A synaptogenesis model applied to Chinese characters learning

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Abstract

Chinese characters are among the most widely adopted writing systems, but due to its “flow” nature, recognizing such characters often requires domain-specific knowledge. This study presents a two-layer synaptogenesis model and assesses its ability to learn and recognize Chinese characters. Neurons in the first layer of the network were trained with an input set containing 25 different Chinese characters. The resulting output vectors were then used as input vectors to the second decoder layer. The model was successful in compressing pixelated information and identifying input patterns from specific characters to some extent. Further expansion and research on this topic may help language learning and improve accuracy of Chinese character generating in machine.

Introduction

Learning is closely related to brain plasticity and the formation of neural synapses. Human beings are born with the potential to learn languages, but it is a hidden ability that needs to be activated and acquired before we can put to good use. Children growing up in presence of only one language are able to master the language with great ease because the constant stimulation in the environment has triggered an explosion of synapse formation during the early brain development of children, known as exuberant synaptogenesis (Huttenlocher & Drabholkar, 1998). As the rate of synaptogenesis decreases throughout the lifespan, an adult will find it hard to learn a second language. Chinese is deemed one of the most difficult languages for western people to learn as second language and is known for its complicated writing system.

Adaptive synaptogenesis is a model used to simulate associate learning in a neural network with repeated stimulation from the input set. There are three basic mechanisms, synaptogenesis, associative synaptic modification, and synapse shedding, with which the model is able to learn and differentiate categories of input. Synaptogenesis is a random Bernoulli process that selects a new excitatory connection between nearby axon and postsynaptic neuron. Associative synaptic modification alters the strength of each existing synapse including the possibility of potentiation, depression, or no change of a synaptic weight. Finally, with enough long-term depression, shedding of a synapse occurs when the weight is appropriately weak, and the possibility of forming a new synapse on certain neuron is determined by its long-term average firing-rate (Thomas, Blaloc, & Levy, 2015).

For this study, we create 25 pixelated Chinese characters consisting of 5 different radicals: 钅(gold), 木 (wood), 氵 (water), 火 (fire), and 土 (earth). Most Chinese characters are phono-semantic compounds with the semantic component giving a broad category of meaning, usually the radical, and a phonetic component suggesting the sound. Although there are various Chinese character structures, we use only the Left-to-right for simplicity of the input world. In order to simulate character learning and recognition, we implement a two-layer network based on the synaptogenesis. The first layer takes the character set at input while the second layer takes the output of the first layer as input and uses a supervised modification rule for decoding purpose. We intend to show that this model can accurately discriminate individual characters after learning.

Results

Figure 1 shows characters with different radicals in a two-dimensional continuous space. Each character is constructed as a 120 dimensional binary vector where pixels can be in one of two states, {0, 1}. Figure 2 shows the pixelated image and the average of all 25 Chinese characters Figure 3 shows the joint variability of the input measured by the covariance:

$$Cov(X, X) = E[(X - E[X])(X - E[X])] = E[XX^T] - E[X]E[X^T]$$

Higher values correspond to pixels that have similar behaviors across the input set while 0s indicate pixels that are always off.

Statistics calculation were conducted on the input and the output after the simulation of the first layer:

$$H(X) = \sum P(X) \cdot log_2(1/X) = 4.6439 \text{ bits}$$

$$H(Z) = \sum P(Z) \cdot log_2(1/Z) = 4.1337 \text{ bits}$$

$$I(X, Z) = \sum P(X) \sum P(Z|X) \cdot log_2[P(Y|X)/P(Y)] = 4.1337 \text{ bits}$$

$$SD(X) = \sum [H(X)_i] - H(X) = 40.8417$$

$$SD(Z) = \sum [H(Z)_i] - H(Z) = 10.9984$$

Entropy is a measure of the average information content of a variable. The difference between the entropy of the input and that of the output indicates that there's a slight information loss in the network. Statistical dependence is a measure of the redundancy within a system. A decrease in statistical dependence marks the success of the network in encoding the information of the input world.

Figure 4 shows the final weight of the output neurons of the second layer, which is not quite desirable as each neuron fires for multiple characters instead of a single character. However, since no two characters are recognized by the exact same neurons, the discrimination can be done by finding out the distinguished set of neurons that fire for each character. For instance, a neuron set [16, 19, 20] is associated with the character 铂 (bo), which means platinum, and a neuron set [1 3 7 8 17 20 21] is linked to 油 (you), meaning oil.

Discussion

The results of this study indicate that our two-layer model is capable of identifying an individual character within a limited dataset through a corresponding firing combination of output neurons. The role of the radical in information encoding and pattern recognition remains, and visual outputs of characters identified are not provided under this setting. Many future works can be conducted. First, we can have separate neurons for the radical and phonetic component of each character so that the first layer learns pixel-wise correlations while the second layer is essentially learning higher-order correlations in the input. In addition, we need to expand the character set to include characters of more structures. Second, much attention regarding language learning has been drawn on the "critical period" during brain development, a time where an individual is highly receptive to environmental stimuli and, therefore, learning (Drachman, 2005). We should also do a comparative study on networks with high and low synaptogenesis rates to simulate different learning processes of children and adults. Finally, recognition is only one aspect for understanding a language, another challenging and interesting task is to teach a non-Chinese speaker or a machine to automatically write Chinese characters. Thus, we can adjust the current model to construct a recurrent neural network that can be used as both a discriminative model for recognizing Chinese characters and a generative model for drawing Chinese characters.

Methods

The model for this study was built upon the old synaptogenesis model using a single layer feed forward network starting with no connections. Each neuron in this network seeks the same, pre-specified, long-term average firing rate. The excitatory inputs to each neuron are positively correlated, and the weights form the best linear filter for the axons selected. Thus, the enhanced unsupervised synaptic modification rule of this model is defined, following the general formula $w_{ij}(t + 1) = w_{ij}(t) + \Delta w_{ij}(t)$, as:

$$\Delta w_{ij}(t) = \varepsilon \cdot y_j(t) \cdot (x_j(t) - E[x_i] - w_{ij}(t))$$

where $E[x_i]$ is the long term average activity of the input and $y_j(t)$ is the postsynaptic excitation. Synaptic shedding happens when a synapse's weight falls below the weight threshold and the connection gets deleted. The shedding threshold in this study is set at 0.05 across all simulations.

The first layer copies everything in the old model while the second layer applies the supervised learning and uses a new modification rule:

$$\Delta w_{ij}(t) = \varepsilon \cdot z_j(t) \cdot (x_i(t) - w_{ij}(t))$$

where $z_j(t)$ is whether neuron j should learn the pattern presented, and the rate constant ε is 0.01. After one simulation, we can get the weights of neurons in the first layer and calculate the outputs, which is then used to create inputs to the second decoder layer. In order to have enough neurons that fire for individual characters, the number of neurons for both layers is raised from 10 to 30.

Acknowledgements

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References

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Drachman, D. (2005). Do we have brain to spare? *Neurology*.

Figures

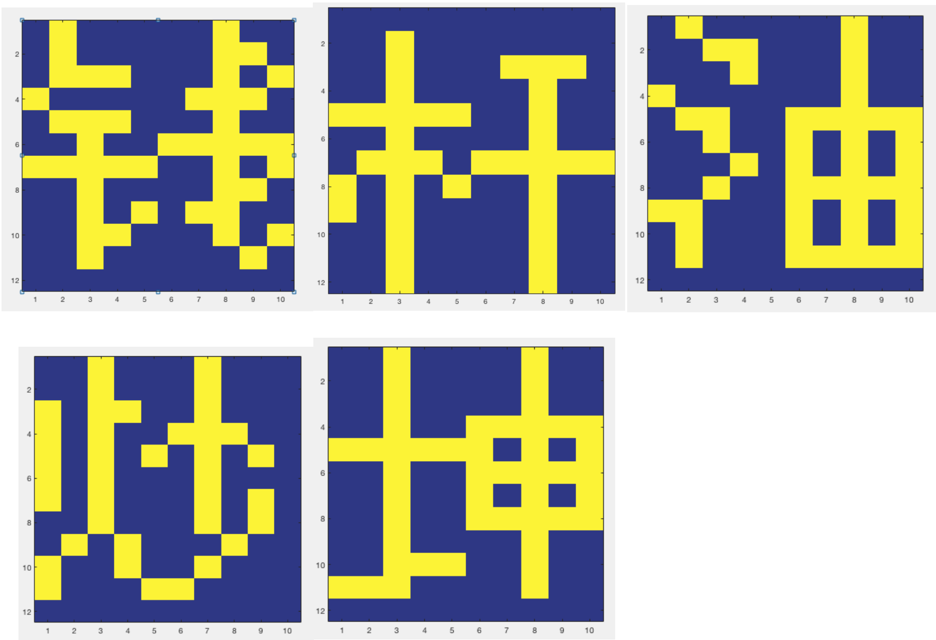

Figure 1: 5 of the 25 characters generated after reshaping and displayed in a 12-by-10 code space.

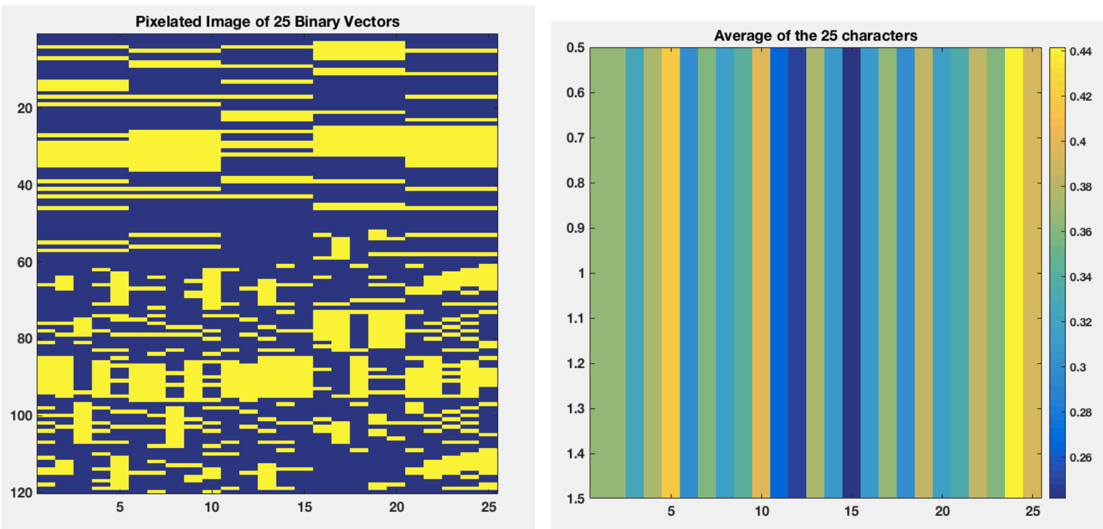

Figure 2: 25 characters are separated into 5 groups and each group shares the same radical. The phonetic parts are not all different. Even in this small set of character, characters may resemble each other in terms of average bits, making it hard for people to distinguish Chinese characters.

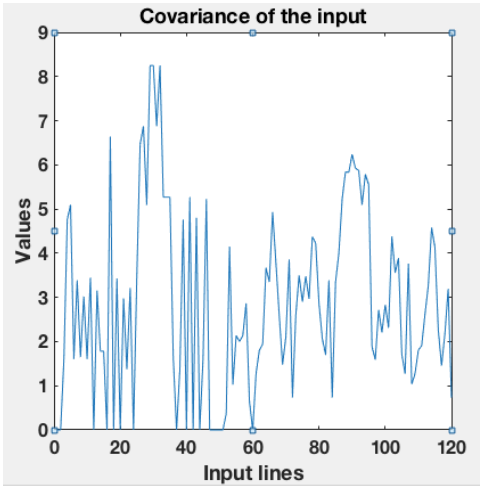

Figure 3: covariance of the input generated using plot() method. Expected value of XX^T, X and X^T were calculated and the difference between the first item and the product of the other two items yield the covariance.

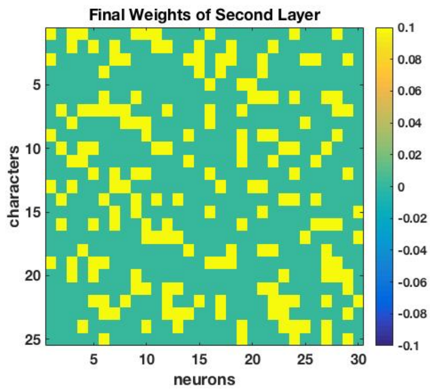

Figure 4: Resulting weights of the second layer indicate firings of neurons for multiple characters.