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A developmental neural model of word perception

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The Interactive Activation model (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982) has been successfully applied to a broad range of phenomena in the "letter-within-word" perception literature. A unique aspect of the Interactive Activation (IA) model is that all processing is based upon very simple local computations similar in spirit to the types of computations that might be performed by neurons. These simple local computations however, give rise to interesting global behaviors at the network level. The IA model operates by attempting to satisfy a great many local constraints between and within a set of letter and word "nodes." These local constraints, nevertheless, are explicitly given to the IA model. How might such constraints evolve over time if learning were incorporated into the IA model?

In this paper, a specific member of the class of neural models known as Brain-State-in-a-Box (BSB) models (Anderson, 1983; Anderson, Silverstein, Ritz, & Jones, 1977) is suggested as a useful approach for considering the development of visual letter within word perception. Interestingly enough, recent theoretical results (Golden, 1985; Hopfield, 1984) indicate that the dynamic behavior of the BSB and IA models share important qualitative similarities. The BSB formalism, however, is comparatively simpler than the IA formalism, makes interesting reaction time predictions, and provides a formal framework for considering how the effects of experience create and organize letter and word representations. More specifically, using both reaction time and letter recognition accuracy as dependent variables, the BSB model suggests how the effects of experience influence the development of the ability to use information about orthographic redundancy (Juola, Schadler, Chabot, & McCaughey, 1978; Lefton & Spragins, 1974) and case type (McClelland, 1976; Pollatsek, Well, & Schindler, 1975).

Description of the neural model

The testing dynamics of the model. The Brain-State-in-a-Box model is based upon a few neurophysiological assumptions. The first assumption is that essential information about the environment is assumed to be coded by a set of neuronal firing frequencies (Anderson, 1983; Anderson et al., 1977). If there are M neurons in the system, the momentary activation pattern across the neuronal set is characterized by an M-dimensional state vector in which the ith element of the state vector represents the firing frequency of the ith neuron in the system minus the spontaneous firing frequency of that neuron. The magnitude of the state vector represents the current signal strength while the direction of the state vector indicates the identity of the activation pattern. The second assumption states that, in general, the current firing rate of a neuron may be approximately represented by the linear combination of the firing rates of the other neurons in the system and a set of "synaptic connectivity coefficients." The connectivity coefficients are an attempt to model the degree of synaptic efficacy between pairs of neurons within the system. Using matrix notation, these coefficients are arranged in a matrix such that the ijth element of the matrix represents the connection strength between the ith and jth neurons in the system. The state vector at discrete time slice $t + 1$ may now be rewritten as the state vector at discrete time slice t plus the state vector at discrete time slice t multiplied by the matrix. The third assumption of the model is that each neuron possesses a maximum and minimum firing rate. This final assumption introduces an essential non-linearity into the previous linear system and gives the model an exceptionally rich range of behavior. This assumption is also the motivation behind the model's nickname since it essentially confines the M-dimensional state vector within the space of an M-dimensional box or hypercube (for additional details see Anderson et al., 1977).

The dynamics of the system are relatively straightforward. An initial pattern of neural activity is amplified using positive feedback until all neurons within the system have obtained their maximum or minimum firing rates. More formally, one cycle through the system may be written as:

$$\mathbf{S}(i + 1) = \mathrm{TRUNC}[\mathbf{AS}(i) + \mathbf{S}(i)] = \mathrm{TRUNC}[(\mathbf{A} + \mathbf{I})\mathbf{S}(i)] \tag{1}$$

where **I** is the identity matrix, the notation **S**(i) indicates the activity vector after the ith feedback cycle, **A** is the synaptic connectivity matrix, and the TRUNC function sets all vector elements whose magnitudes are above some maximum firing frequency equal to that maximum firing frequency and all vector elements whose magnitudes are below some minimum firing frequency equal to that minimum firing frequency.

The initial state vector **S**(0) is presented to the system by applying equation (1) to **S**(0) to generate **S**(1). The state vector **S**(1) is then applied to equation (1) to generate **S**(2). These iterations continue until **S**(i) = **S**(i + 1). At this point, all the elements of the system state vector are firing at their minimum or maximum firing rates. Since in this situation the state vector has reached one of the hypercube corners, we will call this state vector a corner vector. If the state vector arrives at the "correct" hypercube corner, then the stimulus is assumed to have been properly categorized. The number of iterations required to arrive at a hypercube corner is taken as the system's reaction time.

The training algorithm. In typical simulations of the model, we assume that the period over which learning occurs is extremely long, relative to the period over which the model is tested. Therefore, for simplicity, learning is not permitted when the model is tested. The learning assumption implemented in this model is based upon a proposal by Hebb (1949) that states if two neurons within a neural network simultaneously fire, then a change in the nervous system occurs such that if one of the two neurons fires at a future date the probability that the other neuron will fire tends to increase.

During the training phase, a stimulus and response vector pair are randomly selected from the stimulus set. The stimulus vector is then perturbed with random noise and passed through (1) several times. The transformed stimulus vector and the corresponding response vector are then used to modify the matrix. Using linear algebra, the learning assumption is described by the following equation:

$$\mathbf{A}_{new} = \mathbf{A}_{old} + \gamma[\mathbf{g} - \mathbf{S}(K)][\mathbf{g} - \mathbf{S}(K)]^T \tag{2}$$

where **S**(K) is the stimulus vector after K iterations through equation (1), $\mathbf{A}_{new}$ is the updated synaptic connectivity matrix, $\mathbf{A}_{old}$ is the original matrix, **g** is the desired response of the system, and γ is a scalar between zero and one. For the simulations reported here, the value of K remained constant and was always equal to seven.

Equation (2) therefore describes how the synaptic efficacy between individual neurons within the system evolves over time as stimulus and response vectors are presented to the model. The exact form of (2) is not critical. Any learning rule that biases the coefficients of the connectivity matrix such that the stimuli within the training set become eigenvectors (associated with large positive eigenvalues) of the matrix will suffice (Golden, 1985).

Neural encoding of the stimuli. The assignment of "neural activation patterns" to specific symbols is as important to the formulation of the letter within word model as the basic BSB mechanism itself. A unique 28-dimensional state vector was assigned to each of the upper-case and lower-case forms of the nine most frequent letters of the English alphabet using a letter feature encoding scheme. A stimulus representing a letter string could then be represented by concatenating four 28-dimensional letter subvectors. Thus, four-letter words, pseudowords, and nonwords were represented by 112-dimensional vectors.

Theory

Although the proposed model superficially seems rather homogeneous, a great deal of structure exists in the synaptic connectivity matrix after learning has occurred. This specific internal structure is due to two factors. First, the system state vector is a list of position-specific letter features. And second, the learning algorithm effectively extracts frequently appearing pair-wise feature correlations from the stimuli learned by the model. Therefore, the matrix contains two distinct types of synaptic weights or pair-wise letter feature correlations. One set of synaptic weights are referred to as the *within-letter* feature correlations. The second set of weights are referred to as *between-letter* feature correlations. The within-letter feature correlations in the matrix correspond to the system's knowledge of the spatially redundant information in words. The between-letter feature correlations correspond to the system's knowledge of the transgraphemic information in words.

By definition, a nonword is a state vector that has not been "learned" by the system. Such a vector can nevertheless be categorized by the BSB model since the within-letter feature correlations can independently amplify the familiar letter subvectors representing the nonword stimulus, despite interference from the between-letter feature correlations. When a word or pseudoword is presented to the system, both the between-letter and within-letter feature correlations cooperatively amplify the system state vector. Words, however, tend to be recognized faster and more accurately than pseudowords since fewer between-letter feature correlations contribute to the amplification process during pseudoword recognition. Also note that, within the framework of this model, the superiority of letter recognition for same-case relative to mixed-case stimuli is exactly analogous to the word-pseudoword advantage.

Consider now the major effects characterizing the developmental behavior of the model. First, as the system's experience with words increases, letters are recognized faster and more accurately within words, pseudowords, and nonwords. And second, the ability to use information about the orthographic regularities within words develops very quickly. The first effect is a direct consequence of the number of times a given pair of letter features was presented to the system during the learning trials. The rapid acquisition of the ability to detect orthographic information occurs because useful letter feature correlations, obtained from only a few words, are used to categorize many other words possessing those feature correlations.

The model also makes a prediction regarding the development of alternating case effects. As experience with words increases, the advantage of letters within same-case stimuli, relative to mixed-case stimuli, should increase at a fast rate in the initial stages of development and more slowly in the later stages. A theory suggesting that the effects of alternating case are located at the "level of single letter discriminability" (Adams, 1979, p. 154; also see McClelland & Rumelhart, 1981), might not make these predictions.

Computer simulation results

In the first set of experiments, the synaptic coefficients were initialized to zero and then letter stimuli were "taught" to the system with (2). After 1500 presentations of letter stimuli, the system was tested using a set of test stimuli. The test stimulus set consisted of 1176 different mixed-case and same-case words, pseudowords, and nonwords. The reaction time of the system for correctly categorizing each of the initial state vectors representing letter strings was then recorded. The above testing procedure was then repeated after the system had experienced 200 more presentations of word stimuli. Finally, the training of the system upon word stimuli was continued for an additional 800 learning presentations and again the testing procedure was repeated.

The simulation results are summarized in Figure 1. The reaction time of the model for recognizing four letter strings, like human subjects, tended to decrease with age and experience (Juola et al., 1978). In addition, the qualitative effects of a rapid acquisition of orthographic knowledge that becomes increasingly fine-tuned over a relatively longer period of time is also observed (Juola et al., 1978). In addition, as letter strings become more orthographically regular, letters in same-case stimuli are recognized faster than letters in mixed-case stimuli. These latter reaction time results have also been observed in the experimental literature (Pollatsek et al., 1975; Taylor, Miller, & Juola, 1977).

Figure 2 summarizes the results of a similar sequence of simulations where letter recognition errors were used as the dependent measure. In these latter simulations the model made frequent identification errors because of the addition of interfering factors (a mask and additive noise) in the testing procedure. Again, the basic qualitative effects observed in the human experimental literature were also observed in the simulations. Words were recognized more efficiently than pseudowords, which were recognized more efficiently than nonwords, and same-case stimuli were recognized more efficiently than mixed-case stimuli. The simulations also demonstrate a case-type by orthography interaction. Such an effect, although in agreement with reaction time studies of this phenomena and accuracy data obtained by McClelland (1976), was not observed by Adams (1979). The rapid acquisition of orthographic knowledge by the model has also been observed using decision tasks involving human subjects (Lefton & Spragins, 1974; Rosinski & Wheeler, 1972).

Summary

A developmental version of the Interactive Activation model has been proposed based upon a neural network model suggested originally by Anderson et al. (1977). The developmental BSB model offers a formal theory that motivates the use and connection of letter and word nodes in the IA model. To explicitly illustrate these statements, some simulations of the BSB model were then studied. The results of the computer simulations were compatible with the experimental literature. Effects of orthography and case type were observed to increase in magnitude as the system's experience with word-like stimuli was extended.

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Appendix 1

Vector Encodings of Letter Stimuli

The following table indicates the assignment of specific letter subvectors to letters. The assignment of a vector coding to a letter was based upon an extension of Gibson's (1969, p. 88) abstract letter feature set. For example, the first eight elements of the letter subvector representing E are given by (+1,+1,+1,+1,-1,-1,-1,-1). For convenience, letter subvectors are described using hexadecimal notation by treating negative vector elements as zeros and positive vector elements as ones. Thus, the above eight-dimensional component of the letter subvector specifying E is represented as F0 using hexadecimal (base 16) notation. The letter subvector encodings using hexadecimal notation are provided below.

E	F003F3F	e	C0CF030
T	F00333F	t	F03F0FF
A	CF033CF	a	00C3030
O	00C030F	o	00C0300
N	33000CF	n	30300C0
R	33C30CF	r	303F0F0
I	30003CF	i	30003F0
S	000CC0F	s	000CC00
H	F0033CF	h	30300CF
X	0F0330F		

Appendix 2

Letter string stimuli selection

Word, pseudoword, and nonword letter strings were used as word vectors in the following experiments. The word stimuli were selected based upon moderate frequency of occurrence in the English language, and were constructed using only the nine most frequent letters in the English alphabet. The word stimuli were then scrambled, and the scrambled letter strings ranked using a spatial redundancy (i.e., using the likelihood that a particular letter would occur at a given spatial position within a word) table obtained by analyzing the original set of word stimuli (see Mason, 1975, for additional details).

Word Stimuli (ordered row-wise by decreasing frequency): THAT THIS INTO THAN THEN HERE AREA SEEN RATE SOON NEAR EAST SORT REST HEAR HAIR SENT NOTE TEST ONES SHOT NONE RISE HEAT THIN ROSE NINE TONE RAIN ARTS SITE SETS NOSE ONTO TREE SEAT HERO REAR ASIA HANS IRON ANNE EASE HATE RARE EARS OHIO HOST SEES HORN ROOT SONS TONS NOON STAR TORN HITS TIRE NEAT RENT NEST TENT TOES THEE EARN HERS SINS HIRE TIES TORE HATS NEON SHOE ROAR TROT ROSS TEAR SEAS SORE HINT HOOT HOSE IONS THOR TOSS TRIO SANE ANNA ANTS HEIR OATS RENO RIOT STIR TART OATH SITS TEEN

Pseudoword Stimuli(ordered row-wise by decreasing spatial redundancy): TENE TERE TETS TORS SENE TOSE TEOS TEIS SESE SONT SEST TETN RETS TASE TENR SOST THNE TONR TEAN TESN TOSN SOET SARE TEHE SETN TOEN NETS TISE TESR REAT ROES TOOR OENS AETS HONR SOSN TOER THOS NORT SOTR NEES NOOS SAES ROIT NOES RETN HAST TERA SOHE RAAE NOOT SONO HESR EONT SOSR EORS NEET TNOE SAET TROE AEES NOET HEOR TATR REAN HAET TNOS AOST HEER SOER REON SIST NARE EORT SOHT TRIE TRAT RAST HIST HOTO TEAH TEHN SIET SETA TOSH TNET SNAE HTNE RAET HERA HETA TOOH TAHT TAER SROE HASN SESA SERH

Nonword Stimuli (ordered row-wise by decreasing spatial redundancy): IRES AHSN OHNR TSRA OISN OTSS EASR SRTA SNTA OTAS ESSE ITSE IHTN INOT TROI OAHT SNEO ERET EOSH ORIT ESAE NSET HTRO HREO HTNA HSTO TSRI RAIH ESST ERTN STRA ANAN EISR ESAT HTTA EHSR ISST HTNI EHOR RTTO OHTO ANEN ERAN RNEO EHER ONEN ISET HSEO ERON STRI EATH ONNO OTNR ETTN IHER ESTN INEN ARER OTSN ENNO ATTR AISA HTSI EHRA EHTA ORTO OSSN IRNO OSTR AHRI OTEN ASEN EIRH ISSN IRTO ENNA OTNO OSNO ARNI ORRA EHRI ENRA ERRA ENTA OTER ITNO OSER RTOI OHOI NROI ITER ONTI ETRA ESTA OIHO ESSA OTAH ASAI

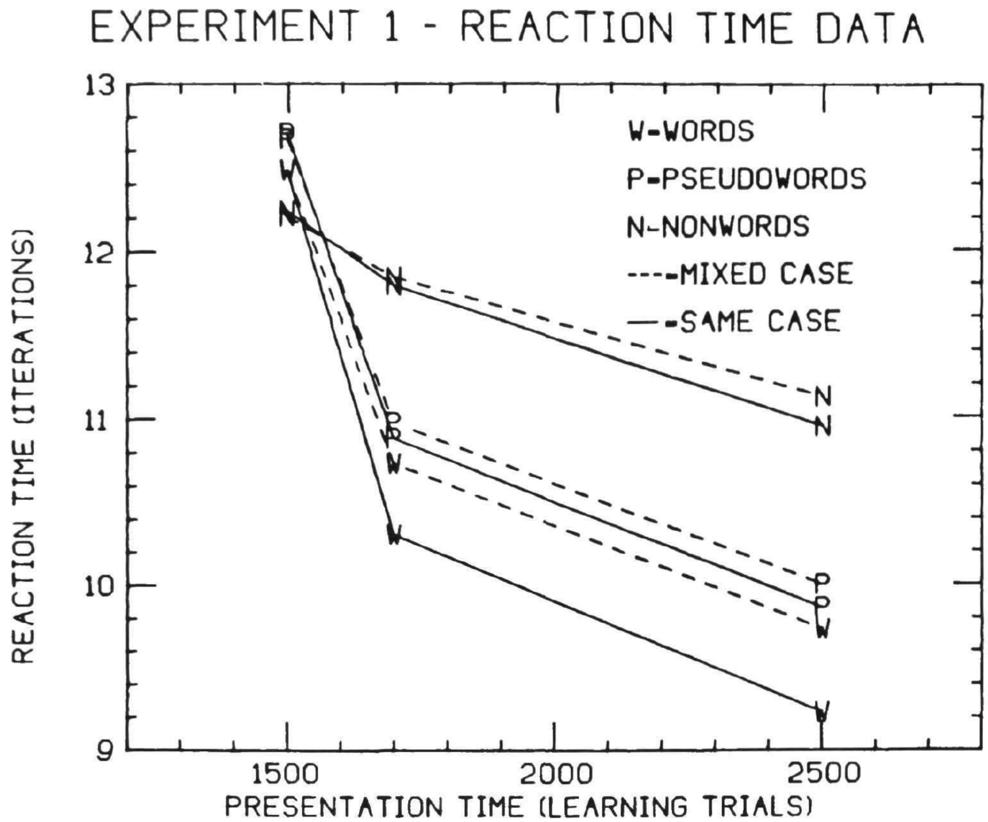

Figure 1. Reaction time plotted as a function of case type, orthography, and learning trials for Experiment 1. Solid lines indicate same-case stimuli. Dashed lines indicate mixed-case stimuli.

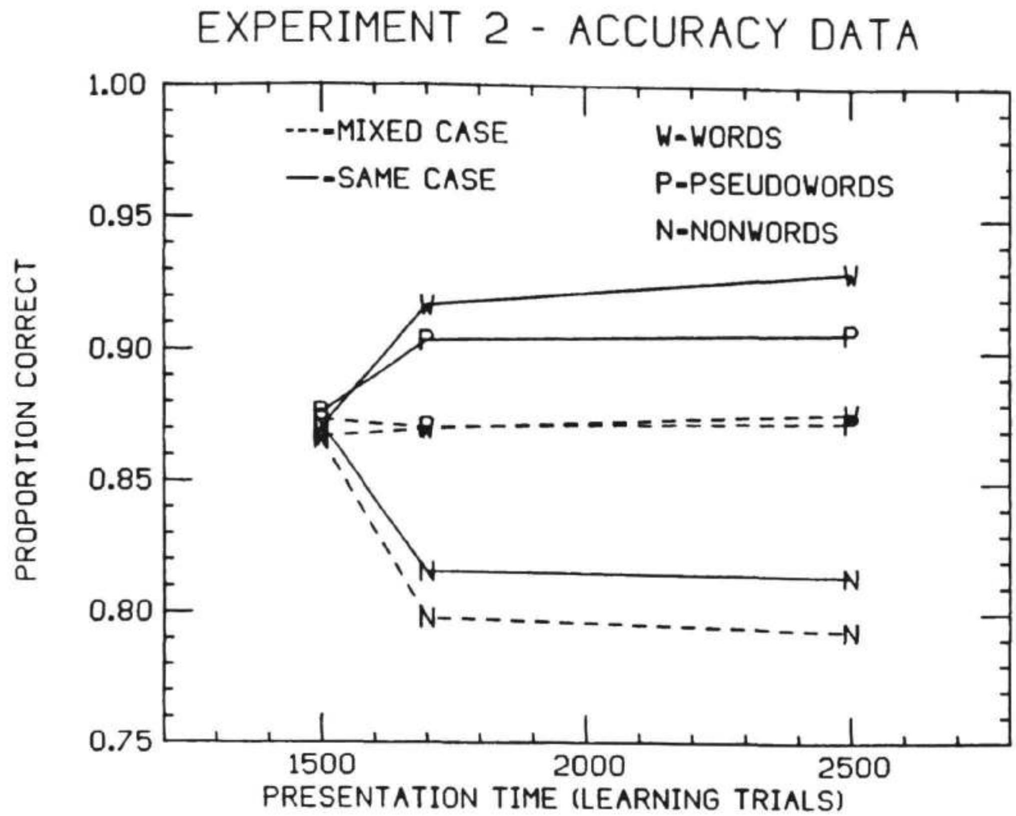

Figure 2. The proportion of correctly recognized letters plotted as a function of case type, orthography, and learning trials for Experiment 2. Solid lines indicate same-case stimuli. Dashed lines indicate mixed-case stimuli.