fact that almost every common word is a homograph or homophone, we almost always access the appropriate one. Although syntactic, semantic, and pragmatic cues constrain the choice to the appropriate one, all meanings seem to be activated initially. A model of lexical memory must account for these properties. With the interest in natural language parsing by computers, a number of AI researchers have also pursued the problem of lexical disambiguation. Recent work by Hirst (1983) describes one recent approach which considers psychological data in the implementation and provides a review of recent AI attempts to resolve this problem.

The-Brain-State-in-a-Box

Neural network: The model presented here is part of a continuing effort of Anderson and his colleagues (for recent reviews, see Anderson et al., 1977; Anderson, 1983) to simulate aspects of memory and categorization using a network of neuron-like elements. The use of a large number of interacting elements functioning simultaneously reflects the large degree of parallelism found in the nervous system. This overcomes the inherent slowness of the individual components and the noisy operating environment. Although we do not make any claims regarding these elements as realistic manifestations of neurons, we do believe that the major constraints imposed by the nervous system have been taken into account. We assume that (1) nervous system activity can be represented as the simultaneous activity of a group of neurons, (2) activities of single neurons are coded by their firing frequency (above and below steady state levels) and bounded by a maximum and minimum level, (3) memory is distributed rather than localized, with each neuron participating in each memory trace, and (4) synapses associate activity in one element with another by incrementing connection weights by a proportion of the product of values dependent on pre- and post-synaptic activity.

In our system, learning results in modification of the synaptic weights coupling two neurons. The entire set of couplings is given by the matrix A, where an element a_{ij} is the synaptic weight coupling neuron i to neuron j. Unlike previous studies where learning occurred in an unsupervised environment, our current efforts are directed toward systems which learn with a "teacher." To begin a learning trial, a stimulus is chosen from the learning set described in the following section and scaled so none of the elements are saturated. The resulting activity pattern is presented to the network and successively iterated by the scheme

$$x_{t+1} = \text{BOUND}[(A + aI)x_t]$$

where a is a decay constant and BOUND limits the activity.

The activity after tau iterations, x_{tau}, is compared with the desired output, X, provided by the "teacher." Rather than simply learning a proportion of the outer-product of x_{tau} (the product of each neuron with every other neuron), a proportion of the outer-product of $(X - x_{tau})$ is learned. This error-correcting scheme limits the amount of learning allowed on any given trial and as the current state approaches the desired state, less learning occurs. In fact, if the current state is equal to the desired state, no learning occurs.

Stimulus coding: Although a number of modelling attempts use non-overlapping stimulus representations, each neuron contributes to every stimulus representation. In the simulations below, each lexical entry is 64-dimensional and is formed by concatenating subvectors comprising its graphemic, phonemic, syntactic, and semantic (GPYS) fields. Each field is a 16-dimensional Walsh-Hadamard vector and each distinct value of a given field is represented by a unique Walsh-Hadamard vector. In these initial attempts, the six words shown in table 1 were learned. The 4 hex values are a shorthand notation where each value represents the corresponding Walsh-Hadarmard vector. Thus, as seen in the table, all nouns have identical values in the third field, and likewise for verbs. The only other case with identical values in the same field for more than a single lexical entry is the homograph *wind*. To simulate the different frequencies of occurrance in language, each stimulus is represented a different number of times in the learning set. *Desk* is the most frequent, and *agar* is the least. Furthermore, for the homograph *wind*, the noun will be regarded as the dominant homograph because of its greater frequency relative to the verb.

Simulation Results

In our simulations, we present part of a given lexical entry and allow the output of the network to be fed back until all elements reach saturation. We take the number of iterations required for all elements to saturate as a measure of reaction time (RT). In all cases, the graphemic field is presented with each element in this field fully saturated. In some cases, activity is also present in the syntactic or semantic fields.

Another method probes the semantic field and measures the activity of the current state relative to a number of different meanings. Because all the meanings are mutually orthogonal in the stimulus coding scheme used here, the dot product of the activity in this field with a particular meaning yields a measure of the degree to which that meaning is activated.

Lexical access: Two of the most important observations regarding retrieval from the lexicon are the effects of frequency and hints on RT. Both of these properties can be observed in Table 2. These results show the number of iterations required for the test stimulus to be correctly regenerated after 200, 500, 1000, 2000, and 5000 learning trials, as well as with a "hint."

The frequency effect is manifested in two ways. First, the greater the frequency, the sooner the word is correctly regenerated. We see that *desk* and *rant,* with relative frequencies of 4 and 3, respectively, are learned by the first 200 trials. *Lurk,* with a relative frequency of 2 is learned by 500 trials, and *rant,* with a relative frequency of 1, is not learned until 5000 trials. Furthermore, until RT reaches some asymptotic level (probably as a result of asymptotic learning), the greater the frequency of presentation, the faster the RT.

The second major property of lexical access, the decrease in RT with contextual cues, has also been simulated. To simulate contextual cues, the semantic field of the entry (with the magnitude of each element in the subvector equal to 0.5) is also presented initially. As seen in the last column of table 2, the presence of these cues decreased the RT for every word except *lurk.* In addition, we have found that as the input becomes more degraded (reversing the activity of a number of elements in the graphemic field), the RTs increase.

Lexical ambiguity: In our approach, ambiguous words are treated in the same fashion as all other words. However, use of the dot-product measure described above after each successive iteration allows the time-course of activation of the semantic field to be revealed. As in the properties of lexical access in general, both frequency and context affect which meaning of a homograph is accessed initially. With no context, the more frequent (dominant) homograph's meaning is initially accessed. With the appropriate contextual cue, the less frequent (subordinate) homograph's meaning is also accessed. As in the results of Simpson (1981), we find that if the appropriate contextual cue is not large enough, the more dominant homograph's meaning is accessed.

However, recent studies reported by Swinney (1982) indicate that *both* meanings are initially activated, independent of context. As seen in figure 1a, with no context, both the dominant and subordinate meanings are activated initially. Even with a contextual cue biasing a particular interpretation, *both* meanings are still activated (see figures 1b and 1c). Even when the syntactic field is specified, again *both* appropriate and inappropriate meanings are initially activated as seen in figure 2.

Summary

In this study, we present a method of learning, storing, and retrieving stimuli constructed as lexical entries. Our formulation allows the different fields comprising a word to interact through coupling weights. It is this property which allows the reconstruction of the entire word from a part of the stimulus. Appropriate hints, implemented as partial activity in fields other than the graphemic one, decrease RTs. In addition, the same scheme used for unambiguous words is used for ambiguous ones. When presented with a homograph, the dominant one is accessed initially. However, when given sufficiently large cues, the subordinate homograph can also be accessed. Moreover, we have been able to show that despite conflicting cues for one of the homographs, *both* meanings are activated initially. We feel that this approach is quite promising and are currently exploring more realistic coding schemes and enlarging the lexicon.

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LEXICON

lexical entry				*code*	*rel. freq.*
WIND	\wind\	n.;	weather	4285	3
WIND	\wInd\	v.;	rotate	491C	2
DESK	\desk\	n.;	furniture	2D83	4
AGAR	\agar\	n.;	gelatin	E78A	1
RANT	\rant\	v.;	yell	9C1D	3
LURK	\lurk\	v.;	hide	CF1E	2

Table 1. Complete lexicon giving Walsh-Hadamard coding representation and relative frequency.

RTs AS A FUNCTION OF LEARNING

word	200	500	1000	2000	5000	hint*
WIND	85	33	19	17	20	11
DESK	32	15	11	11	11	10
AGAR	xx	xx	xx	xx	23	13
RANT	48	22	13	12	12	10
LURK	xx	77	18	11	11	11

xx error
* after 5000 learning trials

Table 2. RTs as a function of learning (200, 500, 1000, 2000, and 5000 learning trials, and effect of hints).

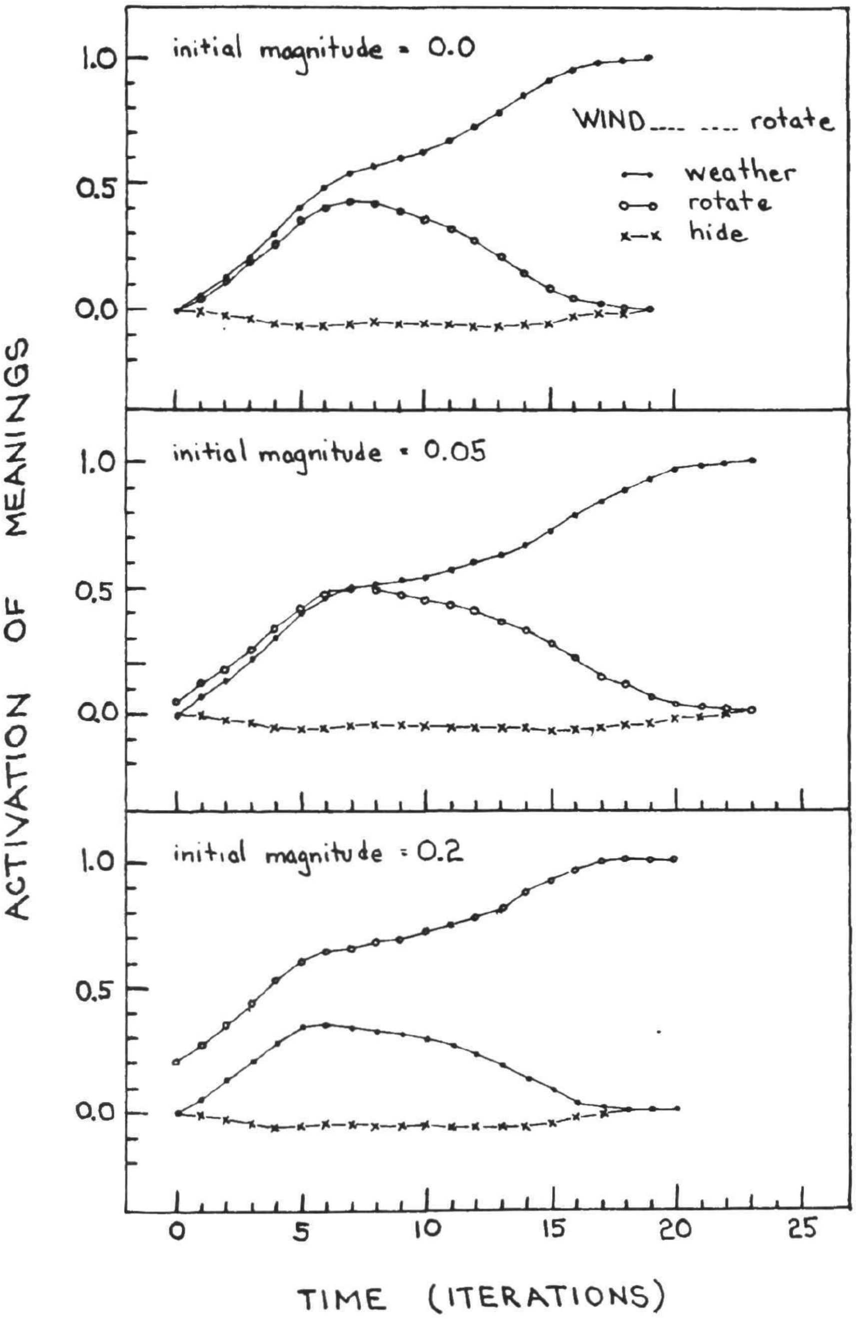

Fig. 1. Time course of activation of meanings with semantic cues. Magnitude of elements in the graphemic field are saturated, and the magnitudes of elements in the semantic field (rotate) are (a) 0.0, (b) 0.05, and (c) 0.2.

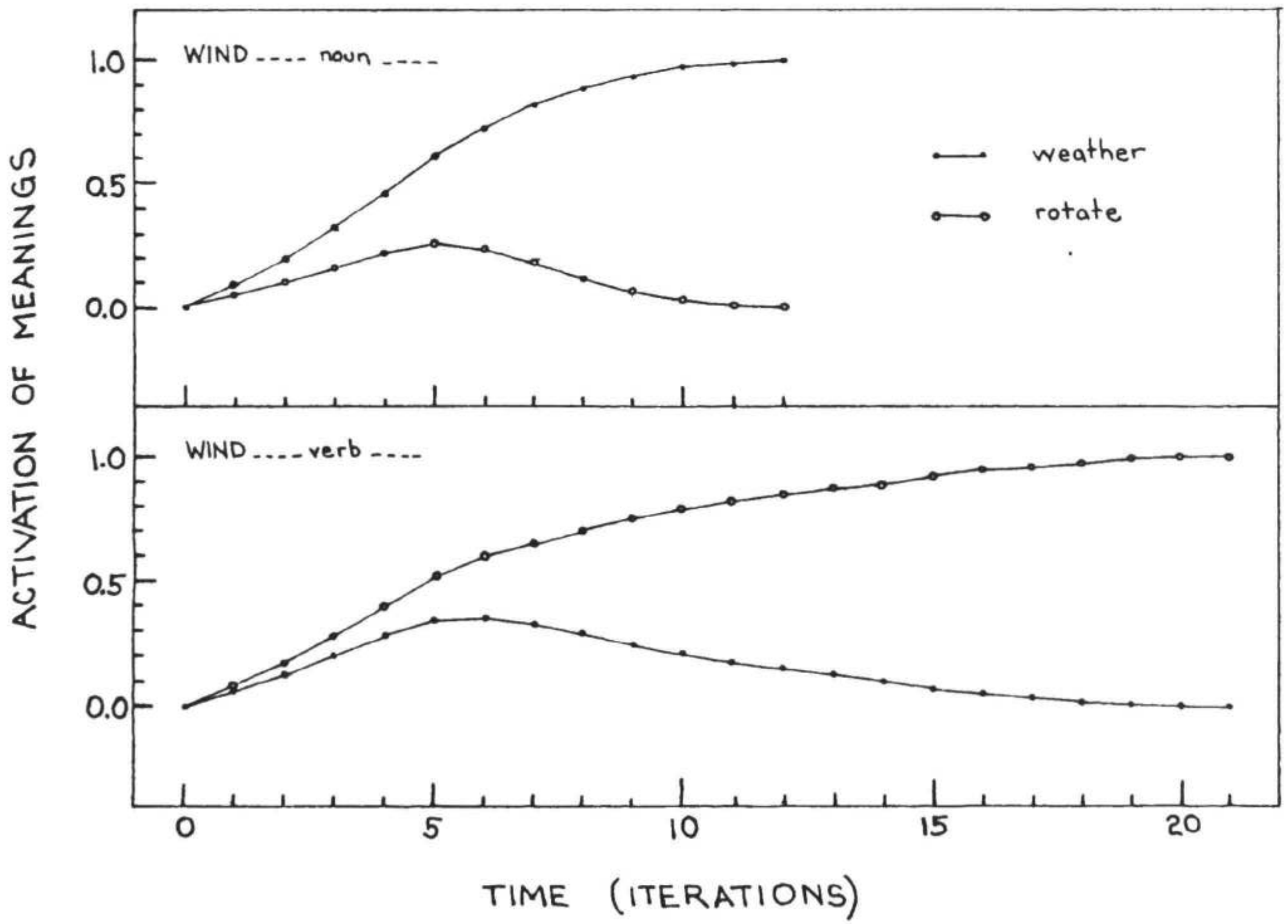

Fig. 2. Time course of activation of meanings with syntactic cues, graphemic field and form class (a) noun, and (b) verb.