

Question 1

We first need to define the formulas for forward propagation. By propagating forward, our model generates a prediction about our classes.

$\mathbf{a}^L = \mathbf{g}(\mathbf{W}^L \mathbf{a}^{L-1} + \mathbf{b}^L)$ is the formula for computing the activations. \mathbf{a}^L is the activation of layer L, \mathbf{g} is the activation function, \mathbf{W}^L is the weights of layer L, \mathbf{a}^{L-1} is the activations of layer L - 1 and \mathbf{b}^L is the bias for layer L.

By using the formula, we can create our neural network as follows:

Input layer(X, N) $\Rightarrow \mathbf{a}^1 = \mathbf{g}(\mathbf{X} + \mathbf{b}^1)$

First hidden layer(N, N') $\Rightarrow \mathbf{a}^2 = \mathbf{g}(\mathbf{W}^2 \mathbf{a}^1 + \mathbf{b}^2)$

Second hidden layer(N', N'') $\Rightarrow \mathbf{a}^3 = \mathbf{g}(\mathbf{W}^3 \mathbf{a}^2 + \mathbf{b}^3)$

Output layer(N'', 2) $\Rightarrow \mathbf{a}^4 = \mathbf{g}^*(\mathbf{W}^4 \mathbf{a}^3 + \mathbf{b}^4)$

$\mathbf{g}(\mathbf{x}) = \text{ReLU} = \max(0, \mathbf{x})$

$\mathbf{g}^*(\mathbf{x}) = \text{Sigmoid} = 1 / (1 + e^{-\mathbf{x}})$

The last step is backward propagation. This step is used for recalculating the weights. The model evaluates its predictions based on a cost function. Then by calculating partial derivative of the cost function with respect to weights, we basically find how much a change in weights would affect our predictions.

As a cost function binary cross entropy(BCE) would be a great choice since we have two classes.

$$BCE = -\frac{1}{N} \sum_{i=0}^N y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i)$$

Where y is the actual label and \hat{y} is the predicted label.

For backward propagation we define

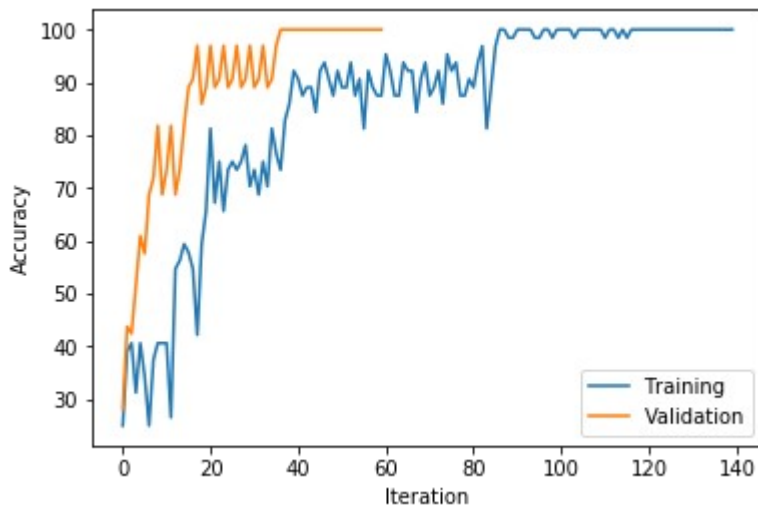
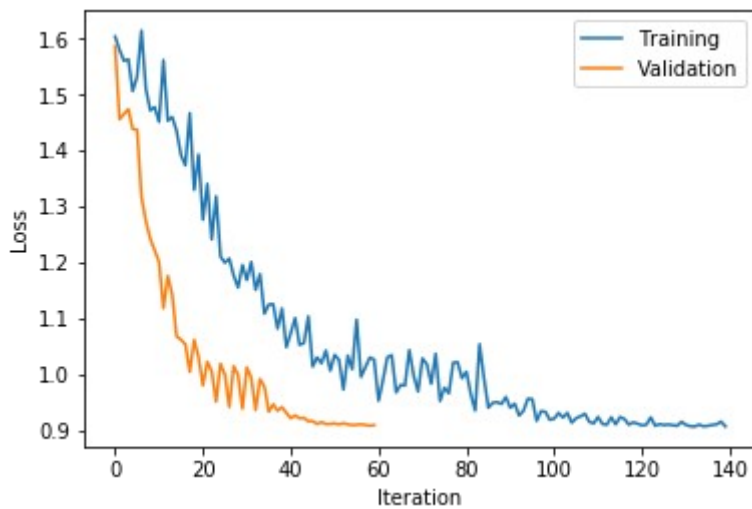
$\mathbf{z}^L = \sum \mathbf{W}^L \mathbf{a}^{(L-1)} + \mathbf{b}^L$ to make calculations easier.

The last step is to find partial derivative of the cost function with respect to weights. Here we use chain rule:

$$\frac{dBCE}{d\mathbf{W}^L} = \frac{dBCE}{d\mathbf{a}^L} \frac{d\mathbf{a}^L}{d\mathbf{z}^L} \frac{d\mathbf{z}^L}{d\mathbf{W}^L}$$

If we take respective derivatives in the formula, we get:

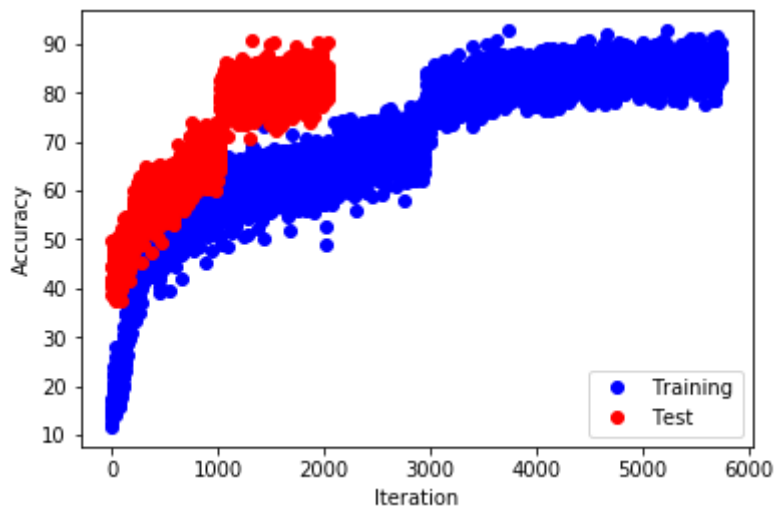
$$\frac{dBCE}{d\mathbf{W}^L} = \left(\frac{dBCE}{d\mathbf{a}^{(L+1)}} * \mathbf{W}^{(L+1)} \right) (\mathbf{g}'(\mathbf{z}^L)) (\mathbf{a}^{(L-1)})$$

Question 2**Graph1.** Accuracy plot for training and validation iterations**Graph2.** Loss plot for training and validation iterations**Confusion matrix for the test set:**

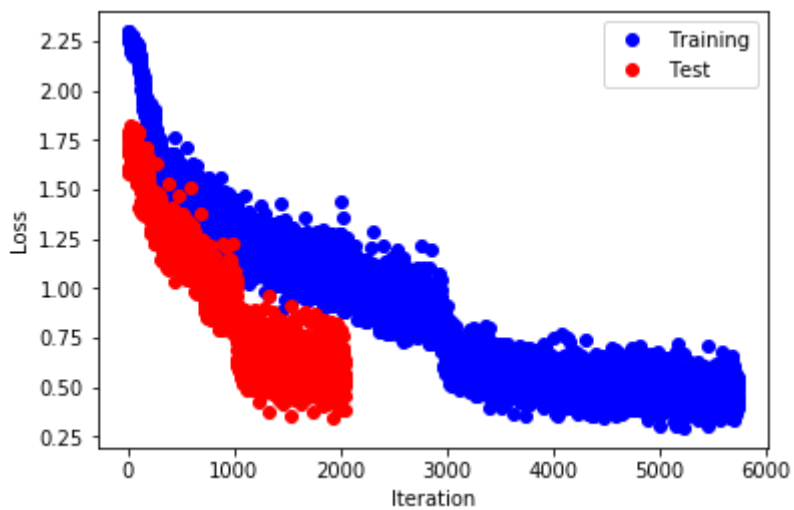
```
[[37.  0.  0.  0.  0.]
 [ 0. 43.  0.  0.  0.]
 [ 0.  0. 92.  0.  0.]
 [ 0.  0.  0. 40.  0.]
 [ 0.  1.  0.  0. 27.]]
```

Accuracy: 100%

Question 3



Graph3. Accuracy plot for training and validation iterations of MLP



Graph4. Loss plot for training and validation iterations of MLP

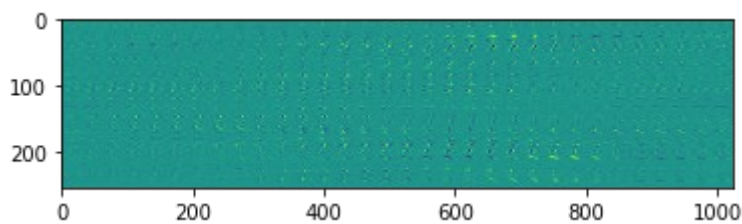


Image1. Weight visualization for MLP