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Character Recognition Using Adaptively Constructed Feed-Forward Networks

Dawn M. Adelsberger-Mangan[1,2] and William B Levy[2]
[1] Department of Biomedical Engineering [2] Department of Neurological Surgery
University of Virginia Health Sciences Center Box 420
Charlottesville, Virginia 22908

Abstract

In this report we demonstrate the effectiveness of two adaptive processes in constructing a simple feed-forward network that transforms alphanumeric input. The two processes build networks that perform transformations that reduce statistical dependence while maintaining almost all of the input information. The two processes build appropriate synaptic connections in initially unconnected networks. The first process, synaptogenesis, creates new synaptic connections; the second process, associative synaptic modification, adjusts the connection strength of existing synapses. Synaptogenesis accrues additional input innervation for each output neuron until each output neuron achieves a firing rate of approximately 0.50. The second process, associative synaptic modification, stores the correlation of input and output neuron firing using an Hebbian modification rule. The two processes create synaptic connectivity using only information available locally at the neurons and synapses. Because of this unsupervised local property, this model of network development seems biologically plausible. The results of a network constructed utilizing these adaptive processes are compared to those obtained with another set of adaptive principles (Földiák 1990).

Introduction

To interact successfully with its environment, an animal must create efficient neural representations from high dimensional sensory input. Creating efficient representations is an issue because the primary input from all sensory modalities contains high levels of redundancy. Removing this redundancy is central in creating efficient neural representations. In fact, well over 30 years ago Barlow proposed that the storage and utilization of sensory input would be made easier if the redundancy of the sensory input were reduced (Barlow 1959).

The utility of removing redundancy can be illustrated from the computational perspective. For reasons of computational complexity, it will always be impossible to implement certain algorithms on multidimensional input. Complexity can be directly identified with statistical dependence. Alternately, fully independent signals are easy to process. When redundancy is completely removed, statistical independence obtains.

Therefore, a network that transforms inputs into outputs with reduced statistical dependence is desirable. However any transformation for the purpose of reducing statistical dependence risks information loss (Richards and Levy 1990). When the value of the lost information is unknown, any information loss must be considered worrisome. Therefore, in addition to measuring the change in statistical dependence by a network transformation, we also quantify the information loss incurred with recoding. During a successful transformation, information loss is minimized while the decrease in statistical dependence is maximized.

In previous work from our laboratory, we illustrated the paramount importance of matching firing threshold and synaptic connectivity in order for a network to perform good transformations on their inputs (Adelsberger-Mangan and Levy 1992a). These results were obtained in networks where the synaptic connectivity was fixed. That is, while synaptic weights were modified, no synaptic connections were added or removed. This research also demonstrated a marked increase in performance in those networks where output firing threshold was dynamically regulated in order to maintain output firing levels at approximately 50%. However, even when optimizing output firing threshold and network connectivity, the networks with fixed connectivity very often lost a significant percentage of the input representational information.

In the present work we demonstrate the combined ability of two adaptive processes to create a network with better performance. The two processes build synaptic connections in initially unconnected networks. The first process, synaptogenesis, places synapses between the input and output layers based on the time-varying receptivity of the output neurons to new input innervation. The second process, associative synaptic modification, adjusts the weights of existing synapses. Rather than dynamically regulating output firing threshold in order to achieve desired output firing levels, the adaptive processes construct a synaptic connectivity which produces the desired output firing level. As demonstrated elsewhere (Adelsberger-Mangan and Levy 1992b), networks constructed using these processes successfully transform a variety of input environments. In this report, the processes confront the more difficult task of creating a network which will successfully transform alphanumeric input.

Simulations

The networks constructed in this research are composed of two layers, an input (X) and an output layer (Y). The input layer is composed of 120 neurons, the output layer is composed of 10 neurons. The neurons of the input and output layer are binary with values of {1,0} corresponding to {firing, not firing} at a particular time step t.

Input Environment. The input for the networks consisted of images of IBM-PC alphanumeric characters in a fixed position on a 8x15 grid (8x15 = 120). There were 82 different input characters, corresponding to the 82 most common alphanumeric characters in a sample of English text (Barlow et al. 1989). During network development the alphanumeric characters were presented randomly to the input layer with the same probabilities as they appeared in the English text (Barlow et. al. 1989). The representational information of the input environment was 4.34 bits and the statistical dependence was 52.14 bits.

There was a wide variability both in the firing rate of the input neurons and in the number of input neurons firing per input character. The firing rate of the input neurons varied between zero (perimeter neurons which never fired) to neurons which fired over 71% of the time (the mean firing rate of the input neurons was 0.20 with a standard deviation of 0.22). And while only four input neurons are firing during the presentation of the character ".", 50 neurons are firing during the presentation of the character "M" (the mean number of neurons firing was 23.4 with a standard deviation of 12.2).

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

$$Y_j(t) = f\left(\Sigma_i \Sigma_k X_i(t) \cdot W_{i,j}(t)\right)$$

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

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

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

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

$$R_j(t) = C / (C + \hat{y}_j(t)^P)$$

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

$$\hat{y}_j(t) = 0.95\hat{y}_j(t-1) + 0.05\hat{y}_j(t).$$

The constants C and P were determined by calculation so that a receptivity of 0.50 resulted when the firing level was 0.25, and a receptivity of 0.001 resulted when the firing level was 0.50. (Specifically, C = $1x10^{-6}$; P = 9.964). $R_j(t)$ ranged from a value of 1.0 when the output neuron never fired over a long period of time to essentially zero as the firing level approached 0.50.

The first of the individual Bernoulli processes that controlled the creation of new synaptic connections at each output neuron occurred at time step 1. Because the rate of synapse formation was very slow, 600 opportunities for synapse creation were necessary to ensure suitable levels of output firing. At each synaptogenesis opportunity, the creation of a new synaptic connection between input neuron i and output neuron j occurred with a probability

$$P_{ij} = \gamma \ R_j(t)$$

where γ was equal to 0.002. After P_{ij} was computed for an input/output neuron pair, a pseudo-random number generator determined whether a new synapse was placed between the pair. The slow rate of synaptogenesis allowed approximate convergence of the strengths of existing synaptic connections and allowed $\hat{y}(t)$ to converge before the next bout of synaptogenesis (Levy and Desmond 1985; Levy and Colbert 1991).

The connection strength of all newly created synapses was 0.20.

Synaptic Modification. Between each synaptogenesis step the alphanumeric input was presented for 820 time steps. At each time step t, the synaptic weight of synapse k between input layer neuron i and output layer neuron j was adjusted according to

$$W_{i,j}(t+1) = W_{i,j}(t) + \Delta W_{i,j}(t,t+1)$$

where $$\Delta W_{i,j}(t,t+1) = .05 \cdot Y_j(t) \cdot (X_i(t) - W_{i,j}(t)).$$

A natural consequence of this synaptic modification rule and of the maximum and minimum values of each X_i was that individual synaptic strengths remained bounded within the range zero to one. Thus, excitatory synapses were not converted into inhibitory synapses. Nevertheless, the sum of the connection weights between input neuron i and output neuron j was unbounded because multiple synapses could exist between a given input/output pair.

After the development period described above, the receptivity of the output layer neurons was essentially zero. To quantify network performance the alphanumeric inputs were presented at the input layer according to their appropriate probabilities and the corresponding output patterns were archived.

Network Measures. The set of input neurons' activities is represented by the random vector X; let x be a particular state of activities of the set. The representational information of the input neuron layer, or the entropy, is

$$H(X) = E[-\log P(X=x)] = -\Sigma_{x \in S} P(X=x) \cdot \log P(X=x)$$

where E[ ] denotes expectation and S is the set of all possible states x. H(X) is the average information in the representation space X.

The conditional entropy, H(X|Y), measures the information lost in the transformation from the input to output layer. However, the transformation performed in this network is noiseless, memoryless and deterministic. Therefore, the joint entropy of the input and output layer, H(X,Y) is equal to H(X), the entropy of the input layer. In this case then, the conditional entropy can be calculated as

$$H(X|Y) = -\Sigma_{xy \in S} P(X,Y) \cdot \log \left(P(X,Y)/P(Y) \right) = H(X,Y) - H(Y) = H(X) - H(Y)$$

Therefore, when no information is lost in the transformation, H(Y) = H(X), the largest possible value.

A good preprocessing transformation creates output representations which contain less statistical dependence than the inputs which drive them. The measure of statistical dependence was introduced by Watanabe (1969) and is a multivariate generalization of Shannon's mutual information (Shannon and Weaver 1949). It is calculated as

$$\text{Statistical Dependence of } X = \Sigma_x P(X) \cdot \log P(X)/\Pi_i P(X) = \Sigma_i H(X_i) - H(X)$$

where $H(X_i)$ is the entropy of neuron i firing. Statistical dependence is a non-negative quantity which is zero when full independence obtains. A good network transformation yields an output statistical dependence which is less than the input environment statistical dependence.

Two additional measures quantify redundancy: the so called "higher-order" redundancy (Statistical Dependence/Representational Information) and Shannon's redundancy (1 - (H(X)/C), where C is the neuron layer representational capacity. When neurons are binary, C equals the number of neurons.).

Comparison to Other Work. In his 1990 report, Földiák demonstrated an unsupervised neural network algorithm that successfully transformed alphanumeric input. Földiák's input environment consisted of the same 82 characters, appearing with the same relative probabilities as employed here. However, Földiák obtained his characters from the standard system font of a Sun-3 workstation, which differs from the IBM fonts used here (see Input Environment). Therefore, while Földiák's input representational entropy was equal to ours, the statistical dependence of his input set differed from that employed in these simulations (19.50 bits vs. 52.14 bits). Földiák also normalized the input characters to unit length before presentation to the input layer.

Results

The results discussed here were obtained with an output firing threshold of 0.10. At this threshold the network produced by synaptogenesis was very sparsely connected with, on average, only 2.6 input neurons innervating each output neuron.

As with Földiák's network, the output code generated by our adaptively constructed network maintained some degree of neighborhoodness, that is, similar inputs map to similar outputs. For example, the output representation of the characters "Q" and "O" differ in their output code by only one neuron. Similarly, the networks confuse the inputs "i","l","1" and "!".

A comparison of input and output information measures for the two networks is detailed in Table 1. Földiák's network outperforms the adaptively constructed networks in the reduction of statistical dependence and in the maintenance of input information, however there are other considerations (see Discussion).

Discussion

This report demonstrates the success of an adaptively constructed network in transforming 82 alphanumeric characters. The adaptively constructed network creates output representations that maintain nearly all of the input representational information but which contain significantly less statistical dependence.

In fact, the results obtained here with the simple, adaptively constructed networks rival those obtained with much more complex neurons and architectures (Földiák 1990). Both networks create output representations that maintain over 95% of the input information but which contain less than 10% of the input statistical dependence.

Table 1: Comparison of Network Performance

	Földiák 1990	Adaptive Networks
Number of Input Neurons	120	120
Number of Output Neurons	16	10
Input Representational Information	4.34	4.34
Output Representational Information	4.22 (97%)	4.17 (96%)
Input Statistical Dependence	19.80	52.14
Output Statistical Dependence	1.64 (8.3%)	5.09 (9.8%)
Input Higher-Order Redundancy	4.56	12.01
Output Higher-Order Redundancy	0.39 (8.6%)	1.22 (10.20%)
Input Redundancy	0.96	0.96
Output Redundancy	0.74 (77%)	0.58 (61%)

Although the two networks perform similarly in terms of the information measures, there are major differences between the networks in terms of synaptic connectivity and neuronal properties. Földiák's networks contain full feed-forward excitatory connectivity (120x16=192 connections) as well as full lateral inhibitory connectivity (15x16=240 connections, for a total of 432). These fully connected networks do not accurately reflect the synaptic organization found in the cortex. The adaptively connected networks contain only sparse, excitatory connectivity (an average of 2.6 connections per output neuron, for a total of only 26 connections).

By using only feed-forward connectivity, the adaptively constructed networks avoid a second difficulty in Földiák's network: the time required for output response convergence. The lateral connections of Földiák's output layer force a series of recurrent operations to achieve output layer response convergence. In contrast, the adaptively constructed networks employ simple, instantaneous, summate and fire neurons.

Both Földiák's network and the adaptively constructed network attempt to construct output representations with a desired output neuron firing level. However, the adaptively constructed networks simply limit the amount of synaptic connectivity in order to achieve the desired levels of output firing. Földiák's networks must dynamically regulate firing threshold on a neuron by neuron basis in order to achieve desired output firing levels.

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