Biologically Extending the Gen 2 Artificial Neural Network

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Biological Neurons

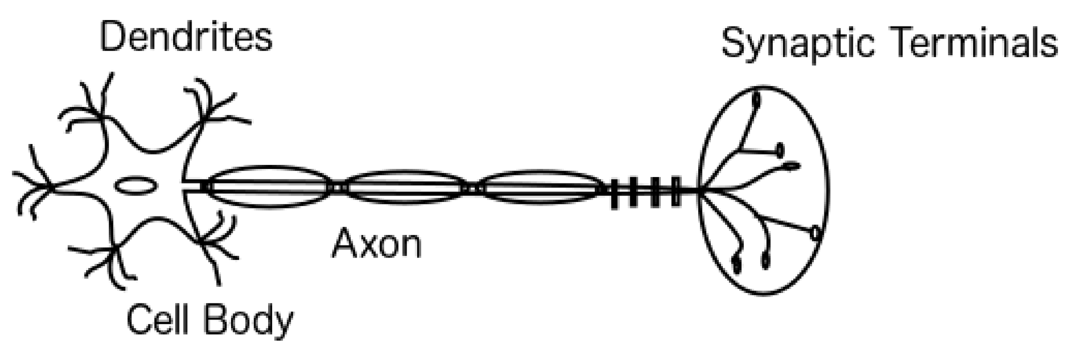


Figure 1. Neuron Diagram

- **Dendrites** provide the input field to the neuron
- The voltage difference from **cell body** to the exterior of the cell controls action potential
- The **axon** carries the action potential to other locations in the network
- **Synaptic terminals** transmit the action potential from the axon to other neural dendrites

With the arrival of each **action potential** at a **synaptic terminal**, **neurotransmitters** are released and carried **into the neuron** by way of **ion channels and pumps**. The ions **change the voltage** present across the **membrane of the cell body**. If the membrane voltage increases **past the action potential threshold**, an **action potential** will occur and **propagate along the axon** to the **synaptic terminals**. A membrane voltage that has been elevated is referred to as **depolarized**. In homeostasis a neuron attempts to enforce **polarization**, remaining ready to receive input leading to an action potential.

$$r_{action} = -r_{pol} + \sum \alpha * r_{depol}, \quad \alpha \geq 0 \tag{1}$$

- **firing rate** of the target neuron is **dependent** upon the **rate of depolarization**
- $\boldsymbol{r_{pol}}$ is the internal **rate of polarization**
- $\boldsymbol{r_{depol}}$ is the **rate** at which a specific **synapse is firing**
- $\boldsymbol{\alpha}$ is the amount of **neurotransmitter released** with each pulse at the synaptic terminal
- $\boldsymbol{r_{action}}$ is the **rate of action potential** propagated along the axon
- Summation accounts for multiple synapses

Biological Interneurons

Interneurons provide external polarization to the biological neural network. Eq 1 is modified to reflect external polarization in 2.

$$r_{action} = -r_{pol} + \sum \alpha * \beta_{Inter} * r_{depol}, \quad 0 \leq \beta \leq 1 \quad \alpha \geq 0 \tag{2}$$

- **Interneurons** allow for **selective gating** of inputs to different regions of the dendrite
- **Interneurons** facilitate **dynamic changes** in the **relative contribution** of inputs
- $\boldsymbol{\beta_{Inter}}$ accounts for the gating associated with a particular synaptic connection

*Neither Eq 1 or 2 is intended to be complete characterizations of a neuron. Rather both should be understood to capture the relevant pieces of neural activity necessary to develop Gen 1 and 2 neural networks.

Artificial Neurons

Gen 1 ANNs are considered those limited to classification. They are incapable of performing regression because the output assumes only the **values one or zero**. The perceptron is such a model. This model characterizes **neurons as switches** as shown in Eq 3.

$$net = \begin{cases} 0 & b + \sum w_j * I_j \geq 0 \\ 1 & b + \sum w_j * I_j < 0 \end{cases} \tag{3}$$

- $\boldsymbol{w_j}$ represents the relative amount of neurotransmitters released or, α in Eq 1
- $\boldsymbol{I_j}$ is the firing rate present at the j^{th} synapse
- $\boldsymbol{b}$ is the bias associated with this neuron or, r_{pol} in Eq 1

Gen 2 ANNs are where the bulk of research in computer science has been focused. The ability to output a **continuous value from zero to one** provided the ability to **learn non-linear regressive approximations** thanks to **continuously differentiable activation functions**. The typical equation for a Gen 2 ANN is presented in Eq 4. The step function has been replaced by the **sigmoid function** represented by $\boldsymbol{\sigma}$.

$$net = \sigma\left(b + \sum w_j * I_j\right) \tag{4}$$

Artificial Interneurons (INNs)

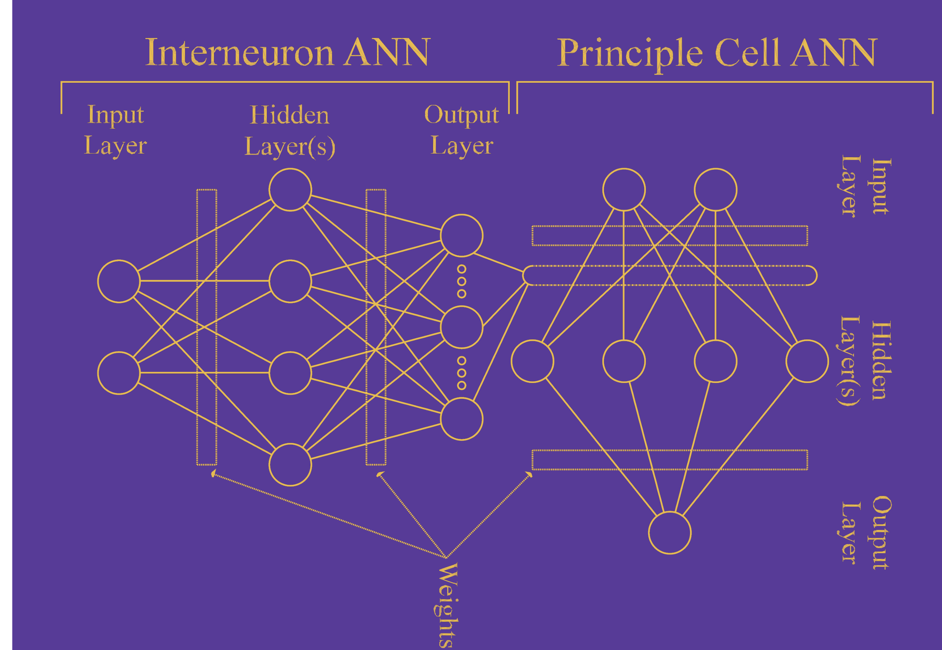
Contribution

- **Extended** the Gen 2 ANN model to include interneurons
- **Facilitated** selectively gating the input along any edge to edge connection between neurons
- **Derived** the backpropagation equations necessary for an arbitrary INN
- **Outperformed** the base ANN when applied to the MNIST dataset

INN Model Requirements

Given a set $\boldsymbol{I}$ of inputs to neuron $\boldsymbol{n}$ it is required that any $\boldsymbol{I'} \in I$ be modifiable such that the set $\boldsymbol{I'} \boldsymbol{\Delta} \boldsymbol{I}$ is left unchanged. This lends itself to the addition of some weight $\boldsymbol{\beta}$ to the ANN equation. $\boldsymbol{\beta}$ must be variable depending on the inputs presented to the ANN.

INN Model



$$net = \sigma\left(b + \sum w_j * \beta_j * I_j\right) \tag{5}$$

$$\beta_j = \sigma\left(b' + \sum w'_j * I'_j\right) \tag{6}$$

*It should be understood that the point of this paper is not to build a better performing ANN. It is the beginning of investigation towards a new more biologically plausible model.

Results: Applying an INN to MNIST

Experimental Setup

- **MNIST** is a well known problem in machine learning
- MNIST Consists of 60000 training images of handwritten digits and 10000 test images
- The experiment proves the model **learns and converges** to a solution in a multi-output, large input environment
- The INN model was implemented in **Tensorflow**
- Interneurons were only applied to the hidden layer
- All other values for the interneuron ANN were the same as the principal cell ANN
- The principal cell ANN and interneuron ANN were optimized simultaneously using backpropogation

Experimental Results

- The INN **outperformed** the ANN
- The performance of the ANN as applied to the test set was 96.9
- The performance of the **INN** was 97.2
- The model has been shown to **converge and perform** better than the naive case
- The INN did not outperform the ANN **more** most likely due to the problem domain
- The power fo the INN is believed to be the abilit to **dynamically contextualize**

Future Work

Neuroscience

Neuroscience has not been able to make a definitive assertion about **interneuron input feature selection**, we intend to provide an **answer using this model**. We have chosen a Gen 2 framework because more is computationally known in this domain. The hope is that through the isolation of variables an answer will be approximated.

Multi-Task and Transfer Learning

The literature review was rich with similar work in **multi-task learning**. It is hoped that by training the principal ANN weights with unity interneuron ANN weights, the special case of INN backpropagation, the principal cell ANN will converge to task 1 and allow the interneuron ANN to **learn task differentiation**. A similar idea can be applied to experiment with **transfer learning**.

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