An Algorithm to Optimize the Routing of Neurons in an Artificial Spiking Neural Network

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***Abstract*—We describe an algorithm that determines the optimal connectivity of a spiking neural network such that it can reach the lowest possible loss for that number of neurons. If the spiking network was as big as the human brain, then a local minimum would have it connected just like a typical brain is connected after the algorithm is done. Giving it all of its functionality to the extent that artificial spiking neurons mimic biological ones. We tested our algorithm on the MNIST dataset and achieved an increase in accuracy of ... over the baseline.**

I. Introduction

In the papers "Structuring Concept Space with the Musical Circle of Fifths by Utilizing Music Grammar Based Activations" Moyo et al compare a piano piece being played on a musical keyboard, to the activations on a spiking neural network. The piano piece consists of notes that can be played at the same time (as in a chord) or notes that are played in sequence (as in a melody). While a spiking network consists of nodes that can either activate at the same time of in sequence.

They proceeded then to describe a way of regularizing a spiking network with the grammars of music theory. They described a way to do this that involved mapping the nodes in a spiking network to the keys on a musical keyboard ,then taking all the activations at one time step and calculating the perceptual consonance of the keys they represent. Then adding this value to the global reward while training a reward modulated spiking network.

This procedure would teach the neural network to form activations that represent meaning chords using meaningful scales. In fact it would use the whole of music theory in its structure bar rhythm. For inclusion of rhythm one might use a oscillatory spiking neural network.

In their paper they described that this would affect the neural network by making its activations be attractors (concepts) while scales are the basins of attraction. They use a population theory of concepts where a population of neurons firing represent a concept. Various equivalences between concepts would then be represented by similar chords under inversions and in different scales with extensions etc.

They followed this paper up with the paper "Spiking networks as non local automata" where they noted that a spiking neural network with random connections is equivalent to a non local automaton where the neurons represent the cells on a grid and the cells are not related by adjacency.A neuron activating being the equivalent of a cell going on.

In their analysis they consider all the activations occurring at one time step as a node of a hyper graph. They describe that if a musical piece was also a viewed as a non local cellular automaton with the keys played at each time step being the cells going on, then it would have a very ordered hyper graph. Ordered by music theory and in particular the circle of fifths and the circle of fourths.

They show that knowing what constitutes the optimal next set of activations is as simple as asking what activations are a fifth and a fourth away form the current ones. Also once generalization occurs it may happen that upon being confronted with a never before seen situation or task, an agent trained this way would simply take the corresponding never before seen activations and move them in steps of a fifth or a fourth in order to solve the task in a one shot manner.

In this paper we extend their ideas to discover the optimal routing of functions and modules in a function of functions such as a spiking network with initially random connections.

II. Optimizing a spiking networks routing

The algorithm is as follows.

We get each set of activations after labeling the nodes as keys of a musical keyboard , and calculate their perceptual consonance. The weight update rule of a reward modulated spiking network is as follows.

Where ......

We will modify it to include the consonance of its activations by changing the update rule to this.

Where c is the perceptual consonance normalized.

Additionally , between time steps, if a neuron firing at time t is separated by a musical fifth or fourth from one firing at time t+1 ,we connect the two neurons or strengthen their connection if it already exists. For the rest of the neurons that activated at both time steps weaken their connections up to a limit, at which point we break it.

This algorithm has as a result the property that it can find the optimal routing in a spiking network for the number of neurons it has in order to reduce the loss. The proof is as follows.

Additionally this algorithm will run in a time complexity of ... and a memory complexity of .....

III. Analysis

What this means is that if we had a spiking neural network with the same number of neurons as the human brain, but with initially random connections, this algorithm will learn to outperform the human brain, all things being equal.

We may imagine it forming configurations that permit long and short term memory as well as executive function. Right now a lot of the functionality of the human brain is currently unknown or unclear. This algorithm will learn to represent all those functions on its own. That is to the extent that a artificial spiking neuron functions like a biological neuron.

IV. Conclusion

We have described a method for optimizing the routing of the functions in a function of functions such as a spiking neural network. To do this we decoupled the activations within each time step as well as between time steps. This results in the optimal configuration for that number of neurons that the spiking neural network could have in order to maximize its expected reward.

This algorithm could potentially rediscover the brains routing of neurons and so could give a spiking network with the same number of neurons all of its functionality.

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