Adaptive Synaptogenesis Constructs Networks Which Allocate Network Resources By Category Frequency

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Abstract— In this report we demonstrate the effectiveness of two adaptive processes in constructing simple, feed-forward networks which allocate the resources of the output layer based on the frequencies of the categories that compose the input environment. Specifically, the adaptive processes build networks which allocate more output layer resources to categories that appear more frequently in the input. In turn, less frequently appearing input categories are allocated fewer output resources. The two adaptive processes, synaptogenesis and associative modification, build a network connectivity in initially unconnected networks. The first process, synaptogenesis, creates new synaptic connections; the second process, associative synaptic modification, modifies the strength of existing synaptic connections. Because these processes operate in a unsupervised fashion using only information available locally at the neurons and synapses, they provide a biologically plausible model for the allocation of neural resources.

I. Introduction

To interact successfully with its world, an animal builds a working model of its external environment. An integral component of this working model is the construction of sensible, efficient neural representations of the sensory input. We conjecture that a sensible recoding of the neural input would provide more resources for those items and ideas, i.e. categories, that appear more frequently in the animal's world. Alternately, fewer neural resources would be allocated for those categories that the animal rarely encounters.

Indeed, it has been well noted in linguistic studies of various cultures that more words are ascribed to common environmental features. For example, the Eskimos have a plethora of words for snow (Boas 1911); some Asian languages differentiate among varieties of rice. Clark and Clark (1977) suggested that the cultural differences in the number of words allocated for "snow" and "rice" do not reflect different ways of thinking between cultures but, rather, simply differences in the environments in which the cultures developed.

The notion of allocating more resources to commonly appearing categories is appealing when viewed from the coding perspective. By allocating more representational resources to commonly appearing categories, it is possible to uniquely code a larger number of category variations. In fact, cognitive studies have illustrated that experts have knowledge structures which are more detailed than those of novices. As an example, Herbert Simon reasoned that chess masters have spent on average 10,000 to 20,000 hours staring at chess positions and, as a result, are thought to be able to distinguish on the order of 50,000 different chess board configurations (Chase and Simon 1973). The storage of such a vast number of configurations, or, in neural terms, the creation of such a vast number of different neural representations, requires the allocation of sufficient representational capacity. In the simplest case, increased representational capacity can be met through the allocation of an increased number of coding elements or, in neural terms, an increased number of neurons. In fact, studies measuring the relative activity of brain regions have demonstrated that, while listening to music, more brain areas of expert musicians are activated as compared with musical novices (Mazziotta et al. 1982).

Therefore, we are motivated to study biologically plausible mechanisms that allocate neural resources based on the frequency of categories in the input. In the present work we demonstrate the ability of two such mechanisms, synaptogenesis and associative modification, to create networks that allocate resources based on category probability. The first process, synaptogenesis, places synapses between input and output neurons based on the output neuron's time-varying receptivity to new innervation. The second process, associative modification, ad-

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0-7803-1901-X/94 $4.00 ©1994 IEEE

justs the synaptic weight of existing synapses. We previously demonstrated that these mechanisms are useful for constructing networks which perform transformations that remove redundancy while preserving representational information (Adelsberger-Mangan and Levy 1992c, 1993ab).

In this study networks are created adaptively using one of two inputs, both of which are composed of four categories; each category appears with a different frequency. In the first input there is a small amount of overlap in the patterns belonging to different categories; in the second input there is no overlap in the patterns belonging to different categories. The allocation of output layer resources are quantified using two measures derived from probability theory: 1) $\Sigma_j P(C = x|Y_j = 1)$, which measures the allocation of the output neurons to each input category, and 2) $\Sigma_j H(Y_j|C = x)$, which measures the representational capacity allocated to each input category. We also investigate the effect of output firing level on the allocation of network resources.

II. Network Simulations

The networks are composed of two layers, an input (X) and an output (Y) layer. The input layer is composed of 80 neurons, the output layer is composed of 40 neurons. The neurons of the input and output layers are binary with values {1,0}, corresponding to {firing,not firing} at a particular time step t.

Input Environments. Two environments provide input to the networks. Each input contains 100 patterns; each pattern is a member of one of four categories. In each input, 10 patterns are members of category one, 20 patterns are members of category two, 30 patterns are members of category three, and 40 patterns are members of category four. The two inputs differ in the amount of overlap between the category patterns.

The first input has a small amount of overlap between the patterns of different categories. This input is created using four orthogonal category prototypes; each prototype has 20 input lines which are equal to one. The remaining patterns of each category are equivalent to the category prototype with the exception that one input line is selected randomly and its value is switched. The average number of coactive input lines of patterns from the same category is 19.4; the average number of coactive lines of patterns from different categories is 0.4. The input contains 6.5 bits of representational information and 55.2 bits of statistical dependence (for details on the calculation of these entropies see Adelsberger-Mangan and Levy 1992a,b).

The second input is created by simply removing all of the between-category overlap from the previous input. Therefore, in this input, each pattern of a given category is orthogonal to all patterns from all other categories. Here the average number of coactive input lines of patterns from the same category is 19.3; the average number of coactive lines of patterns from different categories is 0. This input contains only 3.7 bits of representational information and 56.7 bits of statistical dependence.

Output Neurons. All connections formed by the synaptogenesis mechanism are feed-forward and excitatory. At each time step t, the activity, $Y_j(t)$, of output neuron j is determined by the input activities $X_i(t)$ and by the synaptic connection strengths $W_{i_k j}(t)$ according to

$$Y_j(t) = f\ (\Sigma_i \Sigma_k X_i(t) \cdot W_{i_k j}(t))$$

where k indexes multiple synapses between an input neuron i and an output neuron j, where the summation over i only includes connected neurons, and where

$$f(s) = 1\, if\ s \geq the\ firing\ threshold,\ 0\ otherwise.$$

Network Development. All networks are initially unconnected, i.e., there are no synaptic connections between the input and output layer. The synaptic connectivity between the input and output layer develops adaptively under the control of two local processes: synaptogenesis and associative synaptic modification of existing weights.

Synaptogenesis. For each output neuron, synaptogenesis is a Bernoulli process controlled by that neuron's time-varying receptivity to new innervation. Specifically, for output neuron j, the receptivity at time t is

$$R_j(t) = \frac{C_r}{C_r + \hat{y}_j(t)^P}$$

where $\hat{y}_j(t)$ is the running average of the firing rate of output neuron j and is calculated as

$$\hat{y}_j(t) = 0.998\, \hat{y}_j(t-1) + 0.002\, Y_j(t).$$

The constants C_r and P are determined by calculation depending upon the minimum acceptable level of output neuron firing. In those simulations where an output firing level of at least 0.001 is desired, a receptivity of 0.50 results when the output neuron firing level is 0.025, and a receptivity of 0.0[illegible] results when the output neuron firing level is 0.001 (specifically, $C_r = 6.176 \times 10^{-12}$, $P = 9.964$). In those simulations where an output firing level of at least

0.15 is desired, a receptivity of 0.50 results when the output neuron firing level is 0.075, and a receptivity of 0.001 results when the output firing level is 0.15 (specifically, $C_r = 1.281 \times 10^{-33}$, $P = 9.964$). In both cases, $R_j(t)$ ranges from a value of 1.0, when the output neuron never fires over a long period of time, to essentially zero as the firing level approaches the minimum acceptable output firing level. Note that the receptivity mechanism insures that each output neuron achieves a firing level at least equal to the minimum acceptable level. The output neurons typically achieve a firing level that is greater than the firing level needed to drive receptivity to zero.

Synaptogenesis begins at time step 1 by running the 3,200 (80x40) individual Bernoulli processes that control the creation of new synaptic connections. For each input/output neuron pair, the probability of the creation of a synaptic connection, $P_{ij}(t)$, is equal to

$$P_{ij}(t) = 0.005\, R_j(t)$$

The rate of new synapse formation is set very low to allow for the approximate convergence of the weights of existing synapses (see the Synaptic Modification section) and $\hat{y}_j(t)$ before the next bout of synaptogenesis (Levy and Desmond 1985; Levy and Colbert 1991). Because the rate of synaptogenesis is very slow, many opportunities are necessary to insure that the receptivity of each output neuron is essentially zero. Therefore, after the first synaptogenesis step, the process recurs every 1000 time steps.

Input Presentation. At each time step t an input pattern is selected at random (using a pseudorandom number generator) for presentation to the input layer. However, the choice of an input pattern is biased so that there is a 10% probability that the input pattern is a member of category one, a 20% probability that the input pattern is a member of category two, a 30% probability that the input pattern is a member of category three, and a 40% probability that the input pattern is a member of category four.

Synaptic Modification. Between each synaptogenesis step the input is presented for 1000 time steps. At each time step t, the weight of synapse k between input layer neuron i and output layer neuron j is modified according to

$$W_{i_k j}(t+1) = W_{i_k j}(t) + \Delta W_{i_k j}(t, t+1) \quad where$$

$$\Delta W_{i_k j}(t, t+1) = 0.025 \cdot Y_j(t) \cdot (\, X_i(t) - W_{i_k j}(t)\,).$$

Simulation Duration. The simulation continues until network connectivity stabilizes. Specifically, the number of output neurons with an average firing level ($\hat{y}_j$) greater than, or equal to, the minimum acceptable level (in these simulations either 0.001 or 0.15) is counted at each synaptogenesis time step. If this number equals 40 (i.e, all the output neurons have attained the preset minimum acceptable firing level), and there were no new synapses added to the network at that step, network construction ends.

Network Testing. After the period of network construction just described the input is presented to the input layer and the corresponding output patterns are archived. From these, the probability of a particular category given output neuron firing, $P(C = x|Y_j = 1)$, for each output neuron over each category, is determined. This measure is then summed over the output layer to produce $\Sigma_j P(C = x|Y_j = 1)$. This sum, when summed over the four categories, equals 40, the number of output neurons. This measure thus quantifies the allocation of the output layer neurons to each category. A second measure, the sum over the output layer of the conditional entropies of output neuron firing given a particular category, $\Sigma_j H(Y_j|C = x)$ (measured in bits), is also determined. This entropy measure quantifies the output layer representational capacity allocated to each category.

III. Results

Using two adaptive mechanisms, synaptogenesis and associative weight modification, networks are constructed with the requirement that each output neuron attains a minimum acceptable firing level, in these simulations either 0.001 or 0.150. The networks are constructed using one of two inputs; each input is composed of four categories. The two inputs differ in the amount of overlap between categories. Initially networks are constructed using the input composed of orthogonal categories and with the requirement that each output neuron attains a firing level of at least 0.001. Next, networks are constructed with the same requirement on output firing levels, that is, that each output neuron attains a firing level of at least 0.001, but the input to the networks contains overlapping categories. Finally, networks are constructed using the input with overlapping categories but with the requirement that each output neuron attains a firing level of at least 0.15. For each combination of input and minimum output firing level, networks are constructed with output firing thresholds which range from 0.50 to 5.00. Each reported value is the average obtained from 20 adaptively constructed networks.

As seen in Figure 1, network resources are allocated differently depending upon the presence of overlap in the categories comprising the input and on the minimum output firing level required to end

In general, a minimum output firing level which is greater than a category probability results in a decreased allocation of resources for that category. The distribution of ouput layer resources under the three network construction paradigms is unaffected by firing threshold over the range 0.25 to 5.00.

Networks constructed using synaptogenesis and associative modification create similar output representations when driven by input patterns belonging to the same category. Conversely, output representations driven by input patterns belonging to different categories are unlike (see Table 1). Specifically, there are many more output neurons coactive when the input patterns driving the output are members of the same categories as compared to the number of coactive output lines in outputs driven by input patterns belonging to different categories.

IV. Discussion

In this work we have demonstrated the utility of two adaptive mechanisms, synaptogenesis and associative synapse modification, in constructing networks which allocate output layer resources as a function of input category probability. Specifically, as category probability increases, more output layer neurons signal the presence of the category, and increased output representational capacity is allocated for the coding of the category members. The allocation of network resources is not affected by output firing threshold over the range 0.50 to 5.00. Additionally, as the two adaptive processes use only information available locally at the neurons and synapses, they provide a biologically plausible model for network construction. However, the success of the adaptive mechanisms is affected by the amount of overlap between the input categories and by the minimum required output firing level. Specifically, if no overlap exists between the input categories the adaptive mechanisms allocate equal network resources to each category, regardless of category probability. In addition, a minimum required output firing level which is greater than a input category probability results in a decreased allocation of neural resources for that category.

V. References

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VI. Acknowledgments

This work was supported by NIH RR07864, MH48161, MH00622 and NSF MSS 9216372 and EPRI RP8030-08 and by the Department of Neurological Surgery, University of Virginia Health Sciences Center, Dr. John A Jane, Chairman.

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Volume IV
Pages 2004-2714