

Self-Organizing Dynamics of Lexical Access in Normals and Aphasics

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Abstract

■ The goal of this article is to illustrate the application of self-organizing dynamics in the design of a model of lexical access. We focus particularly on the mapping of sound structure on to the lexicon and the influence of that structure on lexical access. The approach is tested in a series of two sets of simulations that explicate how lexical access might occur in normal subjects and aphasic patients. Both sets of simulations address the behavioral effects of both phonological and phonetic variability of prime stimuli on the magnitude of semantic priming. Results show that the model can successfully account for the behavioral effects associated with several kinds of acoustic manipulation, competitor presence, and the unfolding

of those effects over time—primarily because it balances three important control parameters: resting lexical activation, positive feedback, and negative feedback. These simulations are offered as support (in the form of an existence proof) that deficits in the degree of lexical activation can account for the lexical processing impairments shown by Broca's aphasics who have reduced lexical activation, and Wernicke's aphasics who have increased lexical activation. Overall, results suggest that the present approach promises to offer a coherent theoretical framework within which to link empirical evidence in language processing and cognitive neuroscience in terms of possible underlying mechanisms. ■

INTRODUCTION

One persistent family of questions that has emerged from research on language processing concerns the mechanisms and processes that afford lexical access. Some such questions include: What is the form of the representations of sound structure? What is the manner in which such representations contact the lexicon? How do the activations of lexical entries translate into semantic facilitation of responses to related lexical entries? How do activations of lexical entries influence each other? How do lexical access processes form the basis for behavioral responses, such as lexical decisions? And how do these lexical access processes and representations come to be the way they are?

These issues have been addressed in the literature to varying degrees. Specifically, several models have been proposed that each offer a different perspective on the possible nature of the mechanisms underlying lexical access. One of the most well known of these models is probably the TRACE model (Elman & McClelland, 1986; McClelland & Elman, 1986), which is actually a pair of connectionist, “interactive activation” models of speech perception; this model is often cited in relation to an earlier and highly influential model of lexical access: the “Cohort” model (Marslen-Wilson, 1987; Marslen-Wilson & Welsh, 1978). But

several other models have been proposed as well. Chief models among these are Klatt's Lexical Access from Spectra model (LAFS—see Klatt, 1979, 1986, 1989), the Neighborhood Activation model (Luce, 1986; Luce & Pisoni, 1998), and the Shortlist model by Norris (1994).

In this article, we offer a model of lexical access that builds on a number of the principles and assumptions of these earlier models and extends them within a self-organizing dynamical system. We seek to realize the following three goals:

1. To illustrate the application of self-organizing dynamics in the design of a mechanism for lexical access.
2. To characterize how sound structure maps on to the lexicon and to offer an explanation of how phonetic and phonological variability affect lexical access. We focus particularly on the degree to which such phonological and phonetic manipulations influence the magnitude of semantic priming in a lexical decision task and the potential role of lexical competition on such priming.
3. To model hypothesized deficits in lexical access in Broca's and Wernicke's aphasics. Through a series of simulations we illustrate that deficits in the degree of activation of lexical candidates can account for the behavioral results of aphasic patients in a series of lexical decision experiments investigating the influence of phonetic and phonological manipulations on lexical access.

At the broadest level, our strategy is to use mathematical (dynamical) modeling in order to link language processing with neuroscience for the purposes of developing a method for understanding both the behavioral and neural mechanisms underlying linguistic performance. We apply a small-scale “existence proof” technique to make our claims, although we believe that the same results would emerge from much larger systems (see below). Our long-term goal is to understand how both normal and impaired brains produce and perceive language, although in this paper our focus is on auditory word (lexical) processing.

Some Representative Models of Auditory Lexical Access

The approach to the issues of lexical access that we take builds on the findings of a number of extant models of lexical access. Before considering in detail this approach, we briefly summarize the basic principles that we adopt from these earlier models in an attempt to identify both the origins of our basic assumptions and our reasoning in extending the modeling endeavor in the manner that we do.

One of the first models of lexical access and selection is the Cohort model proposed by Marslen-Wilson and Welsh (1978) and Marslen-Wilson (1987). It is a model of how lexical choice is made, given a sequential input such as a series of phonemes. In this model, the ongoing bottom-up sensory input specifies a subset of word candidates through a process that matches the current input against sound structure (phonemic) templates for all possible words in the system’s lexicon. Subsequent information further constrains that set as time goes on, in that word candidates with characteristics at odds with the input drop out of the subset or “cohort.”

The Cohort model has formed the framework for much of the research on auditory word recognition and lexical access. It incorporates principles of graded activation, competition, and time course of activation—principles that we adopt as well. Nonetheless, the Cohort model was developed descriptively rather than quantitatively. The TRACE model provided a remedy by incorporating many of these principles in its explicit formulation (Elman & McClelland, 1986; McClelland & Elman, 1986).

While the TRACE model addressed other (lower) levels of auditory/speech processing in addition to the lexical one, in many ways it served as a formalization of the Cohort model, even though it did not exactly model Cohort completely. Two versions of the model have been implemented: they are referred to as TRACE 1 (Elman & McClelland, 1986), which deals with real speech input but not with lexical access, and TRACE 2 (McClelland & Elman, 1986), which deals with lexical access, but takes as its input mock spectra rather than real speech. In the spirit of this paper, it is perhaps best to see TRACE as a family of possible models, each with

different strengths and weaknesses, and represented by TRACE 2 in this paper.

The most important principle realized in TRACE 2 is that of interactive activation. In such a model, information processing manifests itself through “excitatory and inhibitory interactions of a large number of simple processing units, each working continuously to update its own activation on the basis of the activations of other units to which it is connected” (McClelland & Elman, 1986).

TRACE can be construed as an organized hierarchy of units or “nodes.” Each of these nodes accepts positive activation from units whose hypotheses are consistent with theirs, and reinforces those units with positive activation; meanwhile they also send inhibition to and receive inhibition from nodes corresponding to hypotheses inconsistent with theirs. These “hypotheses” are hypotheses about the nature of the input (the currently analyzed utterance), and the degree of activation of such a unit varies directly with the strength of the hypothesis for which the unit stands.

The network deals with time itself by duplicating the entire network for every time slice, so that there is a complete set of nodes for features, phonemes, and words at every time slice. Units in the same level at adjacent time slices send inhibition to each other. This property allows the system to recognize words no matter when in the utterance they appear. But it also results in an extremely (and ultimately unrealistically) large system.

The primary motivation of Shortlist (Norris, 1994) is to remedy the massive reduplication of nodes required for time-invariant recognition in TRACE. Shortlist avoids this problem by using a (simulated) recurrent network to generate word candidates, which then get wired into an interactive activation (competitive) network similar to the word level in TRACE.

In theory, the recurrent network generates lexical candidates, which then compete at the lexical level. We build this feature into our model of lexical access as well. However, Norris does not actually simulate the generation of word candidates in his 1994 paper, but draws on earlier work (Norris, 1990, 1992, 1993) in which he simulated supervised learning mechanisms for lexical access explicitly. We have every reason to believe that the simplifying assumption of eliminating reduplication in this case is a valid one. It is also extremely effective: whereas TRACE would require something like 10^{11} connections, Shortlist accomplishes the same tasks with a maximum of only 30 nodes and the connections between them (900).

Although both Shortlist and TRACE invoke the principle of lexical competition via interactive activation, there remain a number of crucial differences between the two models. First, as mentioned above, Shortlist requires many fewer lexical nodes in its architecture. But this advantage in simplicity is tied to a number of other

important differences. For one thing, the system is bottom-up. There is no feedback from the lexical layer to previous, lower-level processing layers. The prelexical levels accomplish their task via the connectionist method developed for the processing of sequences developed by Jordan (1986); that is, temporal sequences are recognized by a three-layer system trained by backpropagation in which the hidden units are interconnected by time-delayed connections.

Our approach to auditory word recognition and lexical access processes is consistent with the reviewed models and rests on several key assumptions:

There is now a fairly broad consensus (a) that perceptual processing is based on a process of competition between simultaneously active candidates, (b) that the activation metaphor is the appropriate one for representing the goodness of fit between sensory inputs and lexical form representations, and (c) that the selection decision is based on the relationship between levels of activation. Perceptual choice is made as the best fitting candidate emerges from among the welter of competing activation levels. (Marslen-Wilson & Warren, 1994, p. 654)

We are interested in extending the modeling to account for a somewhat broader range of issues than these earlier models have addressed. First, we wish to posit a mechanism for lexical access whose architecture arises from self-organizing processes. That is, we wish to incorporate an account of how the system got to be the way it is—in other words, we wish to incorporate a strong learning component. We believe that much learning of novel words occurs without the aid of an external teacher that provides error-driven feedback at every turn, and thus we do not adopt the supervised learning algorithms employed by Norris (1990, 1992, 1993). Second, we are interested in modeling how manipulations of sound structure affect not only word recognition but also lexical access, and we wish to do so in a single model. Of the earlier models, only LAFS does so explicitly (the family of TRACE models does so only when one considers both TRACE 1 and TRACE 2 together), but LAFS does not incorporate a mechanism for semantic priming, lexical decision, or competition, all of which we include in the current model. Third, we wish to include a rough approximation to a semantic component (which none of the above models do), because the ultimate aim of lexical access is to contact meaning, and a model of lexical access must account not only for mapping sound structure to the lexicon, but also for the influence of such mapping on the lexical network. Fourth, we use this model as a framework for considering lexical processing deficits in aphasia and for testing a specific hypothesis about the nature of the deficit for Broca's aphasics, on the one hand, and Wernicke's aphasics, on the other.

We have chosen to develop and test our model by offering small-scale simulations. These existence proofs provide evidence that the theoretical and metaphorical constructs used in the literature to account for empirical data derived from experiments with normal subjects and aphasic patients can actually combine to account for the patterns of results obtained. Since there are a relatively large number of such constructs invoked (both implicitly and explicitly) by the various experiments and subsequent theoretical claims, our current purpose is best served by modeling simple systems that allow us to realize these constructs and to explore the nature of their combination.

DESIGN PRINCIPLES FOR THE PRESENT MODEL

Our approach originates with nonlinear dynamical systems theory (van Gelder, 1998; Kelso, 1995; Port & van Gelder, 1995; Thelen & Smith, 1993). For the purposes of this article, we consider the mind and brain to be engaged in an ongoing effort to establish a better adaptive relationship to the environment on a variety of time scales (Turvey & Carello, 1981; Gibson, 1979). Humans must be able to quickly adjust their internal states in order to improve their relationship to their environment, but at the same time must be able to buffer their internal system such that old internal states are not lost or forgotten when novel adjustments are made. Following Grossberg (1980, 1982), and many others, we refer to this process of balancing plasticity and stability in the absence of an external teacher as self-organization. Notice that we use the term self-organization to refer to both the processes underlying the origins of the lexicon (a developmental time scale) as well as the on-line organization of linguistic behaviors such as lexical decision.

We apply the concept of self-organization in neural networks to attempt to understand how sound structure contacts the lexicon in normal subjects and aphasic individuals. Our approach is to relate the process of auditory lexical decision to a fundamental environmental constraint on humans; namely, inherent variation in the speech input that nonetheless is perceived as a stable perceptual (phonetic/lexical) category representation. In doing so we seek to elucidate how representations of sound structure (the input to the system) elicit representations of lexical status, identity, and meaning (the output of the system), while at the same time offering an account of the origins of the system's overall architecture. At each step, the model is made as simple as possible—retaining only those qualities that are absolutely necessary—in order to ensure the transparency and generality of our account. Note that while this approach may ultimately also illuminate developmental data, our focus in this article is on adult performance.

We call our approach a systems approach, meaning that we identify the effects of lesions in terms of systemic properties, such as a change in control parameter settings (e.g., resting lexical activation), rather than in terms of the loss or impairment of specific functions localizable in the brain. Similar assumptions have been made in a number of models of language impairment. These models have largely focused on simulating naming deficits in aphasia, and have “lesioned” their models by altering such parameters as noise, decay rate, and connection weights (Laine, Tikkala, & Juhola, 1998; Dell, Schwartz, Martin, Saffran, & Gagnon, 1997; Tikkala & Juhola, 1996; Martin et al., 1994).

Self-Organization Defined

As the notion of self-organization plays a strong role in our model, at least a rough description of what we mean by that term is necessary. Following Cilliers (1998, p. 90), we claim that “the capacity for self-organization is a property of complex systems that enables them to develop or change internal structure spontaneously and adaptively in order to cope with, or manipulate, their environment.” In addition, “this process is such that structure is neither a passive reflection of the outside, nor a result of active, pre-programmed internal factors, but the result of a complex interaction between the environment, the present state of the system, and the history of the system” (Cilliers 1998, p. 89). This form of self-organization can occur on multiple time scales. In our model, self-organization occurs on three time scales, two of which are modeled explicitly and computationally. Self-organization at the longest time scale—that of many years—operates on internal codes so as to develop a lexicon without the aid of an external teacher. We model these processes explicitly using the ART 2-A algorithm (Carpenter, Grossberg, & Rosen, 1991; see Appendix). At the intermediate time scale—that of minutes or hours—we assume that subjects are self-organizing so as to “optimize” their performance in a given task. In an experiment, such strategies might take subjects toward a self-configuration that maximizes speed while minimizing errors in responses. While self-organization at this time scale is beyond the scope of the present project, we do hope to focus on it in future work; see the discussion of the “critical state” in the concluding section. At the shortest time scale—that of seconds or milliseconds—brain and behavior self-organize in order to accomplish the immediate tasks at hand (such as making a lexical decision in a laboratory setting, or comprehending and taking part in some linguistic communication in the real world). Specifically, the brain must coordinate its myriad structures so as to come up with responses displaying many fewer degrees of freedom. We also model these processes explicitly, using simple non-

linear difference equations that govern lexical and semantic node activation.

Architecture

The basic architecture of our model is shown in Figure 1. The model essentially has four layers of neuron-like nodes, ordered hierarchically: (1) the input layer, representing the sound structure of the current utterance in a distributed fashion in terms of subphonetic features.

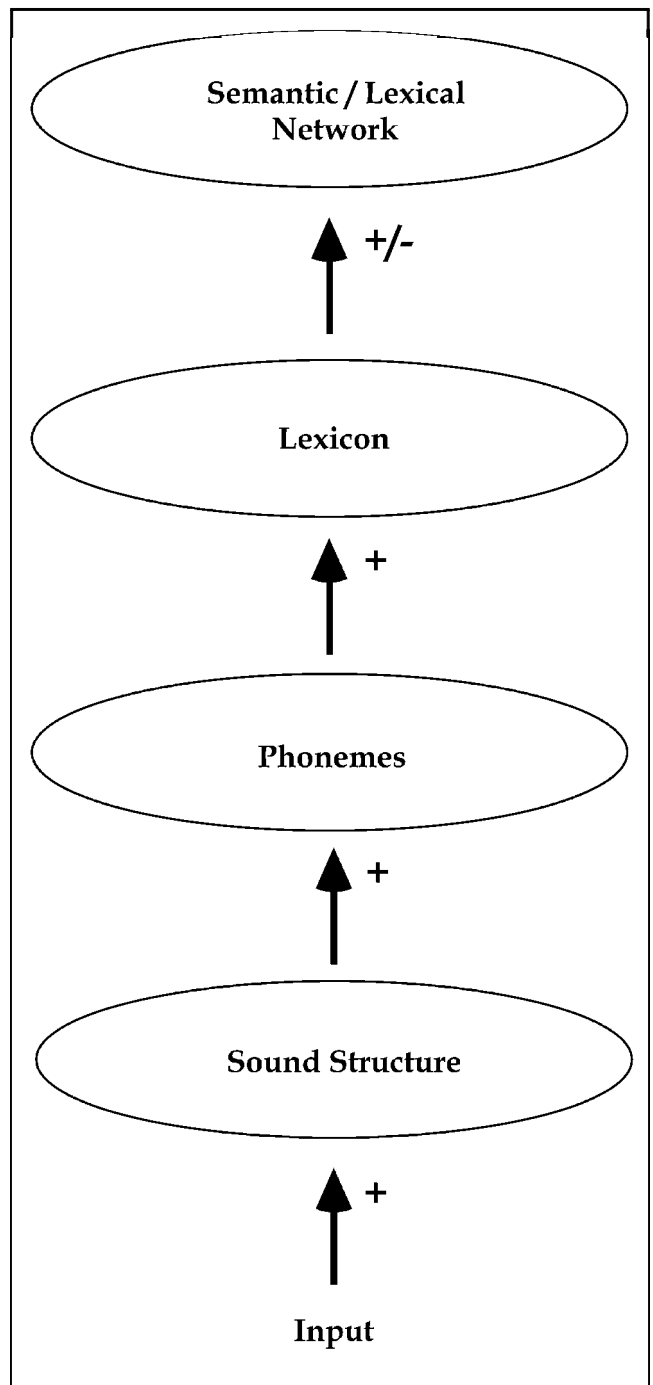


Figure 1. Basic network architecture.

This layer corresponds to auditory input that has been transformed into a spectral representation based on the extraction of more generalized acoustic properties from the acoustic waveform (cf. Blumstein, 1995). For example, a continuum of values of voice-onset time (VOT), an acoustic property important for defining voicing in stop consonants, would be represented at this level, as would spectral properties for identifying place of articulation in stop consonants. Activation patterns at this layer were normalized (i.e., scaled such that the length of the vector was set equal to 1.0) before being passed through weighted connections to (2) the second layer corresponding to the conversion of the spectral representation to phonemes defined in terms of bundles of more abstract feature representations. Here, for example, the range of VOT values would be represented in terms of two phonetic categories, voiced and voiceless, and other acoustic properties would be mapped on to their associated feature representations. Activation patterns at this level were also distributed and were normalized (as above) before being passed on to (3) the next layer representing lexical entries. This layer corresponds to the lexicon and in particular to the phonological form of the individual lexical entries; and (4) the final and uppermost layer representing meaning or semantics of the lexical entries and corresponds to the lexical network. It is at this level that we assume that words that share, for example, properties of meaning or sound structure may influence each other, and ultimately give rise to semantic priming effects and lexical competitor effects, respectively.

The third layer, that of “lexical entries,” is recurrent, meaning that the nodes in that layer feed activation back to themselves in a principled fashion. Specifically, each node feeds activation back to itself. It is this feedback that underlies the unfolding dynamics that make it possible for the model to account for fine-grain reaction-time patterns as described in the sections that follow. The feedback is dependent (in a positive or “excitatory” fashion) on previous activation, as well as (in a negative or “inhibitory” fashion) on time (i.e., time-steps since initial activation). The equation for this feedback is

$$x_{t+1} = (\alpha - \beta \times t)x_t \quad (1)$$

where x_t is the lexical activation at time step t , t is the number of time steps since the last stimulus presentation, α is the positive feedback constant, and β is the negative feedback constant. Thus, this equation establishes a relationship between positive feedback, negative feedback, and the evolution of lexical activation.¹ Note that in this model, the mechanisms by which lexical activations change over time are disabled if the nodes reach either their maximum or minimum values. For the lexical nodes, the minimum was always 0 and the maximum was typically just above 1.0, e.g., 1.05. Thus, these limits are potential steady states. Note that the

behavior of the model beyond this range—greater than the maximum or less than the minimum—was not relevant to the present inquiry.

Notice also from the figure that all between-layer connections in the model are excitatory, with the exception of those that feed from the lexical layer to the semantic layer, which are both excitatory and inhibitory. In the latter case, any given lexical node excites semantic representations that are consistent with it, and inhibits semantic representations that are inconsistent with it. Lexical decisions are assumed to involve the activations of the lexical and semantic layers, and their evolution over time. Since the semantic nodes receive their activation from the lexical ones, their activation patterns also evolve over time. Thus the equation for the semantic layer nodes is

$$s_{t+1} = x_t - c \times y_t \quad (2)$$

where s is the activation at the semantic layer node corresponding to lexical node x , y corresponds to the activation of the competitor lexical node (or nodes), and c is the competition strength. A more detailed depiction of the architecture of the upper two layers of this model is shown in Figure 2.

Weight Derivation (Learning)

The learning of the weights connecting the layers were derived as follows. Those weights connecting the sound structure nodes to the phonemic nodes were self-organized as described in the Appendix section; it is worth noting, however, that we do not make the learning of those connections a major theme of the present article.

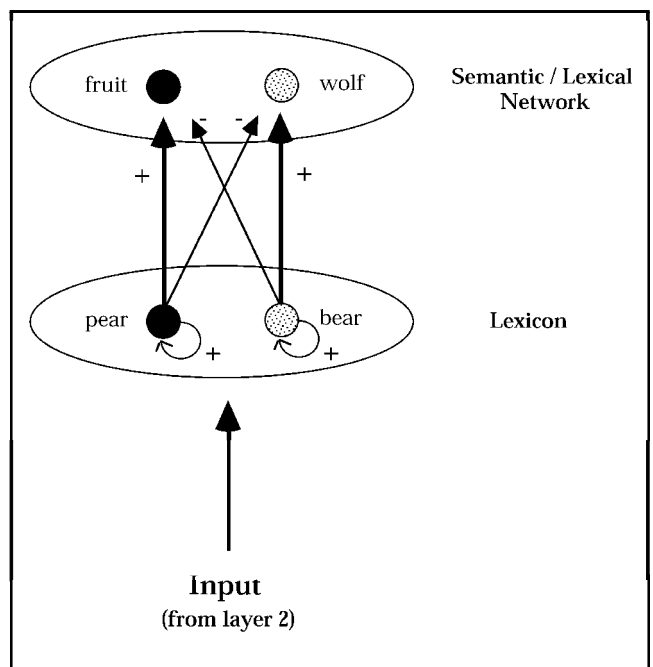


Figure 2. Detailed architecture of the upper two layers of the model.

We do focus on the next (higher) connections: those between the phonemic and the lexical layers. It is for these connections that we make the strong claim of self-organization. Finally, the uppermost connections—those between the lexical and the semantic layers—are assumed to be learned through simple Hebbian learning principles (see Anderson, 1995); however, they were ultimately “hardwired” for convenience (we leave it to future work to explicate this learning). Thus, all nodes in any given lower layer were fully interconnected with feed-forward weighted connections to the next layer up, although the derivation of those weights varied.

Limits

Each layer of nodes in the model has a maximum and minimum activation; for all layers except the lexical one these limits were set rather arbitrarily. If and when patterns presented to the network resulted in activations (built up over time) at the lexical level that reached the maximum level for that layer, activation was maintained at that level for an arbitrary period of time, that is, the feedback no longer plays a role in the determining the activation.

Resting States

A critical aspect of the model is the resting state of the nodes in the lexical layer. This resting state (which was the same for all nodes in the lexical layer, and thus was a single parameter) was varied depending on whether the subjects being modeled were normals, Broca’s aphasics, or Wernicke’s aphasics, and it is these manipulations that allowed us to discriminate between the various types of subjects. As discussed below, we operationally implement an impairment in lexical activation in aphasic patients as a change in the resting state of the system in the model.

Input Representations

In this model we represent the input in terms of acoustic properties corresponding to phonetic features. As this representation is distributed over a number of units (in this case, 10 for each phonetic feature), we call the input layer the “subphonetic” layer, i.e., a number of acoustic variants were used as input representations, which ultimately would be mapped to a particular phonetic feature. The acoustic property that we were most interested in was the VOT of initial stop consonants. VOT represents a continuum of duration values that correspond to the voiced and voiceless phonetic categories. VOT is a measure of the timing relation between the release of the closure of a stop consonant and the onset of vocal cord vibration, and it is a major cue in the perception of voicing in stop consonants. Thus, a voiced stop like /b/ has a short VOT (around 20

msec), whereas a voiceless stop like /p/ has a longer VOT (around 70 msec). It is therefore possible to create a continuum of VOT values, some of which are closer than others to the prototypical values for voiced or voiceless stops, and some of which are closer or further away from the category boundary between voiced and voiceless stops. We represented different lengths of VOT as a moveable bar across the field of 10 units (see Figure 3). This technique has been effectively applied by Anderson (1995) and others, and allows us to represent analog feature values in a distributed fashion. There were 10 units in the preprocessing field dedicated to coding VOT and the moveable bar was 5 units long. These exact lengths were somewhat arbitrary in that there are undoubtedly many such lengths that would have given us the performance we sought for; however, this particular configuration allowed us to represent the kinds of VOT manipulations that we needed quite straightforwardly. For voiced stops (short VOT), the activations of the first five of these units were set to a value of 1.0 (prior to normalization, etc.) and the last five were set to 0, i.e., 1111100000. For voiceless stops (long VOT), the activations of the last five units were set to 1.0 and the first five were set to 0, i.e., 0000011111. Thus, inputs could be made “more voiceless” by shifting the bar to the right and “more voiced” by shifting the bar toward the left. In this way, we could create a continuum of values that would allow for subphonetic manipulations of VOT. For example, the code for canonical voiceless initial stop consonants could be transformed into the code for a voiceless stimulus with VOT shortened by one-third by shifting the bar of high activation one unit to the left and shortened by two-thirds VOT by shifting the bar two units to the left. Thus, every one unit of shift corresponded roughly to one-third of the length of the VOT. Notice that this way of representing VOT is only a first approximation to the dynamics of working memory, an area that has been investigated in more detail by Boardman, Grossberg, Myers, and Cohen (1999) and Grossberg, Boardman, and Cohen (1997).

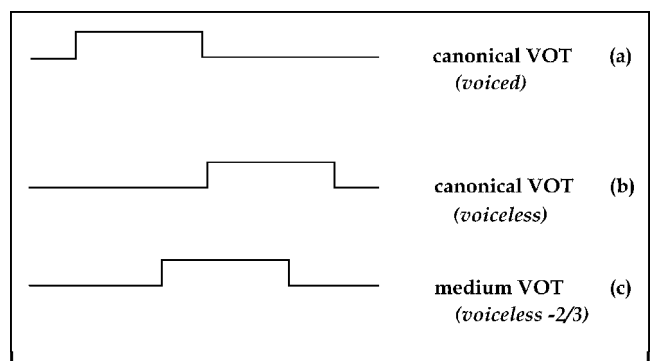


Figure 3. The moving bar used for the representation of voice-onset time (VOT): (a) voiced stops (short VOT), (b) voiceless stops (long VOT), and (c) voiceless stop with the VOT shortened. Other types of phonetic features could be represented in a similar fashion.

The elements in the input layer for VOT feed forward into two units in the phonetic feature layer. These units can be viewed as representing the presence and absence of the relevant feature, respectively. In the case of VOT, one of these units corresponds to voiced initial stops and the other corresponded to voiceless ones. Thus, when values of the first element were high, values of the other were low, and vice versa. Specifically, “pure” or typical instances of features elicited an activation of 1.0 in the node corresponding to that feature’s presence and an activation of 0 in the node corresponding to that feature’s absence. In the interest of simplicity, only four additional pairs of units were added at this layer to correspond to the “rest of the word,” for a total of 10 elements in the layer.

In the current study, we included detailed subphonetic characteristics only for VOT because, at this juncture, we are focusing only on the voicing phonetic contrast in initial position. For this reason, we implemented a set of simple features to differentiate this set in this context. In principle, the input representations would need to include the set of acoustic properties that ultimately map on to the phonetic features of language and in this case English. That is, there would be a set of acoustic properties corresponding to any particular phonetic feature and there would be a bundle of phonetic features corresponding to a given phonetic segment. For the purposes of our simulations, however, with the exception of the voicing characteristics of the initial segment of individual lexical entries, the mapping from subphonetic to the feature layer was transparent and there was a single value (rather than a range of values) at the subphonetic level corresponding to a single value at the feature level, i.e., there was a 1:1 mapping from the input representation to the phonetic feature level. The resulting representation is a distributed representation of the entire word, and forms the input to the lexical layer.

PHONOLOGICAL AND PHONETIC VARIATION AND LEXICAL ACCESS

Spoken language is often produced in a noisy medium in which the listener must extract the properties of speech to ultimately understand what is being said. Moreover, there is a great deal of variability inherent in the speech production process itself. There is variability within a speaker from utterance to utterance due to imprecision in the articulatory implementation of speech. There is variability of the implementation of sound structure as a function of phonetic context and speaking rate. And there is variability across speakers. And yet, despite these sources of variability listeners appear to perceive a stable linguistic percept, whether it be individual sound segments, such as [d] or [t], or individual lexical items such as “cat” or “dog.”

A great deal of research has been conducted exploring the influence of sound structure variations on the processes of word recognition and lexical access (cf. Kessinger, 1998; Connine, Titone, Deelman, & Blasko, 1997; Utman, 1997; Zwisterlood, 1996; Andruski, Blumstein, & Burton, 1994; Warren & Marslen-Wilson, 1987, 1988; Streeter & Nigro, 1979). On balance, these results have shown that indeed listeners are sensitive to phonological as well as within phonetic category differences, and importantly, that these differences affect both word recognition and lexical access processes. It is beyond the scope of this article to provide a detailed review of this literature. Instead, we will focus on the detailed results of a series of studies conducted in our laboratory that have investigated the influence of phonological and phonetic variation on lexical access. Taken together, the results of these studies suggest that initial contact with the lexicon is influenced by the “goodness” of the stimulus input and the extent to which it matches the sound structure representation. As a consequence, poorer exemplars fail to activate a lexical entry to the same degree as a good one, and the initial reduction in activation influences the activation levels within the lexical network itself.

We take as our starting point behavioral results with normal subjects showing semantic priming in a lexical decision task. That is, lexical decision latencies are shorter for a target word when it is preceded by a semantically related word than when it is preceded by a semantically unrelated word or a nonword. Semantic priming presumably arises because the presentation of a word not only changes the activation of the particular lexical representation, but also affects the pattern of activation of those words that are semantically related to it. As a consequence, response latencies are shorter in a lexical decision task for the target word *dog* when it is preceded by the word *cat* because the lexical representation for *dog* has already received partial activation from the preceding semantically related word and thus is closer to its threshold of activation.

Of importance for the purposes of this paper is a series of experiments exploring the effects of stimulus degradation on the magnitude of semantic priming. Namely, normal subjects, presented with a semantically related prime that is either phonologically modified (*cat-dog*; *gat-dog*) or is phonetically a poorer exemplar of the phonetic category show a reduction in the magnitude of semantic priming that appears to be proportional to the degree of “distortion” of the prime. For example, if a prime stimulus such as *cat* is phonologically distorted such that its initial consonant is either one phonetic feature away from [k], e.g., *gat*, or several phonetic features away, e.g., *wat*, normal subjects show a reduction in the magnitude of semantic priming to the target word, *dog* (Milberg, Blumstein, & Dworetzky, 1988a). These same effects emerge not only when there is a phonological change, i.e., a change in the phonetic

category, but also if the initial consonant is phonetically “degraded” by either reducing the initial VOT of the initial [k] (Andruski et al., 1994) or by increasing the initial VOT of the initial [k] (Kessinger, 1998). In both cases of “phonetic degradation,” the initial consonant is still a member of the phonetic category [k]. Subjects identify the initial consonant as [k] and they identify the stimulus prime as the word “cat.” However, the phonetic manipulations render these stimuli as poorer exemplars of the phonetic category.

Of interest, the reduction in semantic priming emerges whether or not the prime stimulus has other voicing lexical competitors, e.g., *pear* as a prime for *fruit*, has a voiced lexical competitor, *bear*, whereas *cat* as a prime for *dog* does not have a real word voice lexical competitor, cf. *gat* (Andruski et al., 1994). These effects emerge not only for within category phonetic manipulations that are made in initial position, but also for changes made in word medial as well as word final position (Utman, 1997). The fact that the magnitude of semantic priming is reduced when the semantically related prime word has been phonologically or phonetically distorted has been interpreted to mean that the initial contact with the lexicon is influenced by the “goodness” of the stimulus input, and that activation levels in the lexicon are graded. As a consequence, poorer exemplars fail to activate a lexical entry to the same degree as a good one, and the initial reduction in activation influences the activation levels within the lexical network itself.

MODELING THE EFFECTS OF PHONOLOGICAL VARIATION IN NORMAL SUBJECTS

In this section, we address data concerning the effects of phonological manipulations on the processes involved in lexical access in normal subjects. Specifically, we simulate the data reported in Milberg et al. (1988a). That paper showed that activation of lexical entries could have a graded quality; that is, a given stimulus that is phonologically similar to a real word may partially activate lexical entries (see also Connine et al., 1997).

Milberg et al. gathered data from normal subjects engaged in an auditory lexical decision task on a target that was preceded by one of several different prime types. There were four such types: (1) real words that were semantically related to the target; (2) nonwords generated by distorting a semantically related word by one phonetic feature; (3) nonwords generated by distorting more than one phonetic feature; and (4) semantically unrelated words. Thus, a target word like *dog*, for example, could be preceded by any of the following primes: (1) *cat*, (2) *gat*, (3) *wat*, or (4) *table*. As in any lexical decision task, the word targets were conjoined with an equal number of distractor nonword targets.

Reaction times to correct responses to the word targets were examined. The results showed a monotonic relationship between the degree of phonetic distortion of the initial phoneme and the degree to which response times to the targets were facilitated (see also Connine et al., 1997). In other words, the amount of semantic priming was proportional to the degree of distortion of the prime. For example, *wat*, which is several phonetic features away from the word *cat* showed less priming for *dog* than did *gat*, which was only one phonetic feature away from the word *cat*.

Based on their findings, Milberg et al. (1988a) concluded that lexical access—in particular, the aspects of such processing that are required to elicit semantic priming—allow for possible noise or distortion of the speech signal, even when such distortion occurs in the initial segments of the items. Moreover, they suggest that access to the lexicon is graded, and even a nonword may activate a lexical representation, if it is phonologically similar to it.

In terms of the present modeling endeavor, these results have very explicit implications. Our system has the potential to show tolerance to mismatch of the above described kind by its very design. While mismatches between inputs and learned patterns will elicit lower levels of activation of lexical and semantic nodes, the system can be set up (by choice of parameters) to balance the positive and negative feedback at the lexical layer such that small mismatches will still result in lexical nodes reaching their maximum, steady-state value over time. In addition, the system can in principle make lexical decisions in this way, since the system can be set up such that only words (or slightly distorted words) will reach the maximum level of activation, whereas nonwords will not reach the maximum level before the negative feedback (which is dependent on time) takes over and brings activation of the lexical nodes back down to below threshold (see Appendix).

How does such a system account for the data reported by Milberg et al. (1988a)? The representations of the stimuli used in this simulation were based on the representation scheme described earlier. We developed a representation of the entire CVC stimulus for the second layer of the model in terms of clusters of phonetic features. Because in this simulation, the mapping from the input layer to the phonemic layer was totally transparent (i.e., the voicing characteristics of the stimuli were the canonical forms of the phonetic input and there were no within phonetic category variants within this stimulus set), we describe only the nature of the representations at the phonemic layer.

For our purposes, the representation for a word like “cat” was $\{0.1, 1.0, 1.0, 1.0, 1.0\}$, with the first two pairs of nodes representing some phonetic features of the initial phoneme. That is $\{0.1 \dots\}$ might represent the feature voice, and $\{\dots 1.0 \dots\}$ might represent the feature for manner of articulation. Together, $\{0.1, 1.0\}$

represent the initial phonetic segment. Distortions of the initial phoneme in this pattern could be represented by changing one or both of the activation patterns of those first two pairs. Thus we represented distortions of a single phonetic feature (in this case voicing) for the representation “cat” as {1,0, 1,0, 1,0, 1,0, 1,0} and distortions of multiple phonetic features as {1,0, 0,1, 1,0, 1,0, 1,0}. Notice that the activation patterns in the last six elements of all three patterns are the same, which corresponds (roughly) to the fact that distorted patterns in the Milberg et al. experiment shared the same “rest of the word.” For example, a completely different word such as “table” was represented as {1,0, 0,1, 0,1, 0,1, 0,1}.

Thus, for the purposes of this existence proof, there are four input stimuli: the word “cat”; a nonword stimulus (not seen before by the network) in which the initial “consonant” differed from the lexical representation for “cat” by one phonetic feature; another nonword stimulus in which the initial consonant differed by more than one phonetic feature; and a real word stimulus that was neither semantically nor phonologically related to “cat.” We investigate the influence of each of these input representations on the lexical representation for “cat” at the lexical level and its semantically related lexical network (for our purposes, “dog”) on the semantic level. The goal is to determine whether activation of a lexical entry is graded whereby phonologically similar stimuli partially activate a lexical entry.

We have chosen to make the lexicon in our model self-organizing. That is, we require our model to “learn” the vocabulary that forms the lexicon used in our simulations without having an external teacher at every step of the process. We also want to elucidate a process whereby the system can map inputs on to stable categories (lexical entries) while allowing a certain tolerance for mismatch between inputs and stored representations. The point of making the lexicon self-organizing is to offer the beginning of an approach of how a lexical system might originate, and how the system might be able to make lexical decisions, i.e., distinguish inputs that are part of the vocabulary (words) from those that are not (nonwords). The Appendix details the learning algorithm. We used the same ART 2-A simulator to demonstrate self-organization weight derivations in the remaining simulations in this article.

The input vectors corresponding to the stimulus input for “cat” and its lexical network (“dog”) was learned by using the ART 2-A network by committing a single node to a critical feature pattern corresponding to a scaled (normalized) version of that input vector. For the purposes of our account, we give that vector the narrative role of the word “cat.” Similarly, the network learned another word, “table.” We then tested this (very simple) network on the three input vectors described above. These patterns were normalized (for mathematical length of the vector) and the input activations were

passed through the weights for the single (“cat”) node at the lexical level as well as the semantic level, and lexical activations were derived.

The lexical activations for the original word, the nonwords with one and multiple phonological distortions, and the unrelated word were 1.0, 0.8, 0.6, and 0.4, respectively. At this point, the dynamics of the upper two layers of the model were applied according to Equations 1 and 2. That is, after the limits and threshold have been applied, activation passes from the lexical layer through two types of weights: (1) the recurrent connections in the lexical layer—allowing activation patterns in that layer to unfold over time—and (2) the weights leading to the semantic layer.

Figure 4 shows the activation of the node in the semantic layer (e.g., “dog”) that results from the presentation of each of the input vectors corresponding to the prime stimuli (e.g., “cat,” “gat,” “wat,” “table”). It is this activation that is assumed to reflect the degree of semantic facilitation of the related target.² Even though these activation curves at first appear to be rather unchanging, clearly the outer curves reach a steady state, while the inner ones grow and then decay (it is this set of properties that underlies the success of the model depicted in Figure 5). The parameters for this simulation were as follows: *a*, the feedback constant, was 1.05; *b*, the temporal decay rate constant, was 0.01; the minimum activation of the lexical nodes was 0.41, while the maximum was 1.05; the minimum activation of the semantic nodes was 0.52, while the maximum was 1.05; finally, the resting state of the lexical nodes was 0, whereas the resting state of the semantic nodes was 0.3. Baseline (minimum) semantic activation was 0.3. Each time step on the figure corresponds to an updated version of activation after it has gone through the recurrent network ($t = t + 1$). Each time step is assumed to correspond to roughly 50 msec of interstimulus interval (ISI). Thus, as the figure shows, the greatest activation occurs for the prime stimulus input “cat,” followed by “gat” and “wat,” whereas the un-

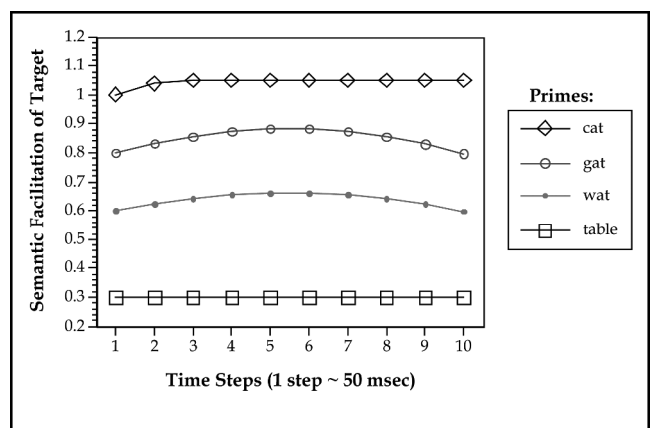


Figure 4. Simulation of the Milberg et al. (1988a) data on the effects of phonological manipulations on semantic priming in normal subjects.

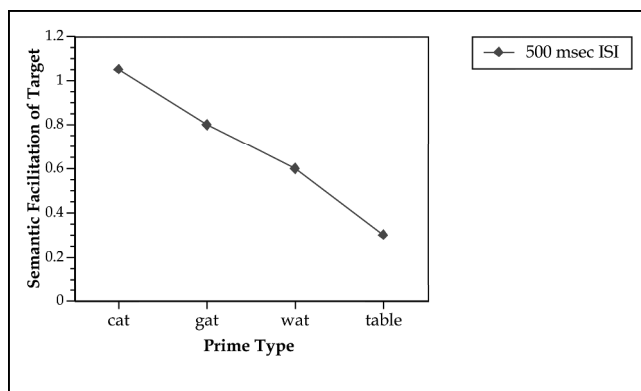


Figure 5. Simulation results for the final time steps of Figure 4, corresponding to the 500-msec ISIs used in the Milberg et al. (1988a) experiment.

related prime stimulus “table” shows minimal semantic activation. Importantly, the activation of the word prime “cat” is greatest, and reaches the maximum level of lexical activation, at which point its activation is maintained for the remaining time steps in what we refer to as a “resonant state.” Activations resulting from the phonologically distorted primes rise and decay over time without ever reaching the resonant state (operationally defined as approaching 1.0), although they both show partial activation of the semantic network over the time course of the simulation. Meanwhile, the activation corresponding to the presentation of the unrelated stimulus is very low, i.e., “table” fails to prime “dog.” Figure 5 shows the pattern of results of the simulation at an ISI of 500 msec (the ISI used in the Milberg et al., 1988a study and the last step of the reiteration in the simulation). The pattern of results is similar to the monotonic pattern of results reported by Milberg et al. (1998a).

It is reasonable to ask whether the patterns of results obtained in this simulation would emerge were the network to have a substantially larger vocabulary, i.e., were the simulations to be scaled up. We believe that our simulations offer a reasonable first approximation to the system we envision even with respect to much larger-sized vocabularies. We assume that the large majority of words in a vocabulary are similar to only a small number of candidates, and are relatively dissimilar to a larger number of others. Thus, even with a larger vocabulary, the inputs would influence only a small subset of the total vocabulary, and hence would not influence the dynamics of the system. This can be seen with respect to the architecture of the model. Namely, we applied a threshold of lexical activation at all time-steps, even prior to the application of bias and feedback. As a result, any activation that fell below threshold initially (0.41 or less) never elicited lexical activations above 0, led to lexical feedback, or took part in competitor effects. In the simulations themselves, we simulated two words that were relatively different, e.g., “cat” and “table,” and each

pattern activated the lexical entry for the other at 0.4 (i.e., below threshold), and thus played no role in the lexical dynamics of the system. Neighborhoods (Luce, 1986) would need to be handled differently. However, the effects of neighborhoods on reaction times are relatively small (see Luce, 1986; Luce, Pisoni, & Goldinger, 1989). We leave consideration of neighborhood effects in terms of our system to future work.

In conclusion, our model succeeds in accounting for the findings of Milberg et al., thereby explicating how phonological manipulations of primes can influence semantic priming of targets. Specifically, the model operationalizes several findings in the literature relating to word recognition and lexical processing—nonwords appear to activate the lexicon but to a lesser extent than words (see McClelland & Rumelhart, 1981); the closer phonologically nonwords are to real words, the greater will be the priming effects obtained (see Connine et al., 1997); and activation of the lexicon appears to be graded (Connine et al., 1997; Andruski et al., 1994; Marslen-Wilson & Warren, 1994; McClelland & Elman, 1986). In addition, the origin of the architecture is explicated in terms of self-organization (Carpenter et al., 1991; see also Carpenter & Grossberg, 1987a, 1987b; Grossberg, 1980).

MODELING THE EFFECTS OF SUBPHONETIC VARIATION IN NORMAL SUBJECTS

Early research in lexical processing generally assumed that “fine” acoustic differences of phonetic category structure are “cleaned” up in earlier stages of processing and thus have little or no effect on word recognition or lexical access. And yet, listeners seem to harness the variability in the speech stream and are able to rely on the fine acoustic details intrinsic in the variation of speech in the process of word recognition (Warren & Marslen-Wilson, 1987, 1988; see also Marslen-Wilson, 1978, 1989). In particular, listeners monitor the acoustic signal continuously, not waiting until the end of a segment in order to guide or constrain their lexical choice.

It has also been shown that listeners are sensitive to fine acoustic differences in word recognition. Streeter and Nigro (1979) showed longer lexical decision latencies when stimuli were altered by either removing medial consonant transitions or juxtaposing conflicting transitions. Because this effect emerged for words but not for nonwords, they concluded that processing was slowed during lexical lookup (Pitt & Samuel, 1995, but see Whalen, 1991 for an alternative point of view).

Fine acoustic differences are inherent to the structure of the phonetic categories of speech. Importantly, however, these differences are not weighted equally. Rather, phonetic categories have an internal structure to them such that some values of an acoustic parameter serve as better exemplars of the phonetic category than do

others. Thus, although there is a continuum of VOT values corresponding to the voiceless phonetic feature, some values are perceived by listeners as better exemplars than others. Experimental findings with normal subjects have shown that these within phonetic category (i.e., subphonetic) differences affect not only word recognition, i.e., access to lexical form, but also lexical access, i.e., activation of the lexical network itself (Utman, 1997; Andruski et al., 1994).

Research in our lab has shown a reduction in the amount of semantic priming in a lexical decision task when a poorer exemplar of a phonetic category is used in the prime word stimulus. Andruski et al. (1994) investigated the effects of shortening the VOT of the initial stop consonant primes on the lexical decision latencies to semantically related targets. They found that reducing the VOT by one-third had no effect on the degree of semantic priming at ISIs of 50 or 250 msec, but that reducing the VOT by two-thirds reduced semantic priming at an ISI of 50 msec; this effect disappeared with an ISI of 250 msec. There was also an effect of competitor status: in the presence of a voiced competitor (as *pear* has with *bear*), RTs were slower overall than if there were no competitor (as *cat* has no voiced competitor, cf. *gat*). However, this effect did not interact with the effects of subphonetic manipulation; i.e., the decrement in semantic priming with phonetic distortion was of a similar magnitude for prime stimuli with or without voiced competitors.

These findings generalize to acoustic properties other than voicing in initial stop consonants. Both removing the closure phonation in voiced final stops consonants in prime words and increasing the vowel duration in medial lax vowels in prime words result in reduced semantic priming (Utman, 1997). Taken together, these results are consistent with the view that the representation that is first abstracted from the speech waveform and that is mapped on to phonetic categories incorporates information about within category subphonetic variation. Moreover, because this low-level acoustic information affects lexical access (at least at short ISI intervals), it suggests that activation levels in the lexicon are graded, and that differences in the magnitude of semantic priming are due to the extent to which the initial consonant of the prime stimulus is a good or poor exemplar of the phonetic category.

To account for these findings in our model, we again focused on the phonetic category for voicing and implemented the more fine-grain VOT representations in the input to the network, as described earlier. This implementation differed from the first simulation that used the “canonical” representations for voiced and voiceless initial consonants. Additionally, in order to simulate competitor effects, we added an additional “word” beginning with an initial voiced consonant in the system’s “lexicon” (and associated lexical network in the semantic level).

The input representations to the model (once it had been trained) corresponded to canonical voiced and voiceless exemplars as well as a subphonetic “distortion” of the voiceless phonetic category by sliding the moving bar in our distributed representation. As described earlier, while the representation for a voiced VOT was {1,1, 1,1, 1,0, 0,0, 0,0} and that for a voiceless VOT was {0,0, 0,0, 0,1, 1,1, 1,1}, we represented a shortening of the VOT of the voiceless exemplars as a shift of the bar of 1s to the left. Thus the representation of a VOT shortened by one-third was {0,0, 0,0, 1,1, 1,1, 1,0}, and the representation of a VOT shortened by two-thirds was {0,0, 0,1, 1,1, 1,1, 0,0}. In this way, the similarity of the distorted shortened voiceless VOTs to the original exemplars was reduced proportionally to the degree of distortion, while still making it most similar to the voiceless pattern (i.e., it was still categorized by our model as “voiceless” similar to the behavioral results of Andruski et al., 1994). The result of using such patterns as input resulted in a weakening in the activation of the voiceless node and an increase in the activation of the corresponding voiced node in the phonetic feature layer. Thus, instead of 1 and 0 (for the activation of the voiceless node and voiced nodes) when the input representation was a canonical voiceless stimulus, it was, respectively, 0.8 and 0.2 for an input representation with a VOT reduction of one-third, and 0.6 and 0.4 for a VOT reduction of minus two-thirds.

In this simulation, we trained the system using the ART 2-A simulator using two “lexical” and corresponding semantic nodes, so that we could implement competition between stimuli such as *pear* and *bear*. We did this by making the lexical entries for these stimuli inhibit each other’s semantic representations. The constant for this inhibition was 0.2. This parameter setting was the same for all simulations.

We then simulated the effects of within phonetic category distortion and lexical competition described above. The stimulus input representations included the exemplar stimulus *cat* and the two-thirds phonetic variant of *cat*,³ as well as the exemplar stimulus *pear*, and its phonetic variant. Figure 6 shows the activation of the node in the semantic layer (e.g., “dog” and “fruit”) unfolding over time that results from the presentation of each of the input vectors. As in the previous simulation of phonological distortion on semantic activation, each time step on the figure corresponds to an updated version of activation after it has gone through the recurrent network ($t = t + 1$). Each time step is assumed to correspond to roughly 50 msec of ISI. Thus, the figure shows the time course of semantic activation from 50 to 250 msec, the two ISI intervals used by Andruski et al. (1994). Several things are clear from these results: first, there was greater semantic activation for exemplar input representations compared to the phonetically distorted representations. Second, the effects of the phonetic distortion were greatest at the

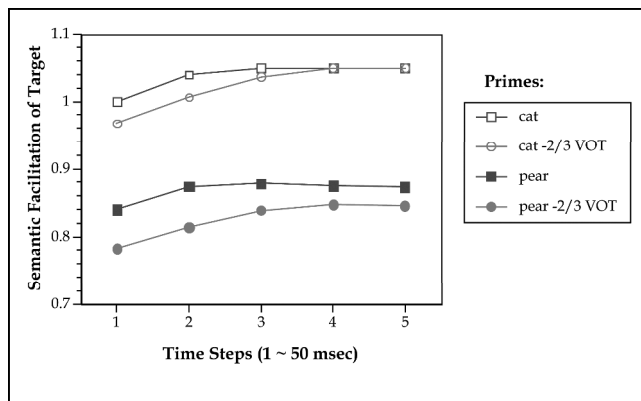


Figure 6. Simulation of the Andruski et al. (1994) data on the effects of subphonetic manipulations on semantic priming in normal subjects. For the solid symbols the target is “fruit” and for the others the target is “dog.”

shortest first iteration (comparable to an ISI of 50 msec), but was much less so after several iterations (comparable to longer ISIs). In fact, the effect of the $-2/3$ VOT manipulation for “cat” on semantic activation for “dog” disappeared completely by 250 msec and was very small for “pear.” Also, a competitor effect appears at all ISIs. Namely, there is less semantic activation for an input representation that has a lexical competitor (“pear”) than for one that does not (“cat”) and this does not seem to interact with the effect of acoustic distortion.

These patterns emerge in the model because lexical activations of the target word are initially lower for input representations that are acoustically distorted, but over time those activations grow towards their maximum activation levels. The effects of acoustic distortion disappear when those maxima are reached. However, as competition is implemented from the lexical layer to the semantic layer (see Figure 2), those effects persist. A small effect of acoustic distortion also persists for stimuli with a competitor, because those activations are influenced by the competitor, whose own activation is reduced in the presence of acoustic modification (and never reaches its maximum).

The patterns of the model parallel the priming results of Andruski et al. (1994). Namely, there was a greater magnitude of priming for target words preceded by exemplar stimuli than semantically related primes containing phonetic distortions; there was a significant effect of distortion in the $-2/3$ condition; the effects of this phonetic distortion were short-lived disappearing by 250 msec; and the presence of a lexical competitor similarly slowed reaction-time latencies in all conditions.

LEXICAL ACCESS IN APHASIA

The issues that we have discussed in this paper concerning the dynamics of lexical processing bear importantly on current research in language deficits in aphasia. Considerable research has shown that both Broca’s and

Wernicke’s aphasics display lexical processing impairments (see Milberg, Blumstein, Katz, Gershberg, & Brown, 1995; Prather, Zurif, Stern, & Rosen, 1992; Swinney, Zurif, & Nicol, 1989; Blumstein, Milberg, & Shrier, 1982; Milberg & Blumstein, 1981; Milberg, Blumstein, & Dworetzky, 1987). Although there is general agreement within the literature that aphasic patients have a lexical processing impairment, there has been considerable controversy over the basis of that deficit. There are some whose focus is on the time course of activation, proposing a delay in the processes of activation, selection or decay of lexical candidates (ter Keurs et al., 1999; Swaab et al., 1998; Tyler & Ostrin, 1994; Prather et al., 1992). Others focus on mechanisms of integration of information suggesting that the deficit reflects an impairment in integrating lexical semantic information into context (Milberg, Sullivan, & Blumstein, 1998; Hagoort, 1993). It is beyond the scope of this article to review the evidence and arguments used to support these various proposals. In this paper, we take one series of experimental findings consistent with a particular hypothesis about the basis of the lexical processing deficits in aphasia and test that hypothesis within a dynamical model of lexical access.

Our hypotheses derive from a series of lexical processing experiments conducted with both Broca’s and Wernicke’s aphasics (Milberg & Blumstein, 1981; Milberg et al., 1987, 1995; Milberg, Blumstein, & Dworetzky, 1998b; Blumstein et al., 1982). On the basis of the pattern of results that have emerged, we have argued that many aphasic language symptoms can be attributed to alterations in the dynamics of lexical activation and the resulting spread of activation from one lexical representation to another rather than a deficit due to alterations in the representations themselves. The nature of the deficit, however, appears to be different between Broca’s and Wernicke’s aphasics, and hence, has different consequences not only for the patterns of comprehension performance of these patients but also for the clinical characteristics that they display (see Blumstein, 1997; Blumstein & Milberg, 2000). In particular, we have proposed that Broca’s aphasics show an initial underactivation of the lexicon whereas Wernicke’s show overactivation of the lexicon either due to a decreased threshold for the activation of lexical representations or an overall increase in the gain of activation.

The evidence that gave rise to these hypotheses comes from a series of semantic priming studies using the lexical decision paradigm. In some experiments, subjects were given a list of words, e.g., *shoe ... pear ... fruit ... gluf*, and they had to make a lexical decision on every stimulus item (Milberg & Blumstein, 1981). In others, the subjects were given either stimulus pairs (Milberg et al., 1995; Blumstein et al., 1982), e.g., *pear-fruit*, or stimulus triplets (Milberg et al., 1987), e.g., *river-bank-money*, and they had to make a lexical decision on the final stimulus target.

Results of these studies exploring semantic priming in a lexical decision task showed that Broca's aphasics displayed priming under some experimental conditions and failed to show priming under other conditions. In particular, when the stimuli were paired and were highly predictable, these patients showed semantic priming. When the stimuli were presented as lists (for a lexical decision on every word) (Prather et al., 1992; Milberg & Blumstein, 1981), or as triplets (for a lexical decision on the third word of the series) (Milberg et al., 1987), and the stimulus target could not be easily predicted based on the preceding pairings (Milberg et al., 1987), they failed to show semantic priming. Thus, in these on-line tasks, Broca's aphasics showed a lexical processing impairment. And yet, in off-line tasks, using the same stimuli (Blumstein et al., 1982; Milberg & Blumstein, 1981), Broca's aphasics performed very well. Namely, although they failed to show semantic priming, they could accurately judge whether stimulus items were related or were not. The failure of Broca's aphasics to show semantic priming under all of the lexical priming conditions described above was interpreted as a lexical processing impairment due to a reduction in the activation of lexical entries (Blumstein & Milberg, 2000; Milberg et al., 1995).

In contrast to Broca's aphasics, Wernicke's aphasics show semantic priming in a lexical decision task under all of the priming conditions regardless of whether the stimuli are presented in lists, in pairs, in triplets, and whether or not a strategy can be invoked for determining the semantic relationship between the prime and the target (Milberg & Blumstein, 1981; Milberg et al., 1988b; Blumstein et al., 1982). Moreover, they are not "garden-pathed" as are normal subjects when an ambiguous word is put in the context of its two alternative meanings, e.g., *river, bank, money*. However, in semantic judgment tasks, Wernicke's aphasics perform at chance levels. Thus, although they appear to be able to access lexical entries and to activate the lexical network as shown by semantic priming, they are unable to use this information in an off-line task. They also show priming under a greater set of stimulus condition suggesting that their lexical system may be "overactivated" or alternatively, insufficiently "inhibited."

There are some models in the literature of considerable relevance to the hypothesized deficits of aphasic patients, and although none address the particular issues with which we are engaged, they do have some bearing on our overall approach. Chief among the models of lexical access in aphasia is the work of Dell et al. (1997). In that paper, the authors offered detailed analysis and predictions for performance (errors) by Wernicke's aphasics in a production task. As our approach focuses on word perception by aphasics, and in particular reaction times rather than errors, the influence of that work on the present work is primarily at the level of general principles. First, the model proposed by

Dell et al. is consistent with the continuity hypothesis, according to which aphasic performance—and errors, in particular—lie on a continuum of distorted performance, with normal performance an upper limit of that continuum. The present project also takes the continuity hypothesis as an operating assumption (see discussion in the section Conclusion: The Critical State). In addition, the paper by Dell et al. account for aphasic performance by making global parameter adjustments, rather than creating "lesions" at specific sites in the model. We also adopt this approach, since it is consistent with the systems view that forms the foundation of our model.

Two other modeling projects in the literature are worth addressing: that of Laine et al. (1998) and Tikkala and Juhola (1996). These projects are, as Dell et al., focused on naming performance in aphasics, and much like our study they address multiple types of aphasia. In fact, for us the observation that the lexical and semantic thresholds in their models tend to be lower for Wernicke's as opposed to Broca's aphasics (particularly in the case of Laine et al.) suggests some form of indirect support for one of the primary issues of the present project: the overactivation/underactivation hypothesis for Wernicke's and Broca's patients, respectively. Further comparison between those two modeling projects and ours is difficult for many reasons, not the least of which is the strong role for noise in those models, which is a parameter we do not invoke at all in the present project.

MODELING THE EFFECTS OF PHONOLOGICAL VARIATION IN BROCA'S AND WERNICKE'S APHASIA

In this section, we consider the results of a study conducted by Milberg et al. (1988b) exploring the effects of phonological variation on semantic priming in Broca's and Wernicke's aphasics. This study was analogous to the Milberg et al. (1988a) study described in detail in the section Modeling the Effects of Phonological Variation in Normal Subjects. In particular, subjects were presented auditorily with stimulus pairs in which the initial consonant of a prime stimulus, e.g., *cat*, was phonologically altered such that its initial consonant was either one phonetic feature away from [k], e.g., *gat*, or several phonetic features away, e.g., *wat*. These prime stimuli were paired with a real word target that was semantically related to the phonologically unaltered prime word, e.g., *dog*, for lexical decision. The magnitude of semantic priming was compared for these pairs compared to a semantically unrelated "baseline" condition, *table-dog*. The ISI used in this experiment was 500 msec, the same as that used for the experiment with normal subjects.

Unlike normal subjects who showed a reduction in the magnitude of semantic priming as the phonological distortion increased, Broca's aphasics showed semantic

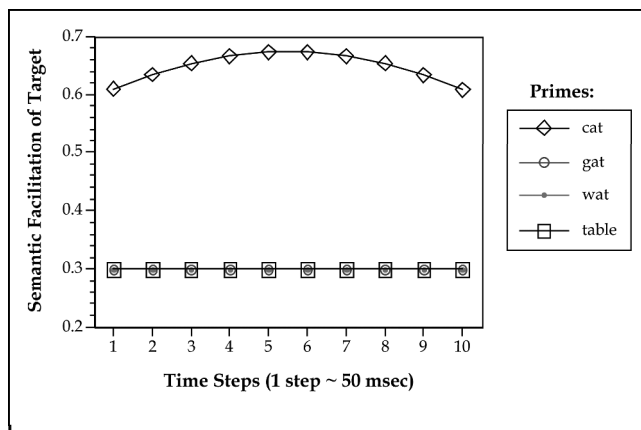


Figure 7. Simulation of the Milberg et al. (1988b) data on the effects of phonological manipulations on semantic priming in Broca's aphasics.

priming only in the phonologically unaltered condition, i.e., *cat-dog*. They failed to show semantic priming for any of the phonologically related prime conditions, i.e., *gat-dog*, *wat-dog*, compared to the baseline unrelated condition, i.e., *table-dog*. In contrast, Wernicke's aphasics showed semantic priming in all phonologically altered conditions, and the magnitude of priming was equivalent to the semantically related, e.g., *cat-dog*, condition. Importantly, despite these "pathological" priming patterns, both groups of aphasic patients were able to make correct lexical decisions on the prime stimuli when they were presented in a separate posttest. Thus, the patients showed that they could perceive the phonological variants by correctly indicating that *cat* was a word but that *gat* and *wat* were not. Thus, we find in the experimental findings a dissociation between the ability to distinguish words from nonwords for the purposes of lexical decision and the influence of nonwords on semantic priming.

The pattern of results that emerged for Broca's and Wernicke's aphasics were interpreted in terms of deficits in lexical activation. The failure of Broca's to show any priming for the nonword stimuli was interpreted in terms of a reduction in initial lexical activation. As such, a phonologically distorted prime such as "gat" would only minimally activate or fail to activate a lexical entry to which it is phonologically related, i.e., "cat." In contrast, the fact that Wernicke's aphasics show semantic priming under all phonologically distorted conditions suggest that there is an overactivation of the lexical system whereby nonwords that are phonologically similar to real words activate the lexicon to the same extent as real words themselves.

We simulated this design principle by simply changing the value of the resting state of the lexical entries for the different types of aphasics. In our simulations of the normal subjects described in the sections Modeling the Effects of Phonological Variation in Normal Subjects and Modeling the Effects of Subphonetic Variation in Normal

Subjects, we set the lexical resting state at 0. For these simulations, we ran the same system as described in the section Modeling the Effects of Phonological Variation in Normal Subjects changing only the lexical resting state from 0 to -0.39 in order to simulate the Broca's aphasics, and from 0 to 0.4 in order to simulate the Wernicke's aphasics. We thereby sought to give support to the notion that a lowered lexical activation would give rise to behavior like the Broca's patients, and a raised activation would give rise to behavior like the Wernicke's patients.

The results of these simulations for the Broca's and Wernicke's aphasics are shown in Figures 7 and 8, respectively. The simulation results for Broca's aphasics (Figure 7) show that semantic activation for "dog" emerges only for the semantically related real word "cat." The amount of activation for "dog" given the stimulus input of the phonological variants is the same as that for the semantically unrelated baseline stimulus "table." In contrast, the simulation of Wernicke's patients (Figure 8) shows comparable activation for "dog" to a semantically related word as to the phonologically distorted primes. Although the behavioral data that are being modeled did not explore the time course of these effects, it is interesting that the time course of the activation in the simulation suggests that at the shortest ISI (50 msec) there might be reduced activation for the primes with the larger phonological distortions.

MODELING THE EFFECTS OF SUBPHONETIC VARIATION IN BROCA'S APHASIA

We now turn to data reported by Utman, Blumstein, and Sullivan (submitted). That study was based on the Andruski et al. (1994) experiment and investigated the effects of subphonetic (VOT) manipulations on semantic priming in Broca's aphasics. Results showed that, similar to normal subjects, shortening the VOT by two-thirds results in a reduction in the magnitude of semantic

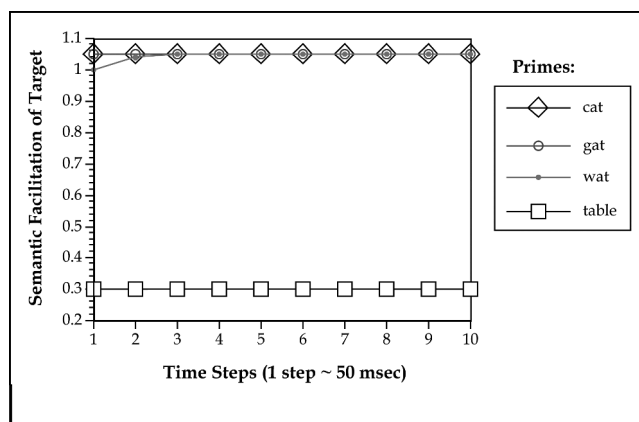


Figure 8. Simulation of the Milberg et al. (1988b) data on the effects of phonological manipulations on semantic priming in Wernicke's aphasics.

priming. However, there were two critical differences in the pattern of results obtained for the Broca's aphasics compared to the normal subjects, one relating to lexical competition and the other relating to the time course of the priming patterns. Turning first to the competitor effects, the reduction in semantic priming emerged only for those prime stimuli that did not have a lexical competitor. That is, phonetically altered *cat* showed a significant reduction in the magnitude of priming for *dog*. However, phonetically altered *pear* (with the lexical competitor *bear*) failed to show any semantic priming for the semantically related word *fruit*. Thus, the presence of a lexical competitor resulted in the loss of semantic priming when the prime stimulus was a poorer exemplar of the phonetic category. Importantly, the Broca's aphasics perceived the initial consonant of the acoustically modified stimulus primes as voiceless, indicating that the failure to show priming under conditions of lexical competition were not due to a problem in perceiving the competitor prime stimuli as beginning with initial voiceless stop consonants.

In addition to the competitor effects that emerged, Broca's patients also showed a different pattern of results compared to normals over the two ISI conditions. Unlike normal subjects, where the effects of the acoustic manipulation were short-lived, emerging at 50 msec and disappearing at 250 msec, for Broca's aphasics, the effects of the acoustic manipulations persisted. That is, the reduction of semantic priming for acoustically manipulated *cat* emerged at both ISI intervals, and the failure of acoustically manipulated *pear* to show semantic priming also emerged at both ISI intervals.

In theory, these behavioral results reflect the same deficit that gave rise to the patterns of results in Milberg et al. (1988b). The next simulation tested this hypothesis by using the same system described in the section Modeling the Effects of Subphonetic Variation in Normal Subjects and changing only the lexical resting state to -0.39 (as was done in the preceding simulation of phonological manipulations). To review, the stimulus input representations included the exemplar stimulus *cat*, the 2/3 phonetic variant of *cat*, the exemplar stimulus *pear*, and its phonetic variant. The activation at the semantic layer for "dog" and for "fruit" was determined for each input representation. Figure 9 shows the activation of the node in the semantic layer (e.g., "dog" and "fruit") unfolding over time that results from the presentation of each of the input vectors. Each time step on the figure corresponds to an updated version of activation after it has gone through the recurrent network ($t = t + 1$) and is assumed to correspond to roughly 50 msec of ISI. Thus, the figure shows the time course of semantic activation from 50 to 250 msec.

The results of the simulations parallel the behavioral results. Semantic activation for both "dog" and "fruit" emerges when the input representation is a "prototy-

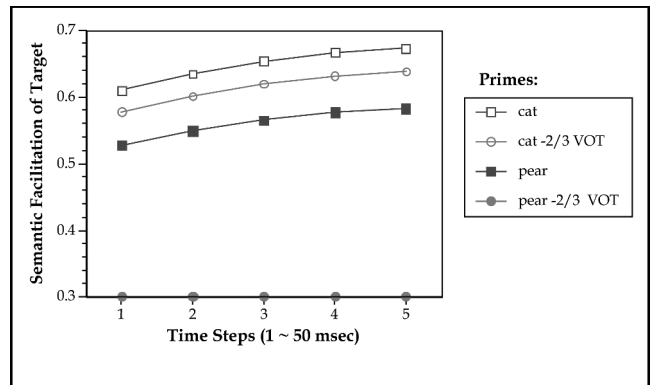


Figure 9. Simulation of the Utman, Blumstein, and Sullivan (submitted) data on the effects of subphonetic manipulations on semantic priming in Broca's aphasics. Again, for the solid symbols the target is "fruit," and for the others the target is "dog."

pical" exemplar of the phonetic category analogous to the finding that semantic priming occurs for the unmodified prime stimuli. Moreover, the amount of activation appears to be less when there is a competitor than when there is not. Importantly, there is a lexical competitor effect that interacts with the subphonetic manipulations. Semantic activation is reduced when there is no voiced lexical competitor and is lost when there is a lexical competitor. These results are comparable to the reduction in semantic priming for acoustically manipulated *cat* and the loss of semantic priming for the acoustically manipulated *pear*. Finally, all of these effects persist over the time course of the simulation. In sum, we were able to account for the Broca's behavioral data simply by altering the resting state of lexical activation to the same degree as the previous simulation, while maintaining all other parameters of the model.

CONCLUSION: THE CRITICAL STATE

The major conclusions that we draw from the present study are threefold in nature. One of the main points of the present project is that the present simulations strongly suggest that the adult lexicon is the product of an ongoing process of self-organization—internal organization without explicit direction from outside the system. Such a principle applies to at least three time scales: the developmental time scale, in which the lexicon is created and extended; the experimental/discourse time scale; and the time scale of immediate responses such as on-line lexical decisions. One of our claims, as detailed in the Appendix, is that developmental processes of self-organization of the lexicon lead to a dynamical system that is capable of making lexical decisions. Once the weights have been established (according to the system described in the Appendix), word activations rise and reach a maximum steady state, while typically nonword activations eventually decrease in value. That evolution of lexical and seman-

tic activations constitutes self-organization at the smallest time scale.

In addition, it is apparent from the literature that any model of semantic priming must provide equations for the dynamics of lexical and semantic activation, as the patterns of the process of semantic priming change over time. However, as is evidenced by our model, those equations can be quite simple. While they do require nonlinearities, they are limited to simple maxima, minima, thresholds, and normalization.

Finally, the present study paves the way for future work using self-organizing nonlinear dynamical systems as the substrate for model building in the investigation of how sound structure contacts the lexicon in normals and aphasics. As we do not believe that any single model will offer a complete answer to all of the relevant issues in the near future, we favor a pluralistic approach (see Cilliers, 1998; Rescher, 1993; James, 1908/1977). But even though we foresee the need for multiple models, we strongly suspect that there will be a number of consistent themes running through the endeavor. Namely, we feel that the necessity of all three of these characteristics—self-organization, nonlinearity, and feedback dynamics—is clearly in evidence given the present work.

Our current strategy is to characterize these self-organizing nonlinear dynamical systems in terms of a so-called critical state (compare with the notion of self-organized criticality—Bak & Chen, 1991). We propose that the normal human brain is poised at a critical state with respect to task demands. This means that the brain possesses a natural tendency to migrate—via processes of self-organization—toward the best possible state that is dynamically achievable given the circumstances. Following Cilliers (1998; who followed Bak & Chen, 1991), “. . . the system organizes itself towards the critical point whose single events have the widest possible range of effects. Put differently, the system tunes itself towards optimum sensitivity to external inputs.” It is in this region of optimum or near-optimum sensitivity that effective linguistic communication takes place. Since we were able to account for both normal and two types of aphasic performance by manipulating only one parameter (resting lexical activation), we may conclude that there is a continuum along which effective communication and the aphasic conditions appear (see Figure 10).

In the case of lexical access, the human perceptual system evolves to a point at which control parameters and the nodal interconnection strengths that code for known words are balanced such that language comprehension is possible, based on lexical and semantic activations. The aim of this self-organization is thus a point of optimal (or at least highly effective) degree of coordination between the organism, its experience, and its environment (compare Turvey & Carello, 1981; see also Van Orden & Goldinger, 1994).

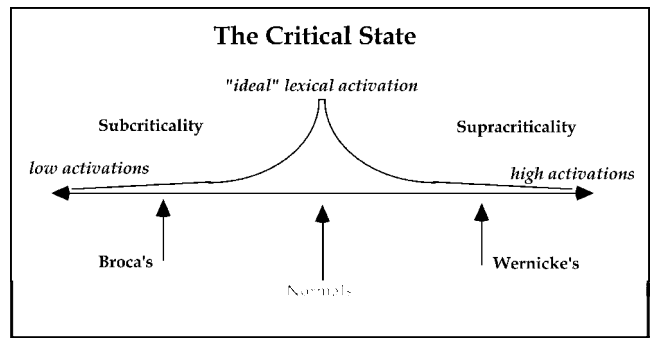


Figure 10. The critical state as a region along a continuum of resting lexical activations.

This point is characterized by a critical balance between a number of crucial variables or control parameters, to use a term consistent with dynamical systems theory. In our case, we considered the balance between resting activation, positive feedback, and negative feedback. The success of our model in incorporating these design principles and accounting for the normal data implies to us that such a balance may be crucial to intact language processing.

We then investigated two ways in which variation in activation (or “resting state” of the lexical entries) would affect the behavior of the system: underactivation (to model Broca’s aphasics) and overactivation (to model Wernicke’s aphasics). The results strongly indicate that such deficits may underlie the patterns of performance observed in the findings addressed in the present study. Further, we feel that lexical activation deficits may have very specific predictions with regard to their implications for the language perception/production system as a whole (although clearly the present study is only a first step towards demonstrating that) (see Blumstein & Milberg, 2000). It is apparent to us that with too little lexical activation, crucial relationships (e.g., syntactic, semantic, or pragmatic) between elements of communication will be lost or missed; whereas with too much activation, the system will be so overwhelmed with extraneous information that processing will also be impaired. In either case, the two types of patients have trouble maintaining consistent success with higher-order linguistic processing, albeit in different ways.

At the critical state the human system makes the best possible use of information as quickly as it can while maintaining stability. Happily, there seems to be a range of parameter values that give rise to the critical state, which may explain variability from subject to subject in performance. Thus the critical state seems to be robust yet flexible, thereby solving the stability–plasticity dilemma (compare Grossberg, 1980, 1982, especially regarding the noise-saturation dilemma as well). However, extreme circumstances (such as brain damage) can radically unbalance the control parameters crucial to the system’s operation. Hence, per-

haps the best way to evaluate aphasics may be in terms of the way in which they have been perturbed from the critical state. Thus, we feel that the present approach opens up numerous possibilities for theoretical and empirical work investigating the nature of the critical state in the language system, both in normal and aphasics.

APPENDIX

The Learning Algorithm

It is the purpose of this token simulation to develop an existence proof of the ART 2-A's self-organizing capabilities. The design principles for the self-organizing neural network used in this paper are based on the system developed by Carpenter et al. (1991) called "ART 2-A." ART 2-A is a simple, algorithmic variant of Grossberg's Adaptive Resonance Theory systems (Carpenter & Grossberg, 1987a, 1987b; Grossberg, 1976a, 1976b, 1980, 1982). Specifically, it mimics the behavior of ART 2 dynamical systems in an algorithmic manner; this means that it takes as input elements whose activation values can vary continuously (as opposed to ART 1, whose input values must be binary), and it can stably form categorization schemes of varying degrees of category coarseness. The basic aspects of the algorithm that are relevant to the discussions in this paper are given below; the reader who seeks a more detailed description of the ART 2-A algorithm is referred to the original paper by Carpenter et al.

In order to simulate the learning of lexical entries, we are focusing on only two levels of the network, the mapping from the phonemic level to the lexical level. Layer F_1 represents the information with which the lexical access system is initially provided (i.e., sound structure), and layer F_2 represents category identity (i.e., entries in the lexicon). Each node in layer F_2 receives inputs through weighted connections from every node in F_1 , and each node in F_2 corresponds to a single category.

There are two types of operation of the network: a learning phase and a testing phase. The learning phase provides an account of how the system manages to acquire category (lexical) representations, while the testing phase is used to account for subject performance on smaller time scales; namely, in the experimental setting.

The learning phase proceeds as follows. Given an M -dimensional input vector I^0 (representing sound structure in our model), the input to the network is normalized through Euclidean normalization:

$$I = N(I) \quad (3)$$

where

$$N(x) = \frac{x}{\|x\|} \quad (4)$$

where

$$\|x\| = \sqrt{\sum_i x_i^2} \quad (5)$$

The vector I forms the input to the network. Initially, all category nodes (F_2 nodes) are uncommitted; that is, they lack any category identity whatsoever. However, as will be described below, ART 2-A quickly establishes certain F_2 nodes as committed—each representing a particular category. When an F_2 node is committed, it acquires a set of weights feeding

into it from F_1 that correspond to a profile of the features characteristic of that category. We refer to this profile of features as a critical feature pattern z , which is a scaled long-term memory trace reflected in the vector of connections from F_1 to that F_2 node.

For our purposes, only activations of committed F_2 nodes are considered, as the uncommitted nodes have no representational value. They are determined by the equation

$$T_j = I \cdot z \quad (6)$$

that is, the activation of each F_2 node is found by taking the dot product between the input vector and the critical feature pattern corresponding to that node. Then a choice function is applied to the activations, where

$$T_j = \max_j (T_j) \quad (7)$$

If

$$T_j \geq \rho \quad (8)$$

where

$$0 \leq \rho \leq 1 \quad (9)$$

then I is considered a member of category j .

The parameter of the model called ρ is known as the vigilance parameter. It corresponds to the minimum degree of match between an input and a category's feature pattern required for the pattern to be considered a member of that category. The higher the vigilance, the greater the degree of match required to include the current input as a member of any existing category. A vigilance equal to 1 requires an exact match, and therefore results in the highest possible number of categories, i.e., equal to the number of input patterns.

If no F_2 node matches the input sufficiently, a new node is committed to that input pattern by setting the critical feature pattern of the new node equal to the pattern I . Otherwise, if the pattern matches a node sufficiently, the weights are adjusted by means of the following equation:⁴

$$z_j^{(\text{new})} = N(\beta I + (1 - \beta)z_j^{(\text{old})}) \quad (10)$$

where β is the learning rate of the system, and

$$0 \leq \beta \leq 1 \quad (11)$$

The higher the value of the learning rate, the faster the learning. Learning proceeds by repeated presentation of the input set until the system has stabilized. We defined stable behavior as a consistent categorization scheme that persists over at least three consecutive presentations of the training set.

The testing phase of the system proceeds according to Equations 3, 4, 5, 6, 7, 8, and 9. That is, no new nodes are committed and existing weights are not altered during the testing phase. This allows a lexical choice to be made according to Equations 7, 8, and 9, resulting in a "word" response. If no such choice is available, then a "nonword" response is given.

Token Simulation

In order to illustrate the efficacy of the ART 2-A algorithm, we ran a simulation that endeavored to illustrate how the ART 2-A system can learn to accept and recognize familiar patterns and reject unfamiliar patterns, even when the unfamiliar patterns are similar to the familiar ones. In this simulation, we created patterns made up of three "parts" each. This is analogous to word-like units having a phonetic structure such as CVC. In this case, the parts were comprised of four units each (analogous to segments each being comprised of a set of

phonetic features), making the whole pattern vector 12 elements long. In each of these groups of four units, one element's activation was set equal to 1.0, while the other three were set equal to 0.2. Since there were four possible "parts" or segments (referred to as A, B, C, and D), and three parts per pattern (phonetic feature comprising these segments), there were 64 possible "words," starting with AAA and AAB and ending with DDD.

We trained the ART 2-A network on 40 of these patterns; it successfully distinguished these patterns from each other (and formed 40 categories) when we set the vigilance parameter equal to 1.0. Lower vigilance settings would lead to different categorizations, resulting in a smaller set of potential words in the lexicon. Note that since the greatest degree of match between different patterns was just less than 0.81, any value for vigilance between 0.81 and 1.0 give the same category structure; further simulations with vigilance settings within that range confirmed this property.

Next, we presented the network with the 24 possible patterns on which it had not been trained. Both the words and the nonwords contained a similar phonology and were comprised of A's, B's, C's, and D's. It successfully categorized all of these as unfamiliar (nonwords), because none of the new vectors activated category nodes to a degree greater than that of the vigilance parameter (which, as before, could range between 0.81 and 1.0). Thus, the mechanism for recognizing new patterns in the ART 2-A system could be applied to a task that might be mapped on to the process of word learning.⁵ The fact that a range of vigilance values was possible indicates that the system could manifest the same qualitative behavior even while tolerating a certain degree of variation in familiar patterns (so long as that variation did not bring the activation of the corresponding category node below the level of vigilance).

The success of the ART 2-A system as applied to lexical access phenomena as demonstrated in this paper illustrates the simplicity and power of the theoretical constructs that make up our account. ART principles were first suggested as a way to approach such phenomena by Grossberg and Stone (1986). We believe that our approach both lives up to the expectations put forward by that paper and improves on the overall methods by simplifying them and offering simulations as evidence of their efficacy. Specifically, we feel that we have demonstrated "that the unifying power of the theory is due to the fact that principles of adaptation—such as the laws regulating development, learning and unitization—are fundamental in determining the design of behavioral mechanisms" (Grossberg & Stone, 1986, p. 46), and we have done so in a novel and useful way.

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Notes

1. Note that this equation can potentially be applied to vectors and thus distributed patterns as well, such as the Brain-State-in-a-Box model (Anderson, Silverstein, Ritz, & Jones, 1977). The main equation for such a system would be: $x_i + 1 =$

$(\alpha - \beta \times t) Ax_i$, where x and A are a vector of activations and a matrix of connection weights, respectively.

2. It is assumed that the greater the unit of activation in the simulation, the greater the magnitude of priming. We are looking for a qualitative match between model behavior and subject performance rather than a 1:1 correspondence between the actual values obtained in the simulations and the particular reaction-time latencies obtained by Milberg et al. (1988a).

3. In this simulation, we reduced the VOT only by 2/3 since results of reducing VOT by 1/3 were nonsignificant (and not tested with aphasic patients).

4. Compare Killeen (1981).

5. We are well aware that the process of word learning is considerably more complex than elaborated here. Our system does not include semantics (cf. also Seidenberg & McClelland, 1989) nor do the input representations in the training phase contain any unallowable phonological strings. Nonetheless, the principles of self-organization could be applied as well to a more complex system with a greater range of inputs.

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