Sequential Memory Generation in the Neuroidal Model

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Abstract

Understanding the process of memory formation in neural systems is of great interest in the field of neuroscience. The Neuroidal Model poses a plausible theory for how memories are created within a computational context. Previously, the algorithm JOIN has been used to show how the brain could perform conjunctive and disjunctive coding to store memories. A limitation of JOIN is that it does not consider the coding of temporal information in a meaningful manner. We propose `SeqMem`, a similar algorithmic primitive that is designed to encode a series of items within a random graph model. We investigate the feasibility of this procedure empirically by observing its stability in our model. Our goal here is to inspire further work in scaling our methods to function at a human-level magnitude of computation.

Keywords: neuroidal computation; unsupervised learning; temporal information; lifelong learning

Introduction

We propose a new memory generation algorithm capable of encoding sequential information for the *Neuroidal model*, by Leslie Valiant (1994). We demonstrate the feasibility and stability of `SeqMem`, which can generate memories of consistent size by empirical simulation within a faithful Neuroidal model.

A key motivation for this model is for it to be as simple as possible, so that if a certain computation can be accomplished in the Neuroidal model then there should be no doubt that the same computation can be accomplished in mammalian brains. A result of successful modeling would allow for computational agents to demonstrate behaviors such as hippocampal replay similarly to humans (Ólafsdóttir et al., 2018).

Background

The Neuroidal model is an algorithmic, deterministic, spiking neural network with uniformly random synaptic connectivity, hetero-associative memory, and with weak and synchronized timing mechanisms (Valiant, 2000). The Neuroidal model is an Erdős–Rényi G_{np} random graph that encodes memories. It consists of a number of neurons with directed and weighted synapses connecting them.

The JOIN algorithm has been introduced to perform memory generation by connecting two existing memories to a newly created memory. JOIN is reminiscent of *coding* within the brain, which has been found to occur in real neural systems (Tacikowski et al., 2024). Extensive results have been found for JOIN's effect on the overall capacity of the model when neuron sharing is allowed (Perrine et al., 2024).

Definition of Memory We define a "memory" as a set of nodes in an Erdős-Rényi G_{np} graph with realistic parameters. This coding of discrete *items* remains a plausible method for memorization in biological systems (Komorowski et al., 2009; Nieh et al., 2021; Tacikowski et al., 2024).

Methodology

A neuron will fire if the weights of incoming synapses sum to equal or exceed a threshold value. Various algorithms, including `SeqMem` and JOIN, will involve an attribute k and set a subset of synapses' weights to $\frac{1}{k}$. Memories are represented by groups of neurons of an expected size, which is a key characteristic of the model (Perrine et al., 2024).

One of the characteristics of `SeqMem` is that a memory derived from another will activate if the other is active. Suppose the original memory is A_1 and the generated memory is A_2. When all of the neurons in A_1 fire, we expect that in the next time step that all the neurons in A_2 will fire.

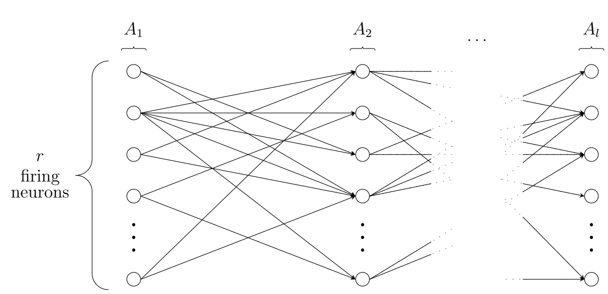

Figure 1: Example of a `SeqMem` memory of length l

Synapse Strength Locality

`SeqMem` relies on variable synapse strength to maintain consistency. Using a constant k leads to a volatile model here. We will use a temporary and local variable s to represent the synapse strength used during the generation of each individual memory using `SeqMem`.

Algorithm

The goal is to take a single memory A_1, generate a new memory A_2, and continue generating memories to reach a defined endpoint of memory A_l. We show an example of this process as Figure 1. One step of the algorithm is defined as follows:

1. Iterate over all synapses. For every neuron in the model, track how many incoming synapses there are from a neuron in A_i in a list K. These values are the max s that would include that neuron in A_{i+1}.

2. Iterate over all neurons. For each possible value of s, track how many neurons have s or more incoming synapses from a neuron in A_1 in a list B. These are how big the memory A_{i+1} would be for each value of s.

3. Find an s such that A_{i+1} is of appropriate memory size.

4. Iterate over all neurons. Each neuron with s or more incoming synapses from a neuron in A_i is added to A_{i+1}.

Simulation

Our simulation repeatedly generates sequences of the same length. The initial memory of each sequence is generated randomly representing noise of uniform, expected size. Data from these trials are given in Figure 2. Our code is available here: `https://github.com/chandradeep24/Valiant/blob/main/notebooks/SeqMem/SeqMem.ipynb`

Results

The goal of our results is to show that `SeqMem` is stable within the Neuroidal Model by demonstrating consistent memory sizes generation, which matches the model's expected memory sizes. Our model parameters reflect well-established biological structures observed within neuroscience, which is imperative to justify its plausibility (Valiant, 2005).

Figure 2 displays the mean and 25th to 75th percentile range of memory sizes for each model. This evidence suggests that longer sequences would remain stable for models closer to biologically accurate size.

It is noted that the first memory in each sequence has different behavior, potentially due to it being generated randomly. For each neuron in each model, we counted the number of memories they appeared in and how many incoming synapses they have. We plotted the mean and 10th to 90th percentile range in Figure 3.

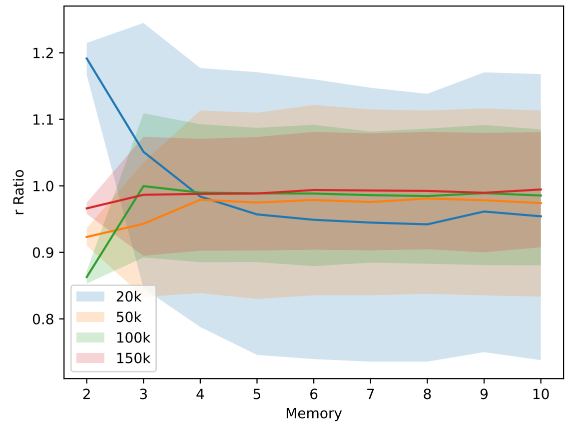

Figure 2: Memories sizes generated by the simulation and scaled to their expected memory size.

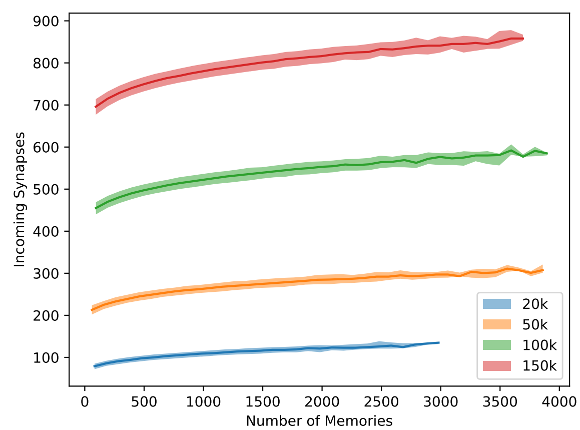

Figure 3: The number memories each neuron appears in vs. the number of incoming synapses it has.

Conclusion

In this paper, we present the first sequential memory generation algorithm for the Neuroidal model. We demonstrate its stability through empirical data which focused on the range of memory sizes and synapse weights to show they are within reasonable bounds. We explore how the number of incoming synapses affects the chances of a neuron being included in a memory. This is a first step for this functionality of the model, which we hope will inspire further work.

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