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ON BUILDING A MIND: THE FUTURE OF ARTIFICIAL INTELLIGENCE

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Abstract

This work is a replication of a paper authored by David Beniaguev, et al, "Single cortical neurons as deep artificial neural networks", published in 2021, in which the authors introduce a neural network[1] model of a neuron[2]. A copy of the trained model was obtained, and a new data set was generated using the same biophysical model from the NEURON program[3] as was described in the paper. Although the same model was used, due to difficulties in understanding the original implementation the neuron's inputs were generated according to a normal distribution[4] rather than the described Poisson[5] process. The neural network model was then tested to observe if it still produced the same results on a different data set. The model performed significantly worse with my generated data, having a receiver operator characteristic[6] (ROC) with an area under curve[7] (AUC) of .5728 compared to the .9926 AUC found by the model's authors using their data. It is suspected that the difference in how the data was generated in the NEURON program is cause of this disparity, but this result does provide insight into the generality of the model and gives avenues for future research.

Introduction

What is intelligence? How is consciousness related to self-awareness? Is there something special that makes a human mind unique? We do not know the answers to these questions, but research into artificial intelligence[8] (AI) may point us in the right direction. One potential path is in emulating the one structure we absolutely know has accomplished this -- our own brain -- beginning by creating an accurate model of the brain's building block, the neuron.

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1 A method of machine learning using a classification model trained on labeled data.
2 The primary cell in a biological brain.
3 https://neuron.yale.edu/neuron/
4 A bell-shaped statistical distribution where most events will be clustered around the average.
5 A statistical distribution that determines the probability of an event occurring with a given rate.
6 A graph of the model's false-positive rate vs the true-positive rate at different thresholds.
7 The area under the ROC curve (a value between 0 and 1). The higher this number is, the more 'accurate' the model.
8 The ability for a computer to think and act in human-like ways.

Having this model would be the foundation of building a mind and possibly creating a consciousness in a computer.

Even since the beginning of the computer age, a common opinion was that digital computers would someday be able to think and function like a human mind (Turing, 1950). While the ensuing seventy years have not produced these expected results, we have seen numerous advancements in artificial intelligence and a refinement of AI capability. A computer has beaten the world masters at chess and Go, can recognize and classify images far faster than humans, and is capable of learning and discovering new solutions to problems through evolutionary algorithms[9] (Bostrom, 2017). We have created computers that are extraordinarily good at specific tasks, but none that have the general intelligence and problem-solving ability of a toddler.

Is the reality of a computer with human-level intelligence unobtainable? Perhaps not. We know that the universe has produced it at least once, so it could be the lack of progress lies in our current approach of starting with the specific problem rather than the general structure.

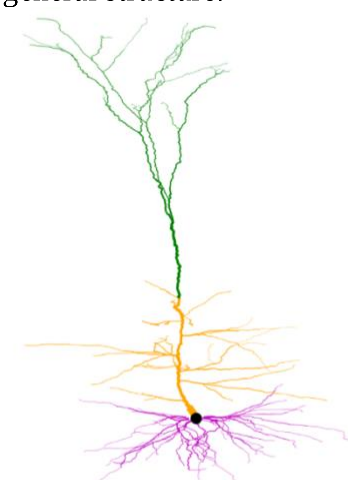
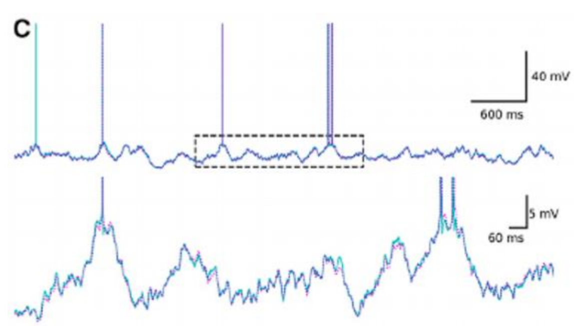


Figure 1: Image of the neuron model generated by the NEURON program. The three different colors represent different groups of dendrites with the soma as a black dot.

Method

In September 2021, the journal *Neuron* published a paper by David Beniaguev, et al. describing the creation of a neural network model that accurately predicts the output of a single layer-5 pyramidal cortical[10] (L5PC) neuron based on the synaptic[11] inputs from nearby cells. The data used to train and test the model was generated from the NEURON program—software for the accurate biophysical, mathematical modeling of neurons. My work is a replication and testing of their model using a new data set generated for this purpose.

The authors of the *Neuron* paper posted the entirety of their code and data in public repositories. I obtained a copy of one of the models they created and used parts of their computer code to load and run the neural network model with one of the provided data sets. This produced results consistent with those reported by the published paper, with approximately a 99.7% accuracy rating when compared to the actual outputs (Beniaguev, 2021).



9 A technique that allows the program to try thousands of possibilities at once then saves the most successful of those to repeat the process.

10 Most common type of neuron and principal signal communicator in the brain's gray matter.

11 A synapse is a junction between two neurons, where communication occurs.

Figure 2: Output generated by NEURON model (cyan) along with predicted output from neural network (magenta) from the original NEURON *paper. Bottom shows closeup of top inset.*

After determining that the model was operational and produced the same result with the same data, I began to generate my own data set to test the model. This required the use of the NEURON model which was not directly provided in the repositories. Going to the original source of the model used by Beniaguev in another paper, I did find the L5PC model, but it did not have the exact synaptic structures the authors used (Hay, 2011). In a neuron, not all synapses are the same. Some use different chemical markers to regulate how it propagates signals. For instance, the synapses used in the *Neuron* paper were AMPA[12]/NMDA[13] which send excitatory signals, and GABA[14] which send inhibitory signals. Fortunately, the code for these synapses were included in the public repository and just needed to be integrated into the model.

To modify the model to match the one used in the paper, I had to use additional programming languages to define the structure of the neuron and provide it with a series of inputs for each synapse. The neuron itself consists of the cell body (soma) with many branches of dendrites[15] each with their own biophysical properties. Along the dendrites are also the synapses that transmit signals from other cells. This model has the soma along with 192 dendrites split into 639 total segments. Each segment has one each of the AMPA/NMDA and GABA synapses, with properties described by the *Neuron* paper, for a total of 1278 inputs into the cell. Given the baseline, at-rest starting properties of the cell, each simulation is run for a period of 6000 milliseconds, a time arbitrarily chosen by the *Neuron* authors, during which each of the synapses provides an input to the cell at random intervals. These inputs and the voltages of the soma are recorded as well as the times at which the neuron achieves a spiking action potential[16] (Carnevale, 2006).

Besides writing the code to assemble the model, additional code was required to generate the inputs for it and to record the data produced by the cell (Gillies and Sterratt, n.d.). While I believe my recreation of the NEURON model is close to the original, because of difficulties creating a Poisson distribution for input times I had to approximate it with a normal distribution instead, with the expectation that the accuracy on my data would be affected. I collected all data for a total of 128 simulations to match the number of simulations and format of data used to train and test the neural network. The model also required the data to be in a specific format to be tested on it, which required more code to be written to accomplish that. Once the data was collected and compiled, it was loaded into the neural network which made a prediction of the soma voltage for each millisecond, as well as predicting whether the soma fired or not.

Results

12 α-amino-3-hydroxy-5-methyl-4-isoxazole propionic acid, a major synaptic signaling channel

13 N-methyl-D-aspartate, another major signaling channel

14 gamma-aminobutyric acid, the chief inhibitory compound in nervous systems

15 Segments that branch off the main body of a neuron.

16 The point when a neuron fires and propagates a signal to the next cells.

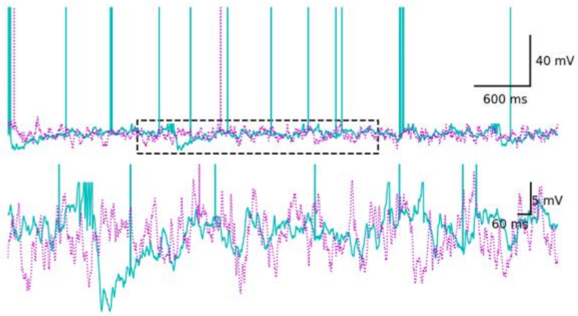
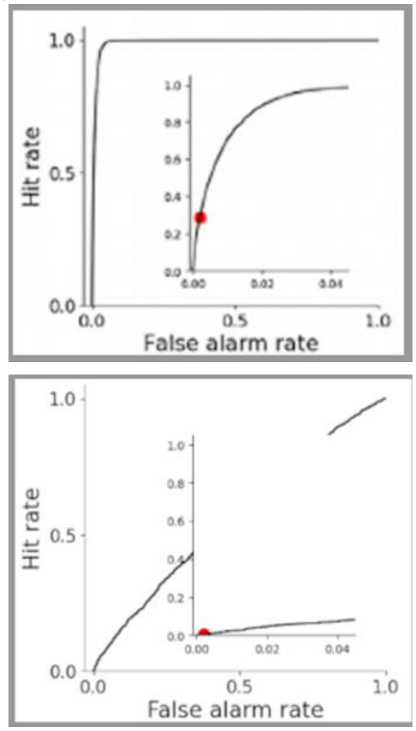


Figure 3: Output generated by NEURON model (cyan) along with predicted output from neural network (magenta) from my replication. Bottom shows closeup of top inset.

While my NEURON model generated a sensible soma voltage plot[17] and spike train[18], as expected it did not quite match the author's data and thus the accuracy suffered. The author's dataset produced an AUC of .9926 with an explained variance[19] of 95.10%. My data produced an AUC of .5728 with an explained variance of -106.45%, indicating a significant amount of noise and an inability for the model to accurately predict the results of my generated inputs. Besides the use of a normal distribution instead of Poisson I suspect that there may be undiscovered problems with the dataset I generated, but these results also provide a strong indication that the neural network model is limited to the exact parameters that produced the author's dataset.

Figure 4: (first) ROC curve for spike prediction from the Beniaguev paper. (second) ROC from my replication. The red dot indicates the threshold used for this neural network model. Inner graph is a zoom of the first 4% false alarm rate for each.



My next step is to conduct more research into the way that biological neurons generate signals under normal circumstances and to determine if the Beniaguev paper generated them in this manner. Either way, I will attempt to create more realistic inputs for the neural network and test it again. Once I have acceptable results that are like Beniaguev's, I plan on generating a data set that demonstrates long-term potentiation[20] to see if the neural network can accurately predict that behavior.

Although my replication may show some of the limitations of the neural network in perfectly modeling neurons, this line of research is extremely important in both uncovering the complexities of the cells and in creating faster, more efficient models of them. While it took my desktop computer

17 A graph of the soma's voltage over time.

18 The times in which the soma fires a signal

19 The percent of results that can be explained by the model.

20 When a synapse is strengthened by repeated strong signals resulting in a long-lasting increase in signal transmission. Is strongly associated with learning and NMDA receptors.

over five hours to calculate all the simulations for the NEURON model, the neural network was able to make predictions in less than three minutes. This is the type of speedup that will be necessary for us to take singular neurons and network them together into larger structures similar to those found in the brain, and eventually connecting billions of artificial neurons together to build a single artificial mind.

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