Instituto Tecnológico de Costa Rica

Inteligencia Articial
Proyecto #2 - Redes Neuronales

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1 Abstract

Artificial neural networks or simply "neural nets" go by many names such as connectionist models, parallel distributed processing models, and neuromorphic systems. Whatever terminology it may be, they all attempt to borrow the structure and running way of the biological nervous system based on our present understanding of it. Instead of performing a program consisting of instructions sequentially as in a von Neumann computer, artificial neural nets have their structures in dense interconnection of simple computational elements— the artificial neurons or simply "neurons", and operate the massive computational elements in parallel to achieve high performance speed.

2 Introduction

An Artificial Neural Network (ANN) is a computational model that is inspired by the way biological neural networks in the human brain process information. Artificial Neural Networks have generated a lot of excitement in Machine Learning research and industry, thanks to many breakthrough results in speech recognition, computer vision and text processing. In this blog post we will try to develop an understanding of a particular type of Artificial Neural Network called the Multi Layer Perceptron.

2.1 A Single Neuron

The basic unit of computation in a neural network is the **neuron**, often called a **node** or **unit**. It receives input from some other nodes, or from an external source and computes an output. Each input has an associated **weight** (w), which is assigned on the basis of its relative importance to other inputs. The node applies a function $\boldsymbol{f}$ (defined in Figure 1) to the weighted sum of its inputs as shown in Figure 1.

The above network takes numerical inputs **X1** and **X2** and has weights **w1** and **w2** associated with those inputs. Additionally, there is another input **1** with weight **b** (called the **Bias**) associated with it. We will learn more details about role of the bias later.

The output Y from the neuron is computed as shown in the Figure 1. The function $\boldsymbol{f}$ is non-linear and is called the **Activation Function**. The purpose of the activation function is to introduce non-linearity into the output of a neuron. This is important because most real world data is non linear and we want neurons to learn these non linear representations.

Every activation function (or non-linearity) takes a single number and performs a certain fixed mathematical operation on it. There are several activation functions you may encounter in practice:

- **Sigmoid**: takes a real-valued input and squashes it to range between 0 and 1

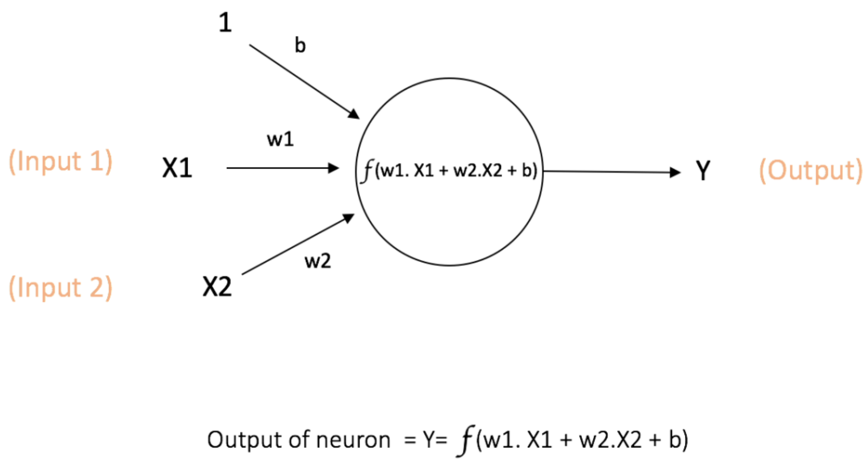


Figure 1: A single neuron

- **tanh**: takes a real-valued input and squashes it to the range [-1, 1]
- **ReLu**: ReLU stands for Rectified Linear Unit. It takes a real-valued input and thresholds it at zero (replaces negative values with zero)

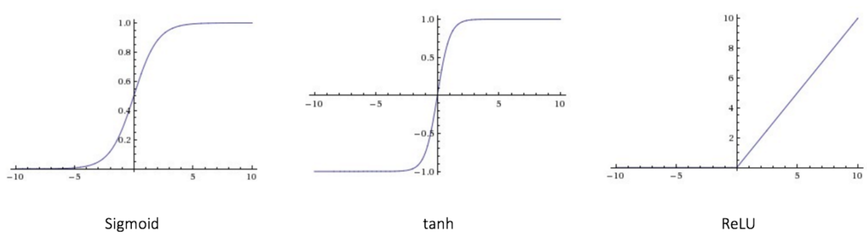


Figure 2: Different activation functions

3 Methods

3.1 Neural Network

This project implements a feedforward neural network, which is the first and simplest type of artificial neural network devised. It contains multiple neurons (nodes) arranged in **layers**. Nodes from adjacent layers have **connections** or **edges** between them. All these connections have **weights** associated with them.

A feedforward neural network can consist of three types of nodes:

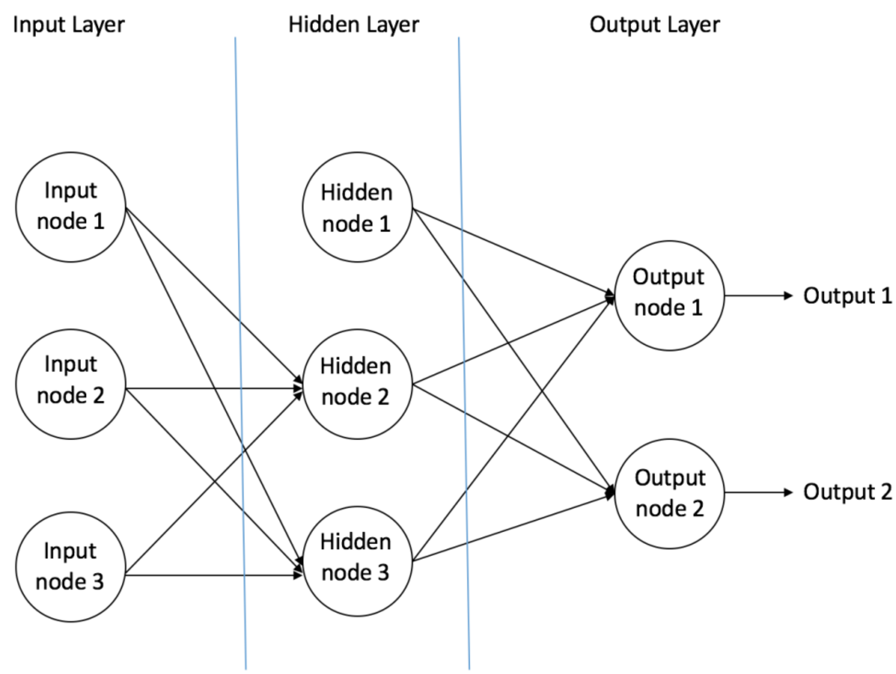


Figure 3: Example of feedforward neural network

- **Input Nodes**: provide information from the outside world to the network and are together referred to as the "Input Layer". No computation is performed in any of the Input nodes – they just pass on the information to the hidden nodes.
- **Hidden Nodes**: they have no direct connection with the outside world (hence the name "hidden"). They perform computations and transfer information from the input nodes to the output nodes. A collection of hidden nodes forms a "Hidden Layer". While a feedforward network will only have a single input layer and a single output layer, it can have zero or multiple Hidden Layers.
- **Output Nodes**: they are collectively referred to as the "Output Layer" and are responsible for computations and transferring information from the network to the outside world.

In a feedforward network, the information moves in only one direction – forward – from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network (this property of feed forward networks is different from Recurrent Neural Networks in which the connections between the nodes form a cycle).

3.1.1 Multilayer Perceptron

A Multi Layer Perceptron (MLP) has one or more hidden layers. We will only discuss Multi Layer Perceptrons as they are the ones implemented in this project. An MLP contains one or more hidden layers (apart from one input and one output layer). While a single layer perceptron can only learn linear functions, a multi layer perceptron can also learn non – linear functions.

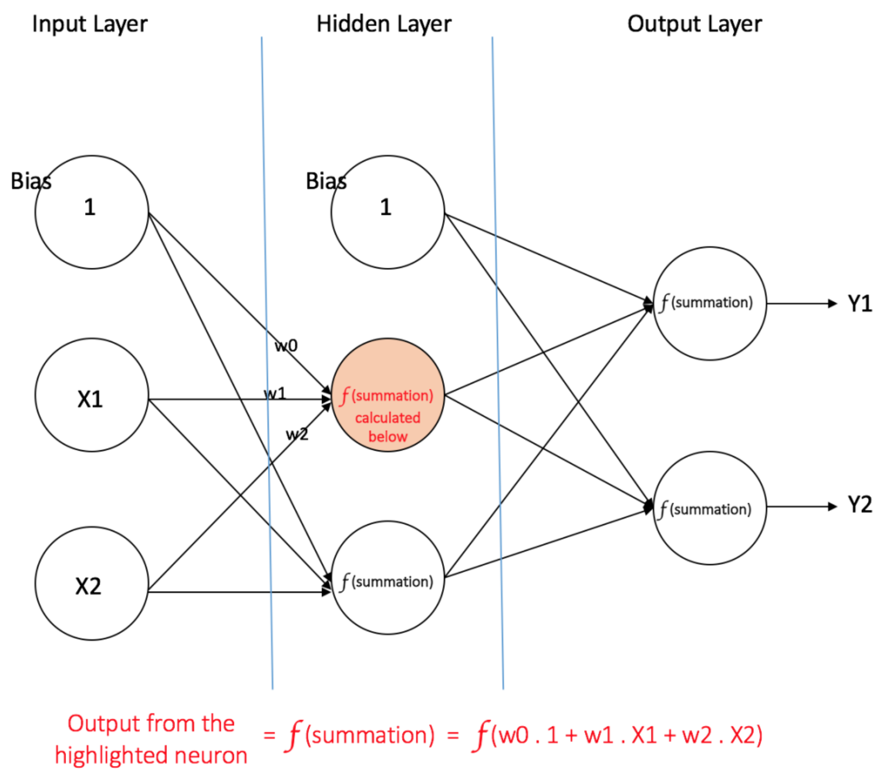


Figure 4: Example a multi layer perceptron having one hidden layer

Figure 4 shows a multi layer perceptron with a single hidden layer. Note that all connections have weights associated with them, but only three weights (w0, w1, w2) are shown in the figure.

- **Input Layer**: The Input layer has three nodes. The Bias node has a value of 1. The other two nodes take X1 and X2 as external inputs (which are numerical values depending upon the input dataset). As discussed above, no computation is performed in the Input layer, so the outputs from nodes in the Input layer are 1, X1 and X2 respectively, which are fed into the Hidden Layer.

- **Hidden Layer**: The Hidden layer also has three nodes with the Bias node having an output of 1. The output of the other two nodes in the Hidden layer depends on the outputs from the Input layer (1, X1, X2) as well as the weights associated with the connections (edges). Figure 4 shows the output calculation for one of the hidden nodes (highlighted). Similarly, the output from other hidden node can be calculated. Remember that f refers to the activation function. These outputs are then fed to the nodes in the Output layer.

- **Output Layer**: The Output layer has two nodes which take inputs from the Hidden layer and perform similar computations as shown for the highlighted hidden node. The values calculated (Y1 and Y2) as a result of these computations act as outputs of the Multi Layer Perceptron.

Given a set of features $X = (x1, x2, \dots)$ and a target $\mathbf{y}$, a MLP can learn the relationship between the features and the target, for either classification or regression.

3.2 TensorFlow

This project uses TensorFlow to help process the training and test images to feed the neural network.

TensorFlow is an open-source software library for dataflow programming across a range of tasks. It is a symbolic math library, and is also used for machine learning applications such as neural networks. It is used for both research and production at Google.

TensorFlow is Google Brain's second-generation system. Version 1.0.0 was released on February 11, 2017. While the reference implementation runs on single devices, TensorFlow can run on multiple CPUs and GPUs (with optional CUDA and SYCL extensions for general-purpose computing on graphics processing units). TensorFlow is available on 64-bit Linux, macOS, Windows, and mobile computing platforms including Android and iOS.

Its flexible architecture allows for the easy deployment of computation across a variety of platforms (CPUs, GPUs, TPUs), and from desktops to clusters of servers to mobile and edge devices.

TensorFlow computations are expressed as stateful dataflow graphs. The name TensorFlow derives from the operations that such neural networks perform on multidimensional data arrays. These arrays are referred to as "tensors". In June 2016, Dean stated that 1,500 repositories on GitHub mentioned TensorFlow, of which only 5 were from Google.

3.3 MNIST

The MNIST database (Modified National Institute of Standards and Technology database) is a large database of handwritten digits that is commonly used for training various image processing systems. The database is also widely used for training and testing in the field of machine learning. It was created by "re-mixing" the samples from NIST's original datasets. The creators felt that since NIST's training dataset was taken from American Census Bureau employees, while the testing dataset was taken from American high school students, it was not well-suited for machine learning experiments. Furthermore, the black and white images from NIST were normalized to fit into a 28x28 pixel bounding box and anti-aliased, which introduced grayscale levels.

The MNIST database contains 60,000 training images and 10,000 testing images. Half of the training set and half of the test set were taken from NIST's training dataset, while the other half of the training set and the other half of the test set were taken from NIST's testing dataset. There have been a number of scientific papers on attempts to achieve the lowest error rate; one paper, using a hierarchical system of convolutional neural networks, manages to get an error rate on the MNIST database of 0.23%. The original creators of the database keep a list of some of the methods tested on it. In their original paper, they use a support vector machine to get an error rate of 0.8%. An extended dataset similar to MNIST called EMNIST has been published in 2017, which contains 240,000 training images, and 40,000 testing images of handwritten digits and characters.

4 Results

This project implemented 6 different configurations for the MLP, and the results show as follows:

- 128 neurons per layer, 2 layers
- 256 neurons per layer, 2 layers
- 512 neurons per layer, 2 layers
- 128 neurons per layer, 3 layers
- 256 neurons per layer, 3 layers
- 512 neurons per layer, 3 layers

4.1 Neural Network Trainning Results

Step	Batch Loss	Training Accuracy
1	3122.9219	0.438
100	36.4435	0.898
200	19.4324	0.891
300	29.9501	0.844
400	18.6390	0.828
500	9.7420	0.875

Table 1: 128 neurons per layer, 2 layers

Step	Batch Loss	Training Accuracy
1	8788.0879	0.453
100	328.0475	0.820
200	132.2209	0.875
300	78.5238	0.844
400	49.2364	0.836
500	75.1907	0.820

Table 2: 256 neurons per layer, 2 layers

Step	Batch Loss	Training Accuracy
1	39196.4062	0.359
100	1610.4182	0.812
200	524.1964	0.883
300	210.3122	0.867
400	276.1759	0.812
500	150.8354	0.867

Table 3: 512 neurons per layer, 2 layers

Step	Batch Loss	Training Accuracy
1	28933.5605	0.344
100	741.4419	0.852
200	255.7320	0.914
300	325.6880	0.859
400	244.8334	0.867
500	130.3818	0.883

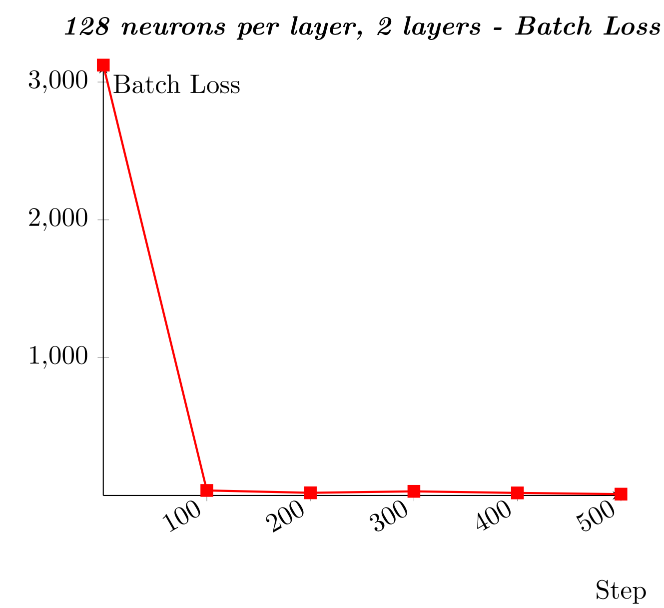
Table 4: 128 neurons per layer, 3 layers

Step	Batch Loss	Training Accuracy
1	222537.9219	0.359
100	4577.3066	0.867
200	2686.8589	0.875
300	2361.8943	0.820
400	720.9211	0.875
500	920.4222	0.875

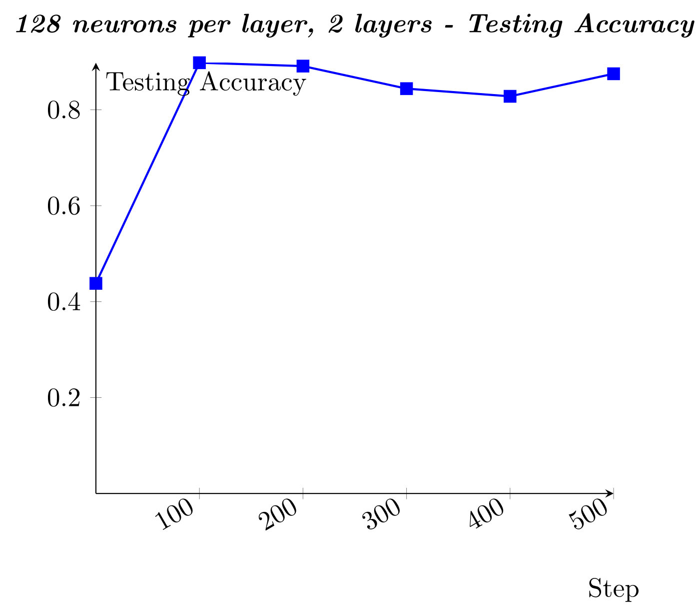
Table 5: 256 neurons per layer, 3 layers

Step	Batch Loss	Training Accuracy
1	825527.0000	0.422
100	15847.6143	0.891
200	16547.9551	0.836
300	4125.0908	0.898
400	3149.9961	0.891
500	5895.4766	0.867

Table 6: 512 neurons per layer, 3 layers

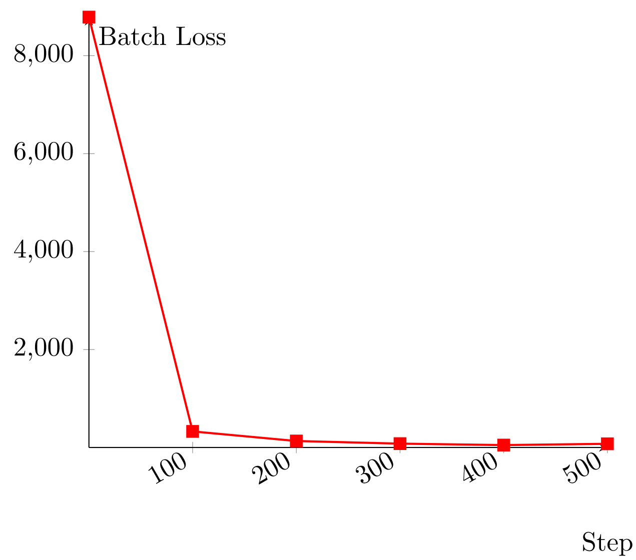


128 neurons per layer, 2 layers - Batch Loss
Batch Loss
3,000
2,000
1,000
100
200
300
400
500
Step

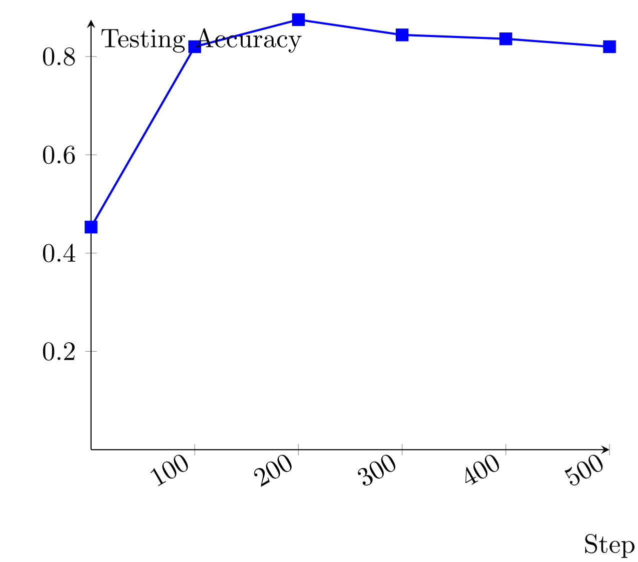


128 neurons per layer, 2 layers - Testing Accuracy
Testing Accuracy
0.8
0.6
0.4
0.2
100
200
300
400
500
Step

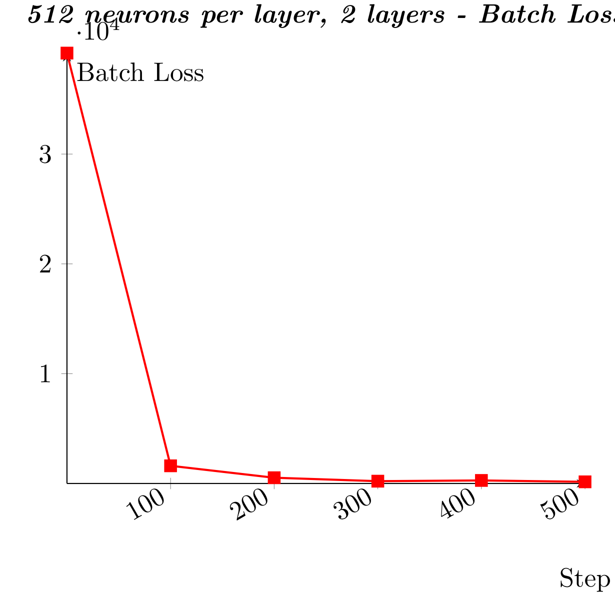
256 neurons per layer, 2 layers - Batch Loss



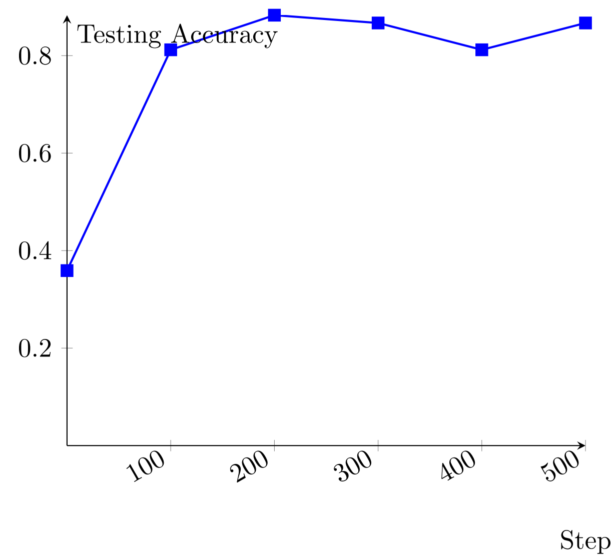
256 neurons per layer, 2 layers - Testing Accuracy



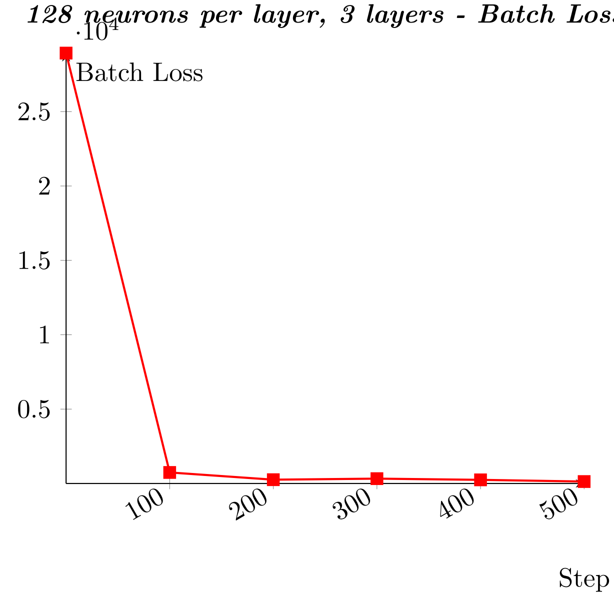
512 neurons per layer, 2 layers - Batch Loss



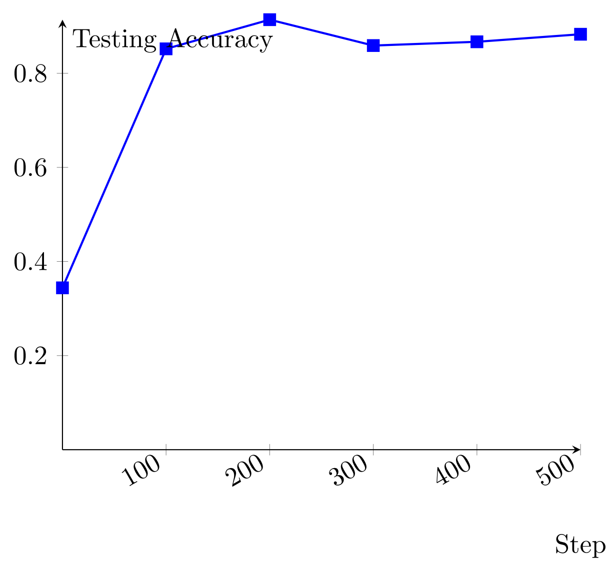
512 neurons per layer, 2 layers - Testing Accuracy



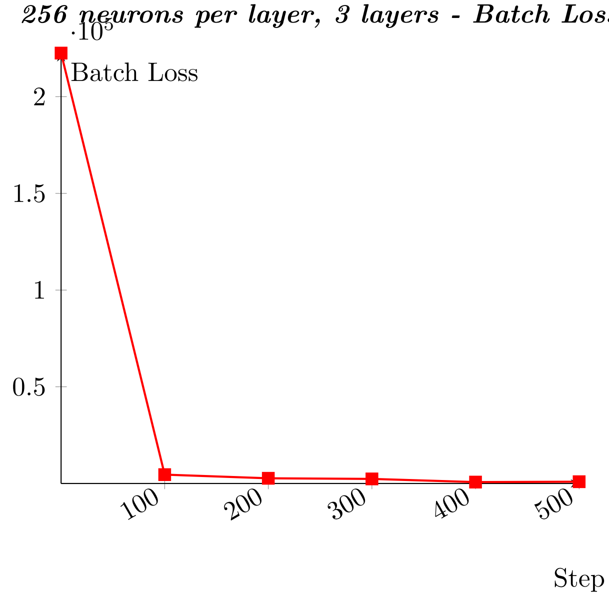
128 neurons per layer, 3 layers - Batch Loss



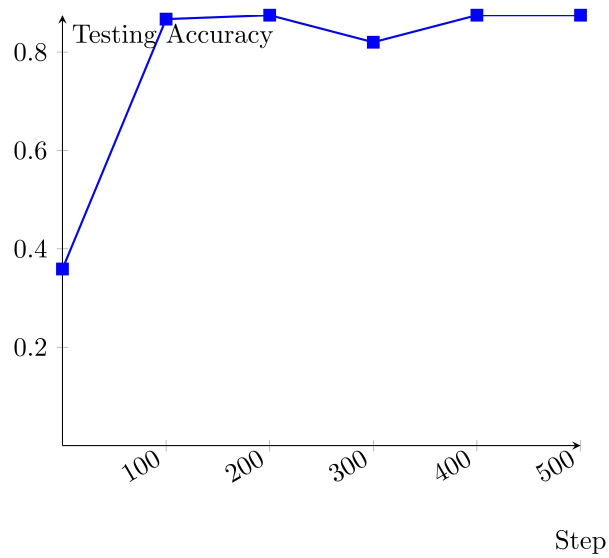
128 neurons per layer, 3 layers - Testing Accuracy



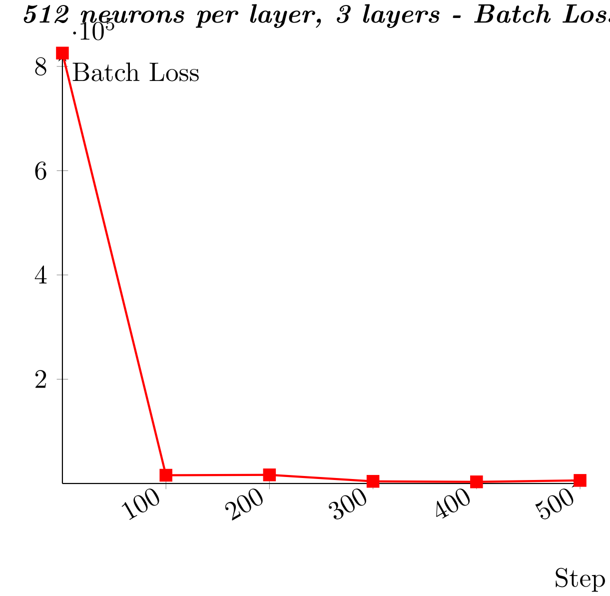
256 neurons per layer, 3 layers - Batch Loss



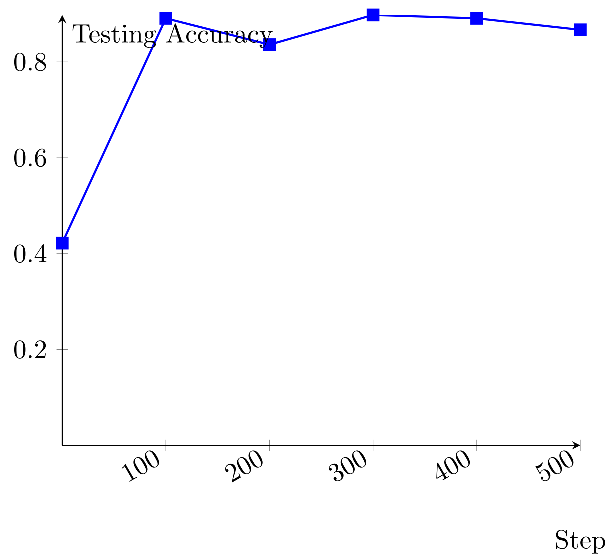
256 neurons per layer, 3 layers - Testing Accuracy



512 neurons per layer, 3 layers - Batch Loss



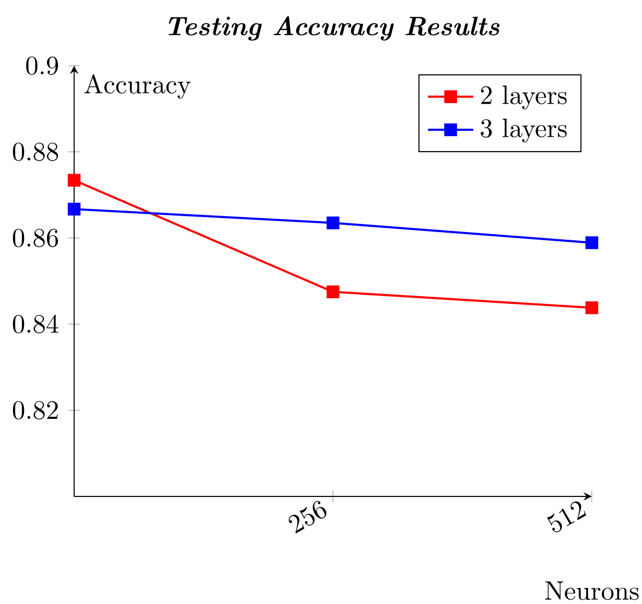
512 neurons per layer, 3 layers - Testing Accuracy



4.2 Neural Network Testing Results

Neurons	2 layers	3 layers
128	0.8734	0.8667
256	0.8475	0.8635
512	0.8438	0.8589

Table 7: Testing Accuracy



5 Conclusions

- Effects of increasing the number of neurons in both 2 and 3 layered NN:
  - Trainning accuracy does not suffers much.
  - Batch loss increases massively.
  - Testing accuracy decreases.
- By adding an extra layer to the neural network, the impact of adding extra neurons to the layers is much less than with only two layers.

References

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