

# CS671: Deep Learning and Applications

## Programming Assignment I

### Group 16

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## Classification Tasks

### Perceptron

We wrote code for a sigmoid perceptron from scratch and used it to train on both the Linearly Separable and Non-Linearly Separable Data.

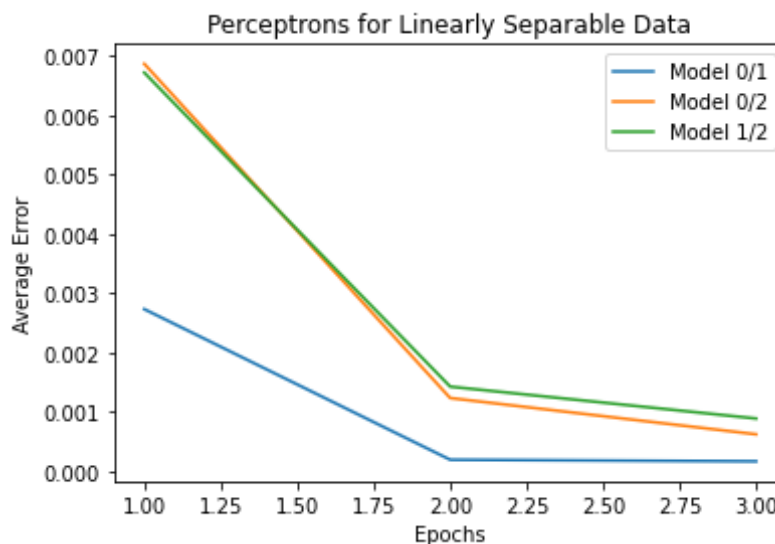
The parameters for both models were set as:

- Eta (Learning Rate Parameter) = 0.4
- Max Epochs = 10
- Error Threshold for successive epochs =  $1 \times 10^{-3}$

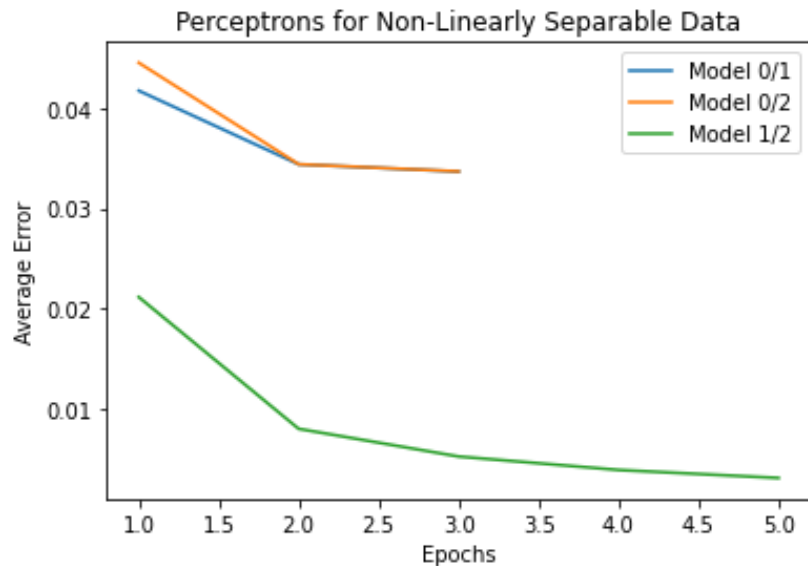
Train Test Split was done in the ratio 60:40 since the 20% from validation was also supposed to be considered as additional test data.

Both Linearly Separable Data and Non-Linearly Separable Data had three classes each.

### Q1 Plot of average error vs epochs



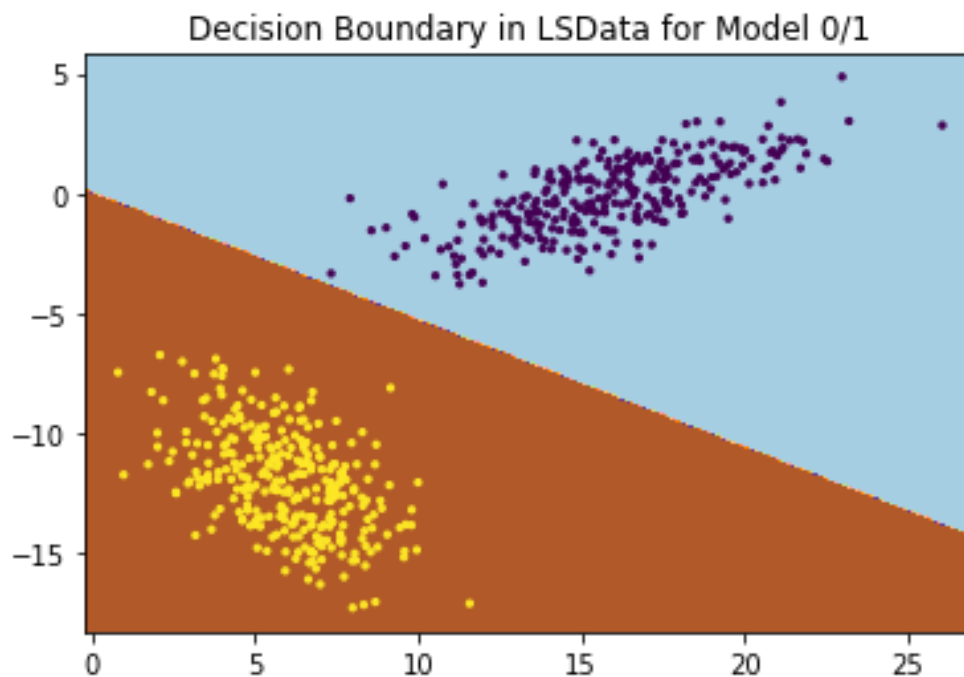
Since the one-vs-one approach was used, three different perceptrons were created to separate between classes 0/1, 1/2 & 2/0. All three perceptrons converged within 3 epochs each.



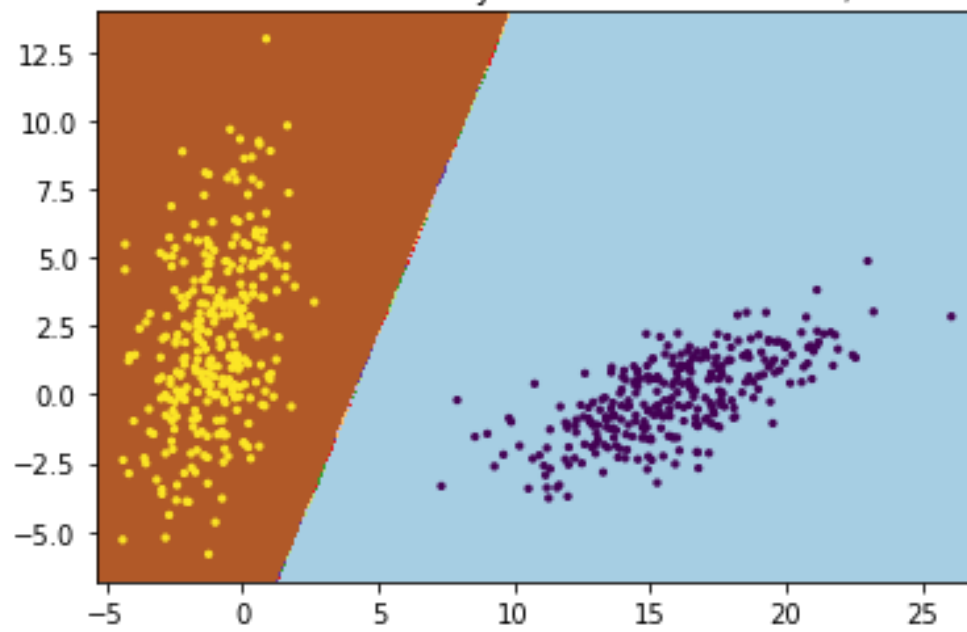
Once again three different perceptrons had to be created to classify among three classes but here the first two perceptrons i.e. 0/1 and 0/2 converged within 3 epochs while the last perceptron took 5 full epochs to converge.

Additionally, final average errors after model convergence for the first two models were also relatively higher than the third model.

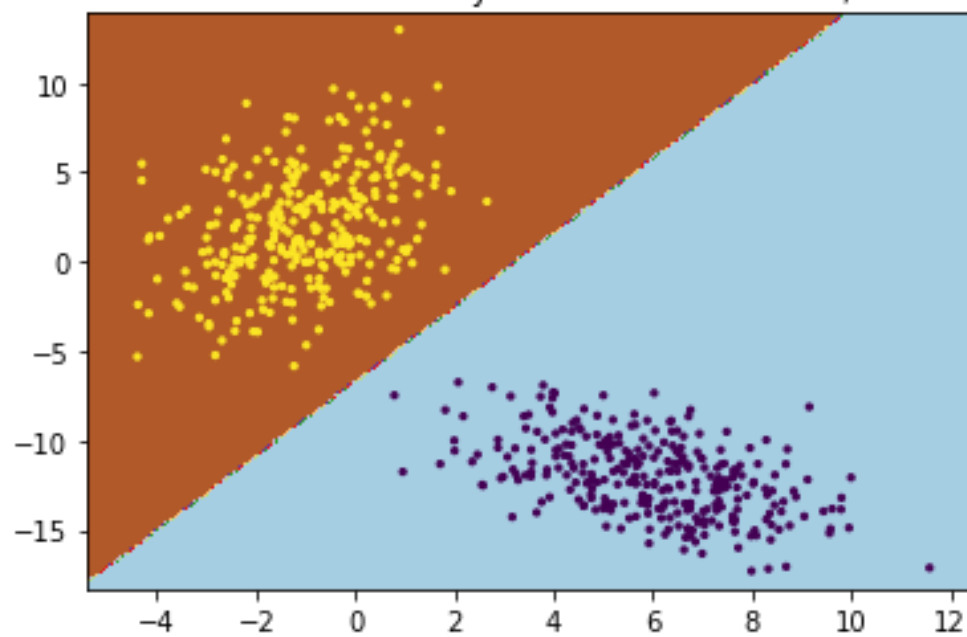
## Q2 Decision Region Plot superimposed by training data



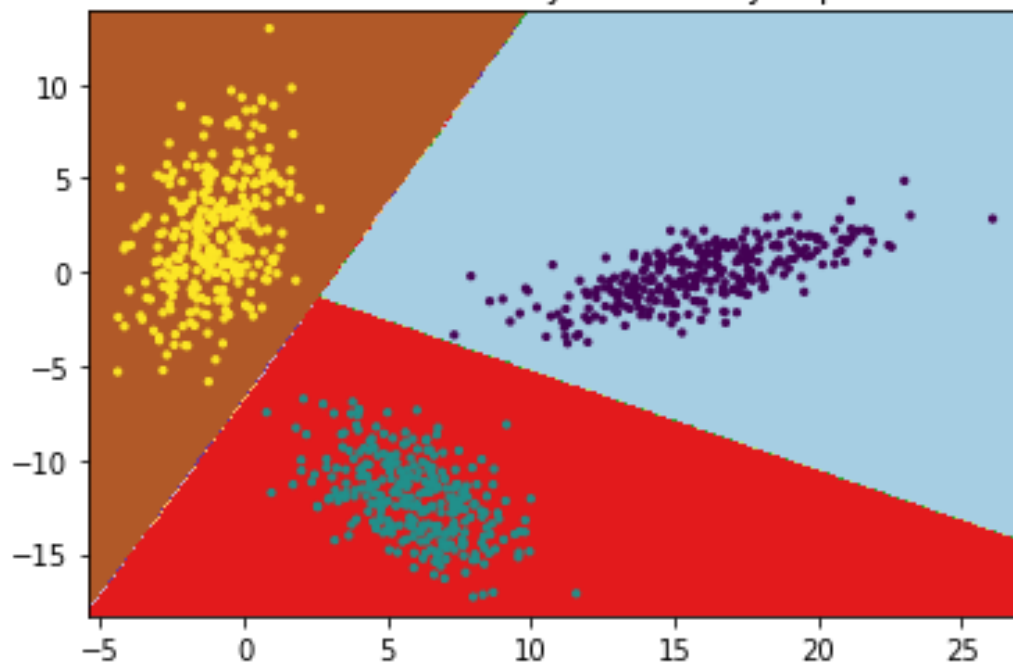
Decision Boundary in LSData for Model 0/2



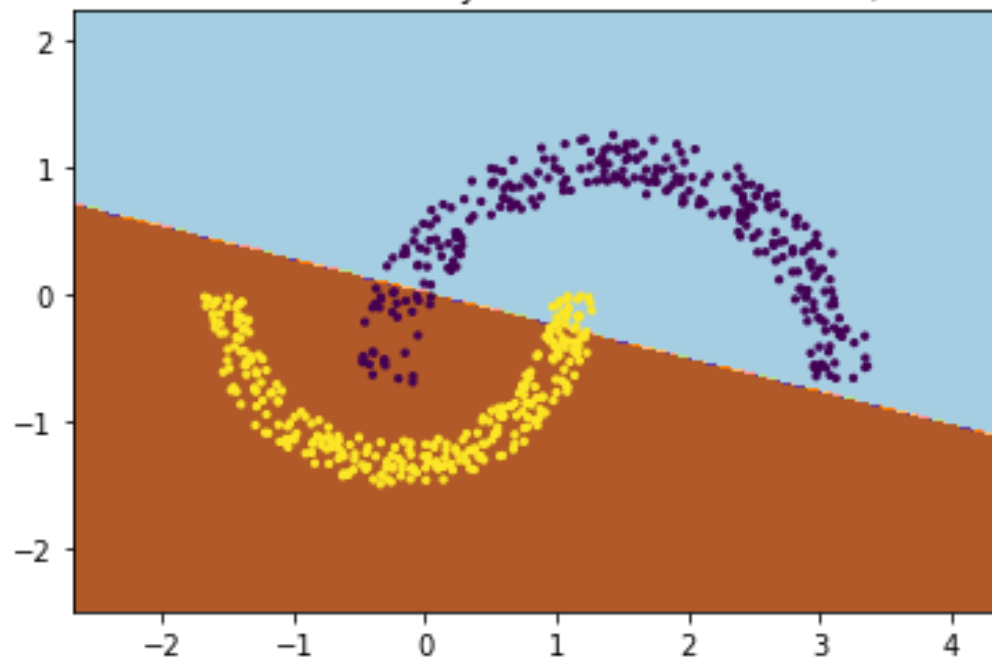
Decision Boundary in LSData for Model 1/2



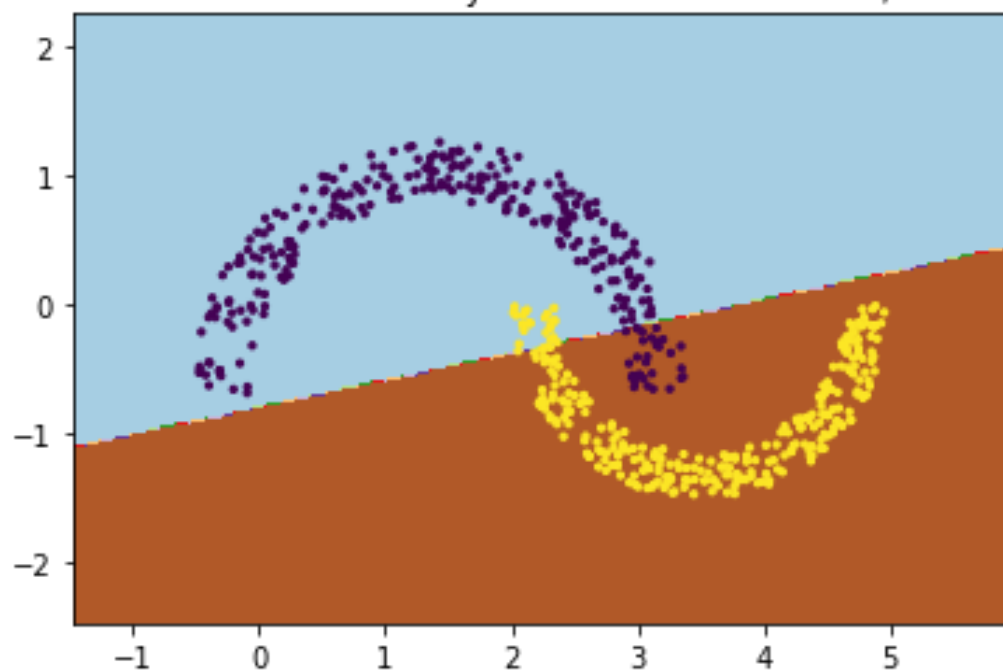
Combined Decision Boundary for Linearly Separable Data



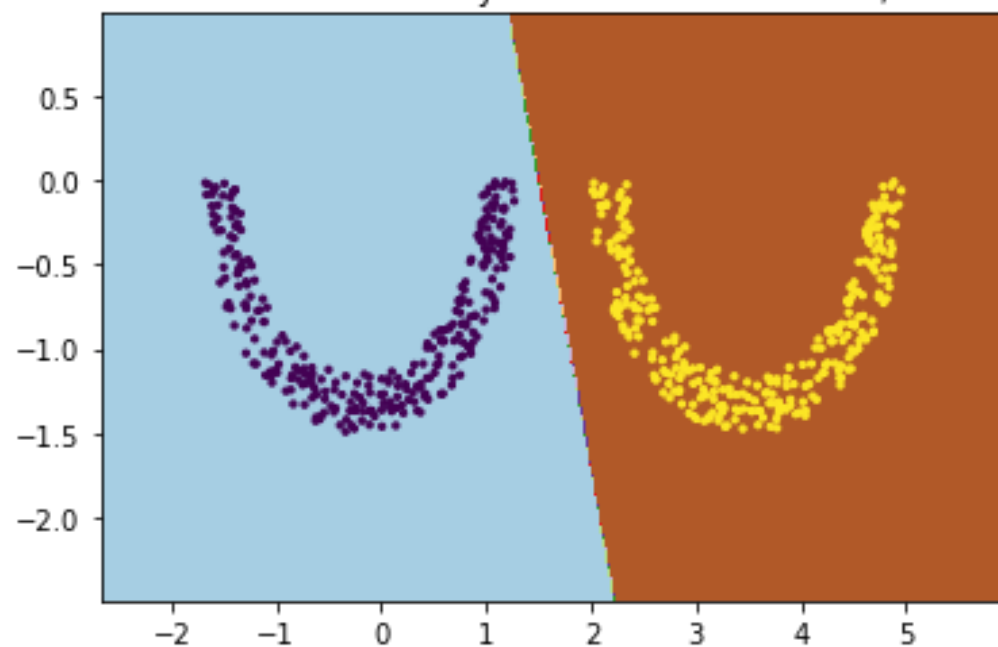
Decision Boundary in NLSData for Model 0/1



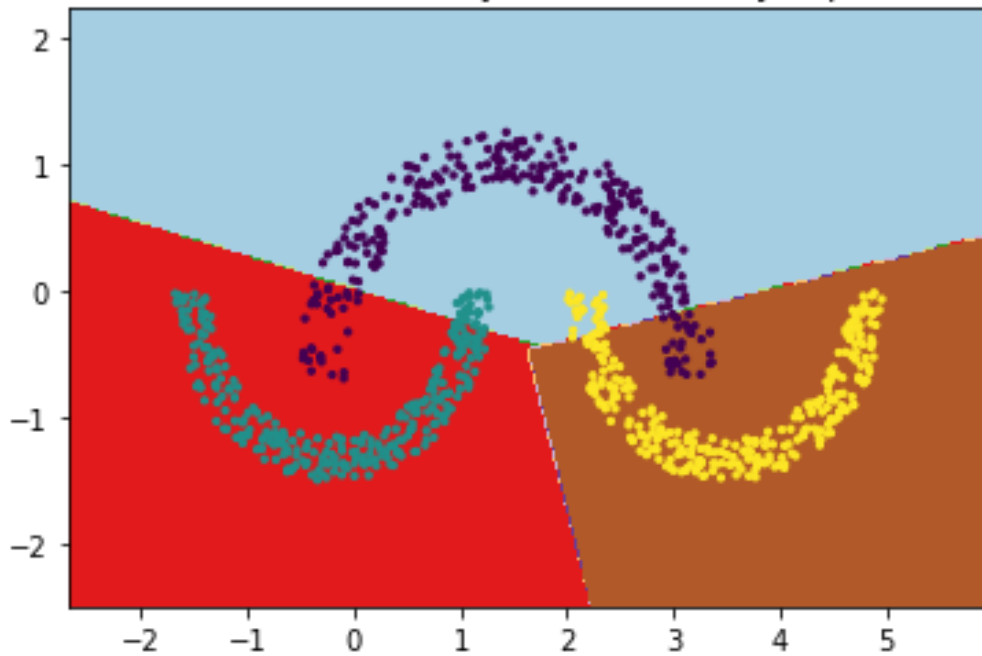
Decision Boundary in NLSData for Model 0/2



Decision Boundary in NLSData for Model 1/2



Combined Decision Boundary for Non-Linearly Separable Data



### Q3 Confusion Matrices and Accuracy Scores

For Linearly Separable Data

Confusion Matrix:

```
[[204  0  0]
 [  0 197  0]
 [  0  0 199]]
```

Accuracy Score = 1.0

For Non-Linearly Separable Data

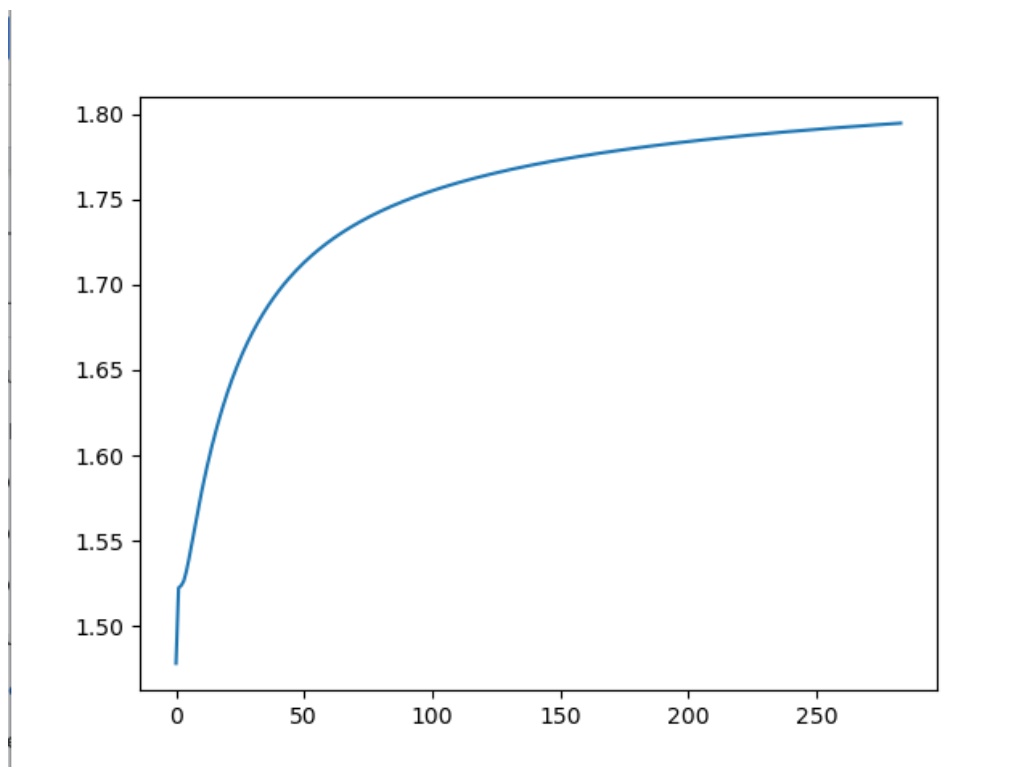
Confusion Matrix:

```
[[155  26  23]
 [  9 188  0]
 [ 19  0 180]]
```

Accuracy Score = 0.8716666666666667

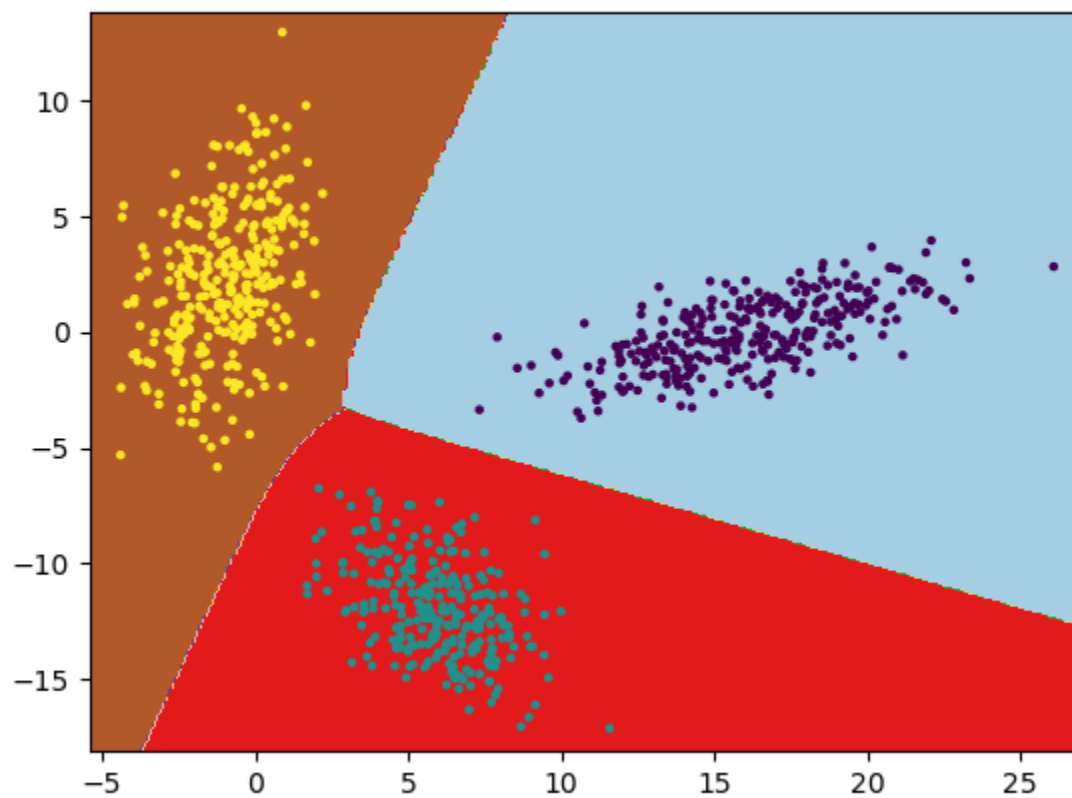
### Fully Connected Neural Network

Que 1.

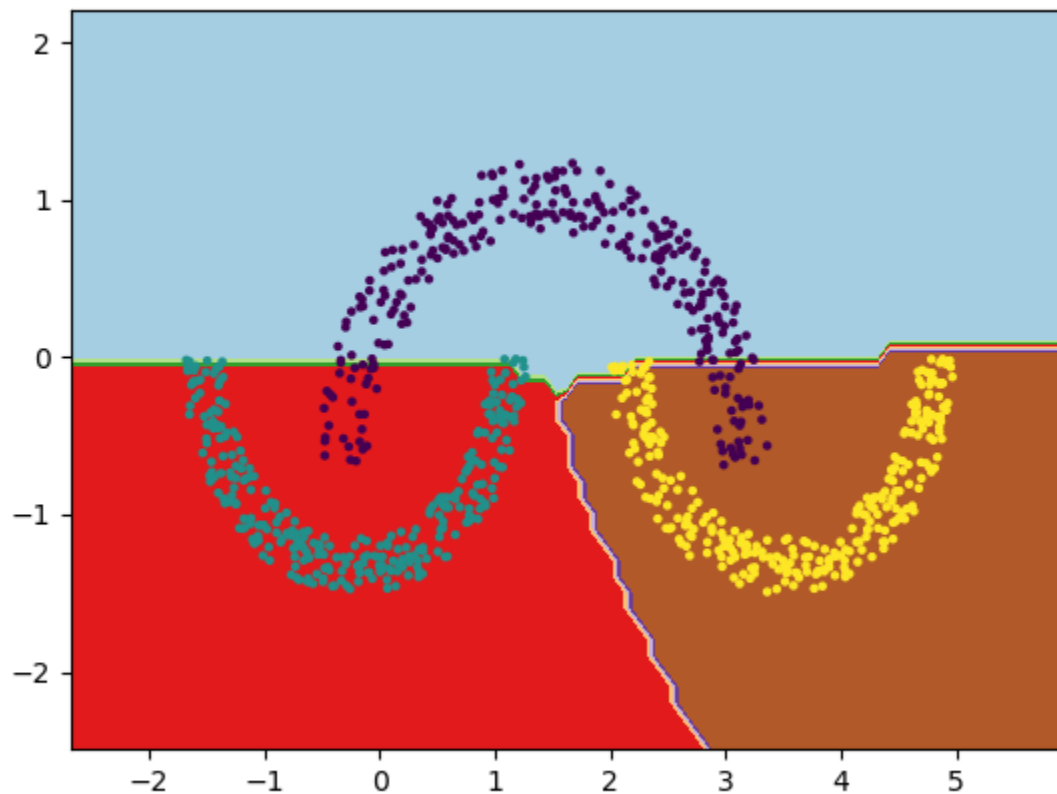


Que 2.

Decision boundary for LS data



### Decision boundary for NLS data



Que 3.

Linearly Separable:

We have taken 3 nodes in the hidden layer.  
When we had taken 1 node accuracy was 60%.  
For nodes  $\geq 2$  accuracy was 100%.

Confusion matrix:

```
[106  0  0]
[  0 92  0]
[  0  0 102]
```

Accuracy = 100 %

Non-linearly Separable:

Confusion matrix :

```
[[ 73 13 14]
```



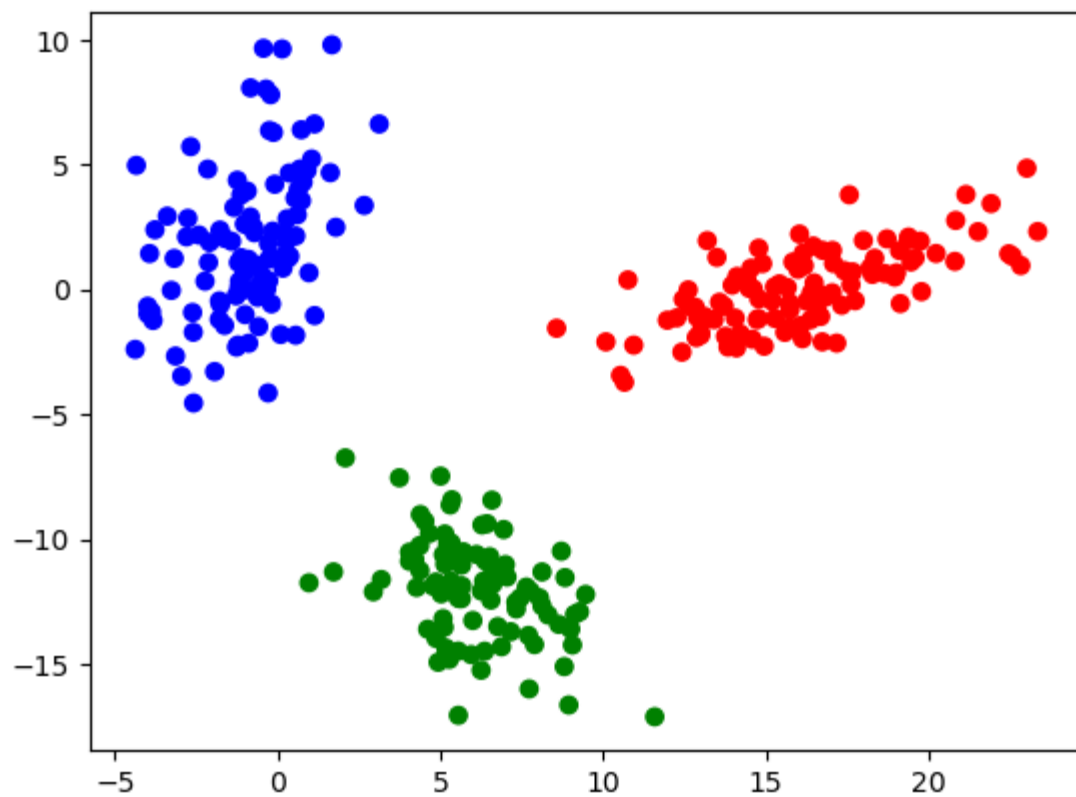
[ 2 93 0]  
[ 4 0 101]]

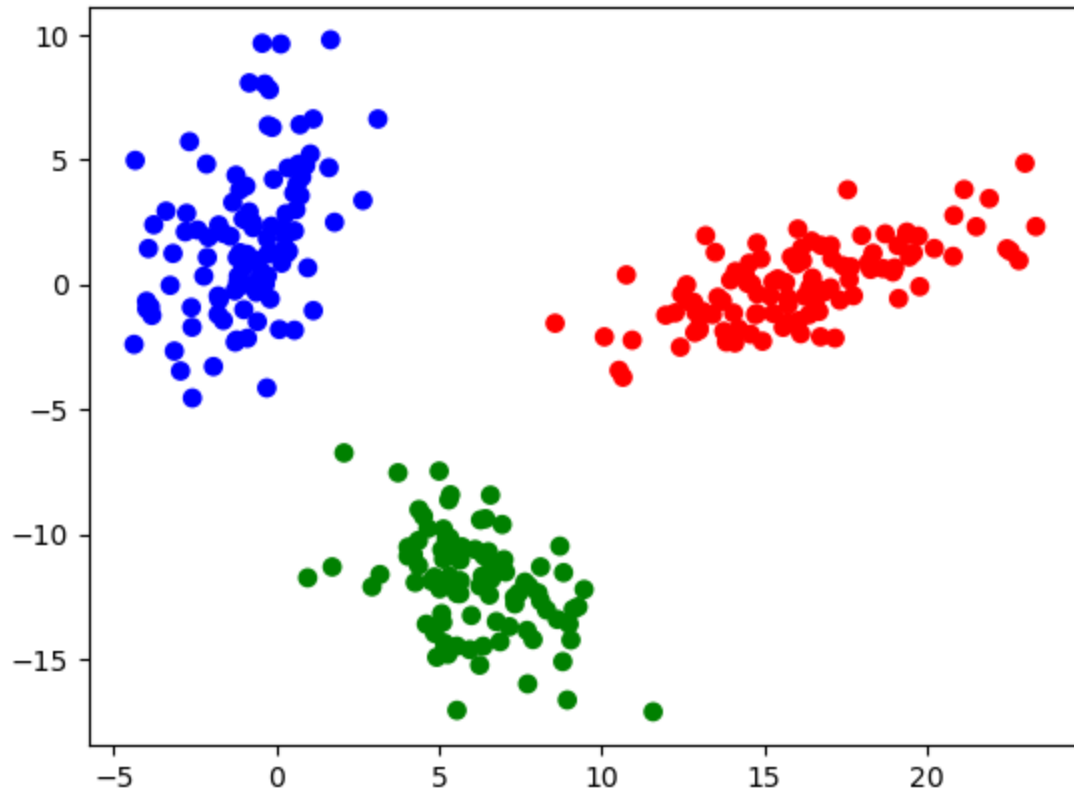
Accuracy : 0.89

#### **Ques 4**

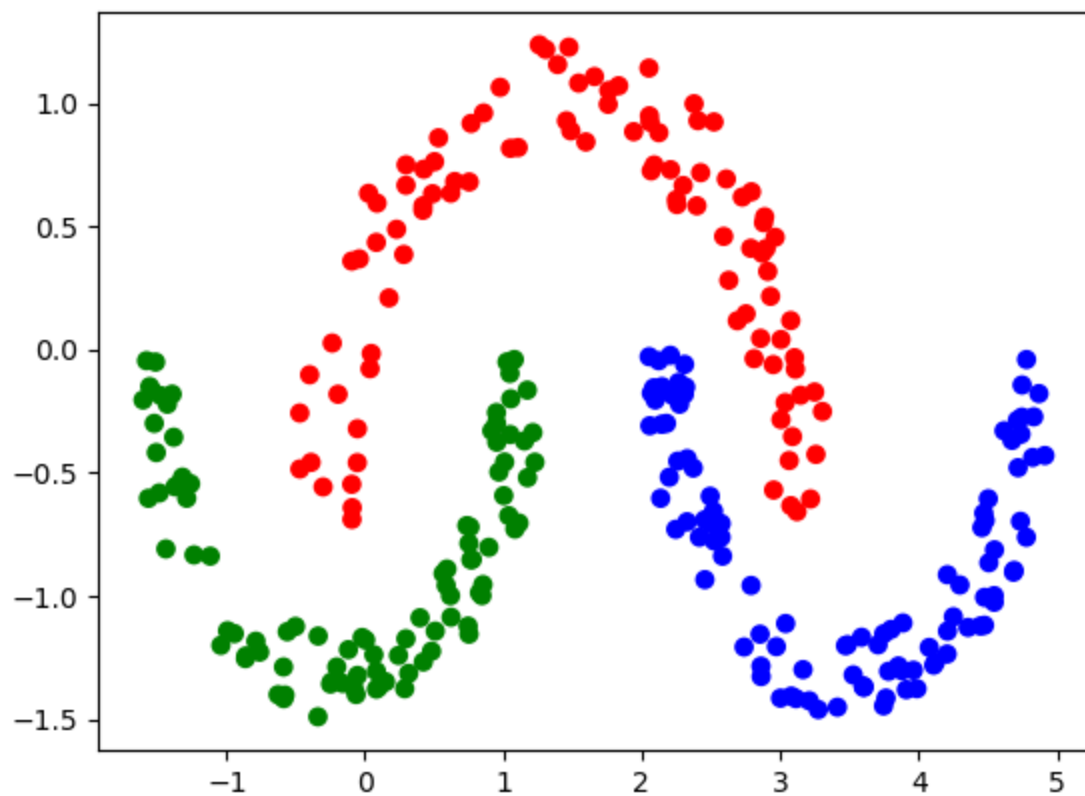
For linearly separable data, both perceptron and FCNN will perform well with an accuracy of 100%. However, in case of non linearly separable data, performance of FCNN will be better than perceptron:

A perceptron will just give a linear boundary whereas FCNN will stitch the linear boundaries obtained from all the neurons present in the model to give an approximated non-linear boundary. The performance further increases with an increase in the number of hidden layers.



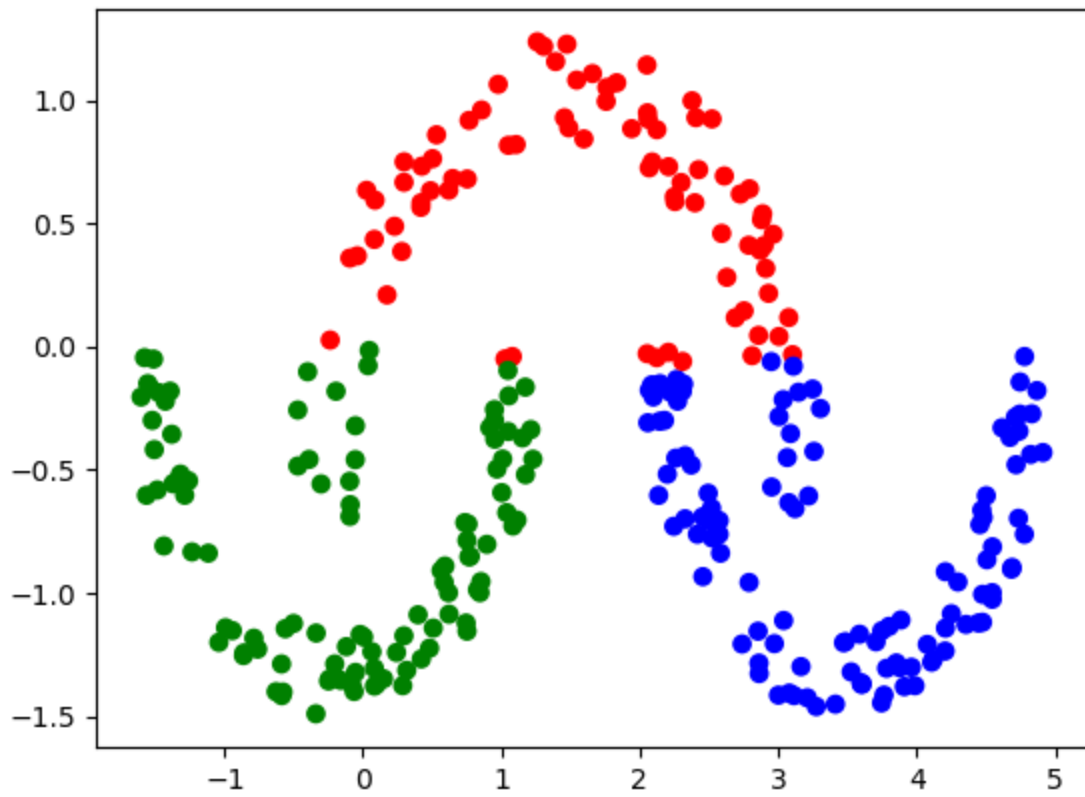


**Predicted classes for LS test data**



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**Actual classes for NLS test data**



**Predicted classes for NLS test data**

**Que 6.**

$$\Delta w_{jk}^{(0)} = n \delta_{nk}^{(0)} h_{nj}$$

$$\text{where } \delta_{nk}^{(0)} = (y_{nk} - \hat{y}_{nk}) \frac{\partial f(a_{nk}^{(0)})}{\partial a_{nk}^{(0)}}$$

$$\Delta w_{ij}^{(L)} = -n \frac{\partial E_n}{\partial w_{ij}^{(L)}}$$

$$= n \delta_{nj}^{(L)} x_i$$

$$\text{where } \delta_{nj}^{(L)} = \left[ \sum_{k=1}^K \delta_{nk}^{(0)} w_{jk}^{(0)} \right] \frac{\partial g(a_{nj})}{\partial a_{nj}}$$

Expressions for 1 hidden layer

$$\frac{\partial E_n}{\partial w_{ij}} = \frac{1}{2} \frac{\partial \sum_{k=1}^K (y_{nk} - \hat{y}_{nk})^2}{\partial w_{ij}^{(h_1)}}$$

$$= - \sum_{k=1}^K (y_{nk} - \hat{y}_{nk}) \times \frac{\partial f(a_{nk})}{\partial (a_{nk})}$$

$$\times \sum_{l=0}^L w_{lk}^{(0)} \times \left[ \frac{\partial h_{2nl}}{\partial w_{ij}^{(h_1)}} \right]$$

$$\downarrow \quad \downarrow$$

$$\frac{\partial g(a_{nl})}{\partial a_{nl}} \times w_{jl} \times \frac{\partial f(a_{nj})}{\partial (a_{nj})}$$

$$\times \kappa_{ni}$$

Expression for 2 hidden layers

Regression Tasks

## Perceptron

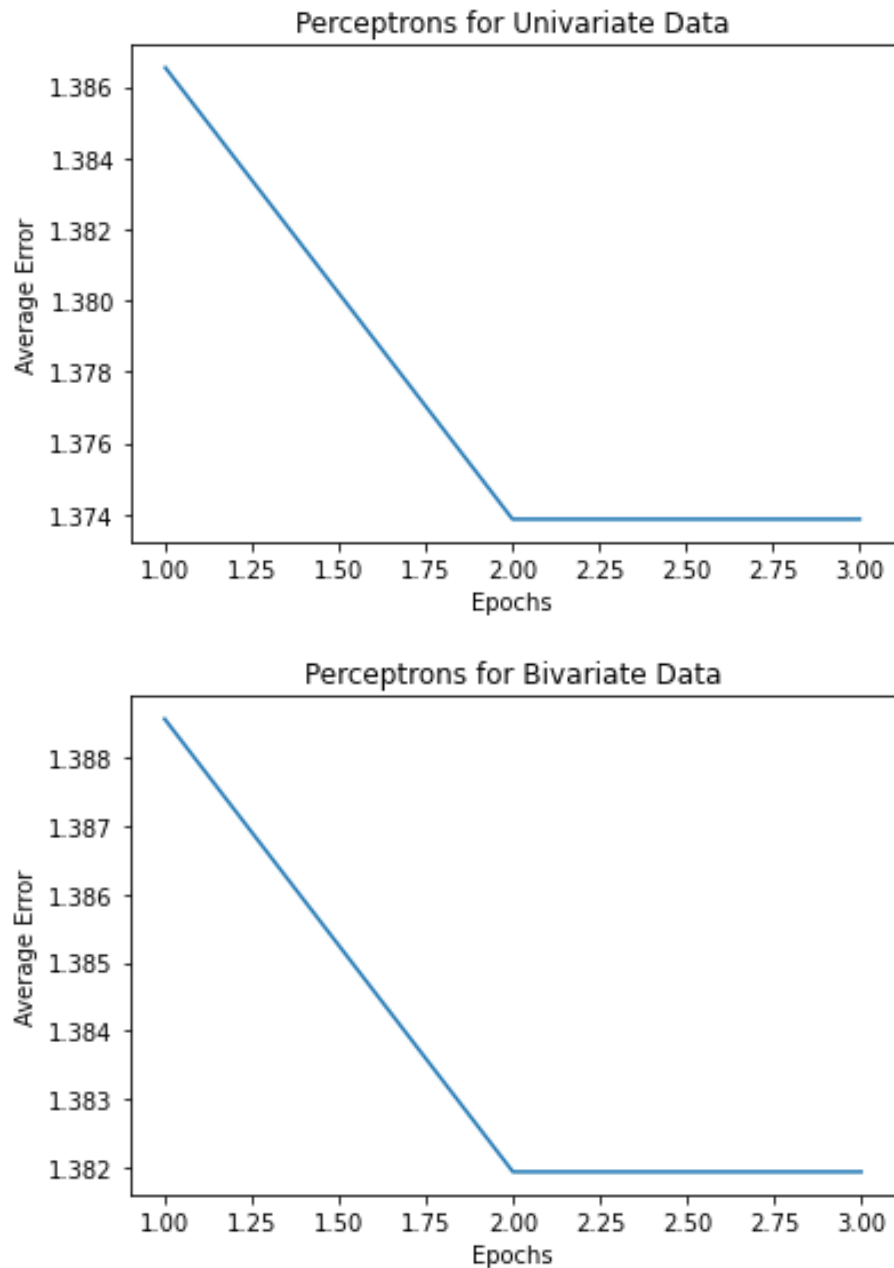
We wrote code for a linear perceptron from scratch and used it to train on both the Univariate and Bivariate Data.

The parameters for both models were set as:

- Eta (Learning Rate Parameter) = 0.4
- Max Epochs = 10
- Error Threshold for successive epochs =  $1 \times 10^{-3}$

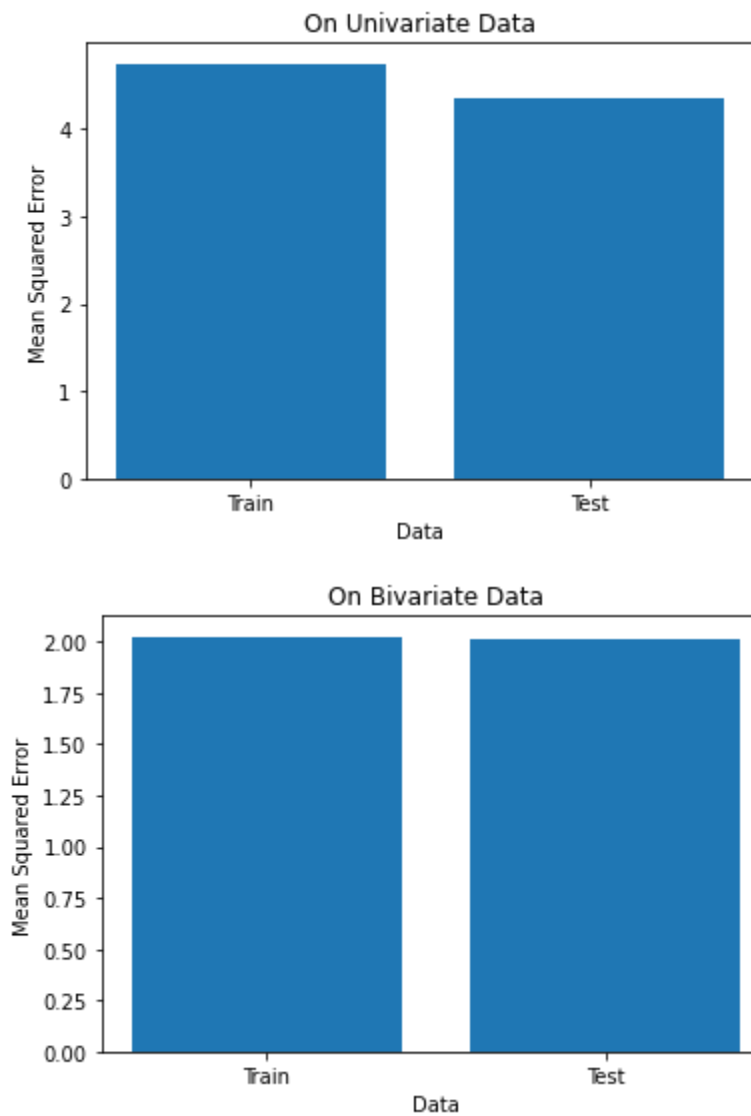
Train Test Split was done in the ratio 60:40 since the 20% from validation was also supposed to be considered as additional test data.

### Q1 Plot of average error vs epochs



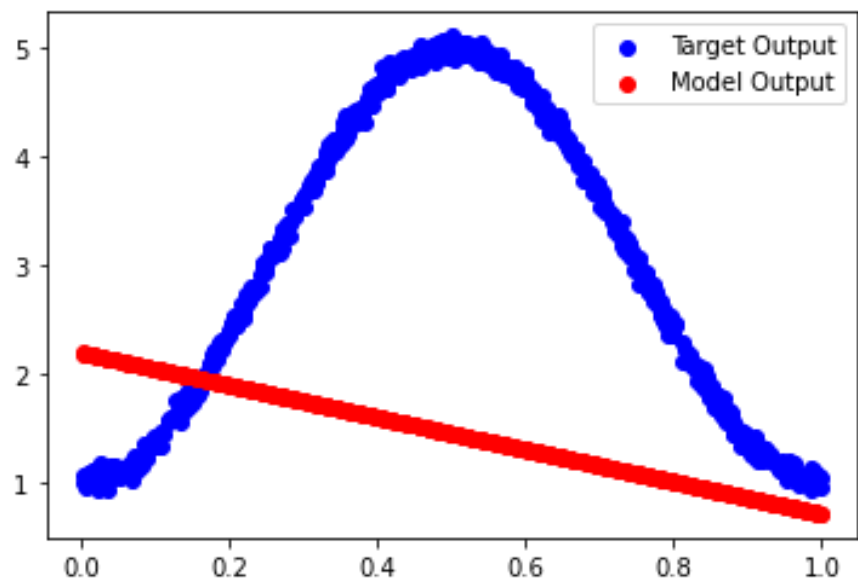


## Q2 Plot of average error vs epochs

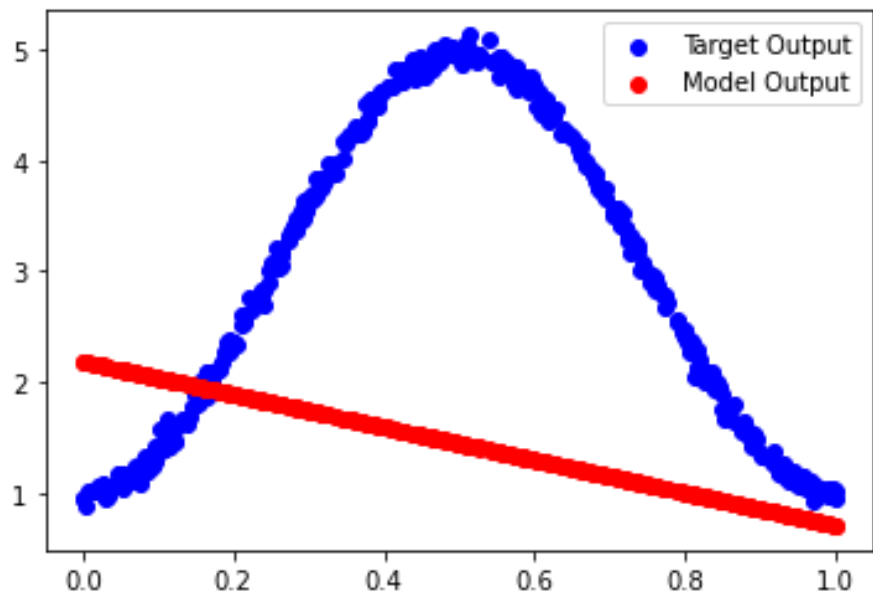


## Q3 Model Output and Target Output

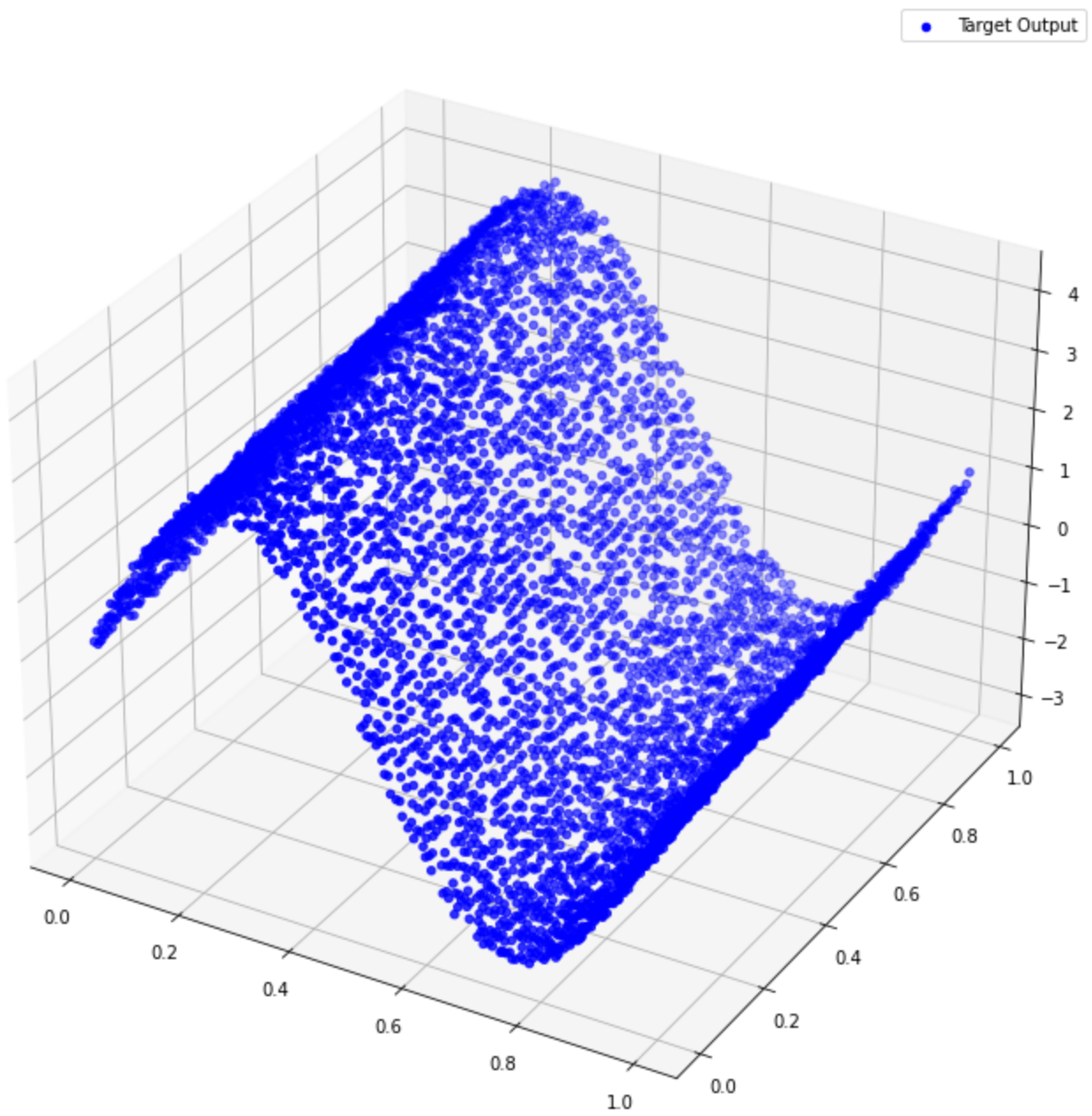
Univariate Train Data



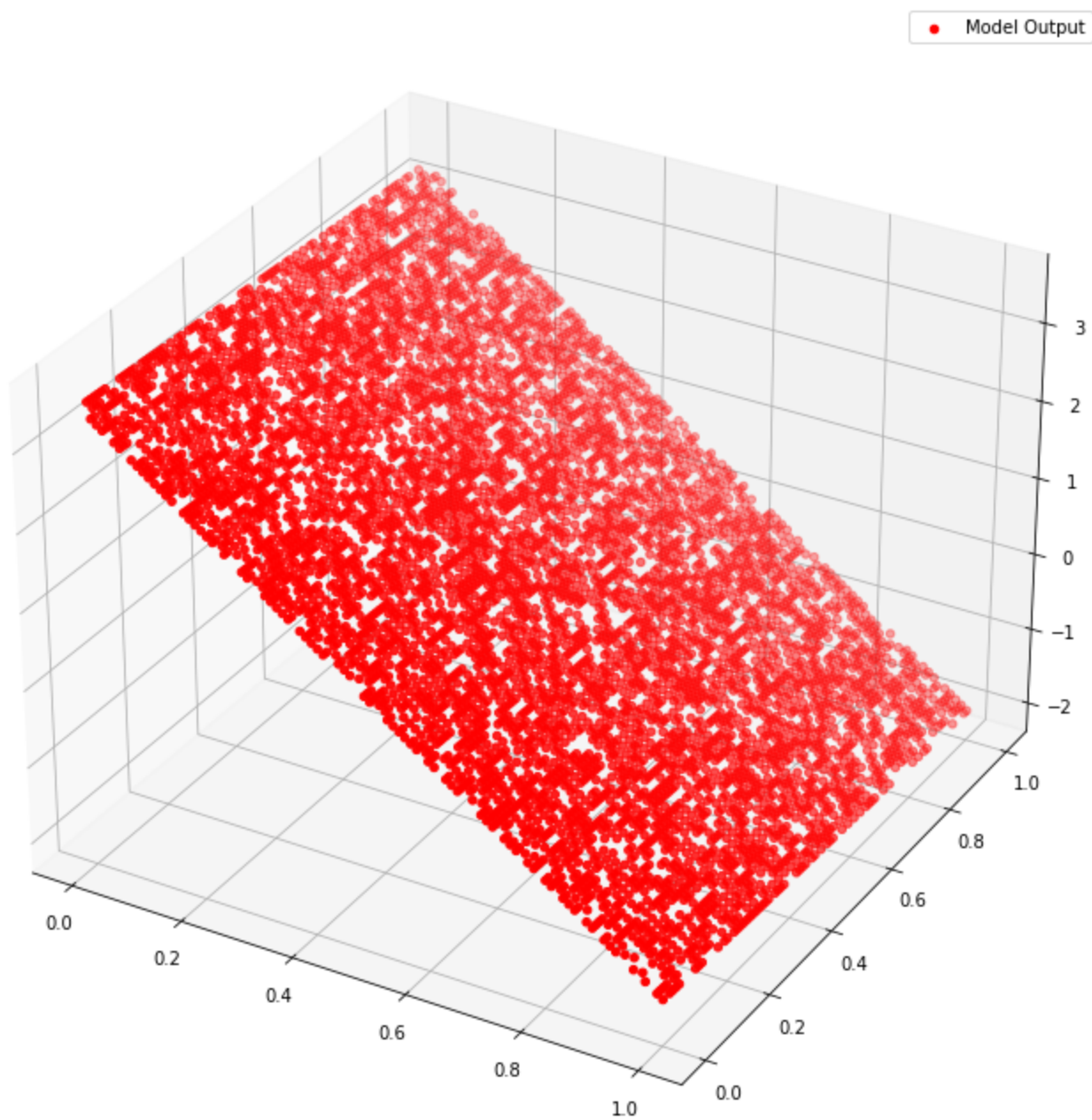
Univariate Test Data



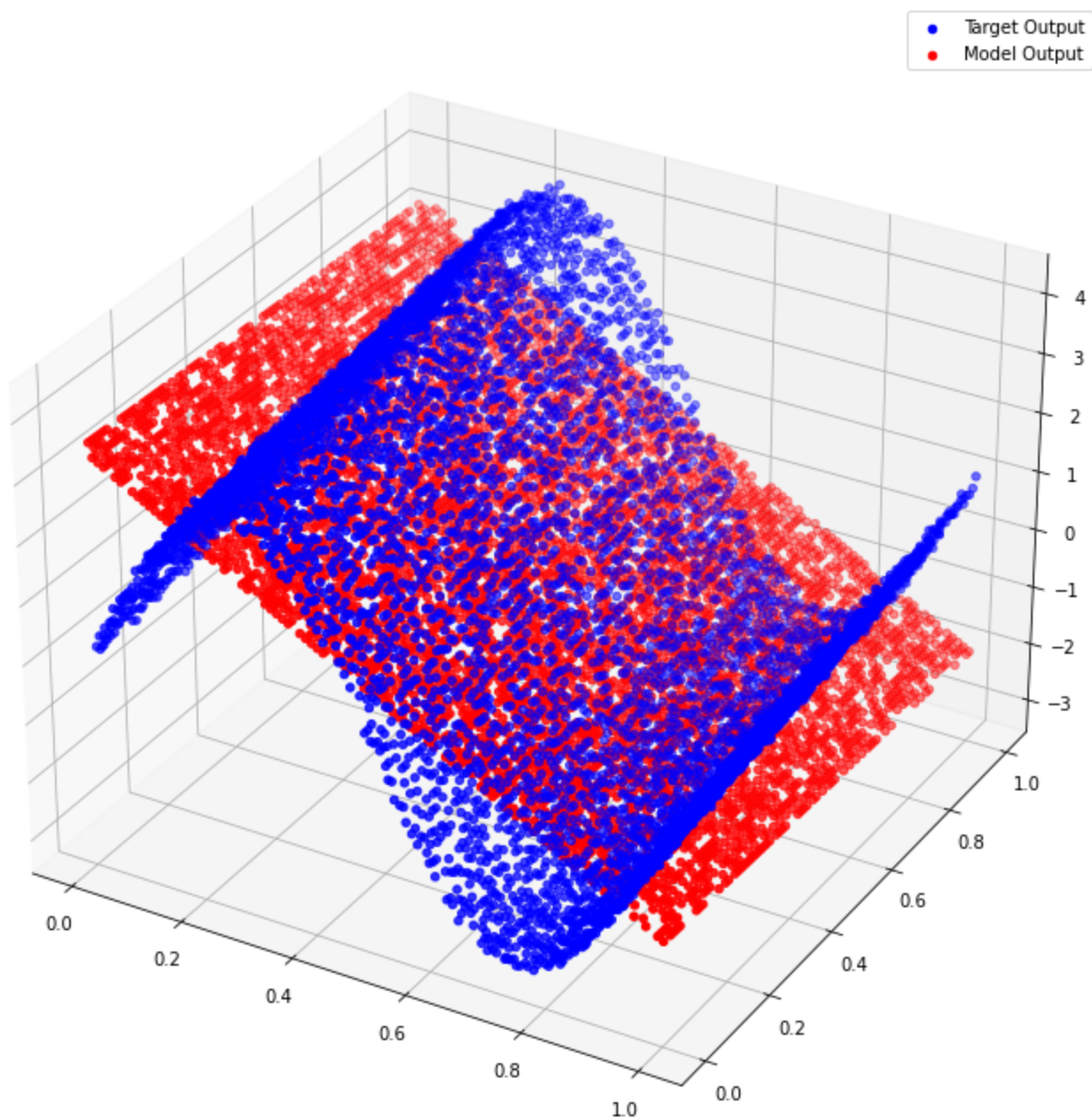
Bivariate Train Data

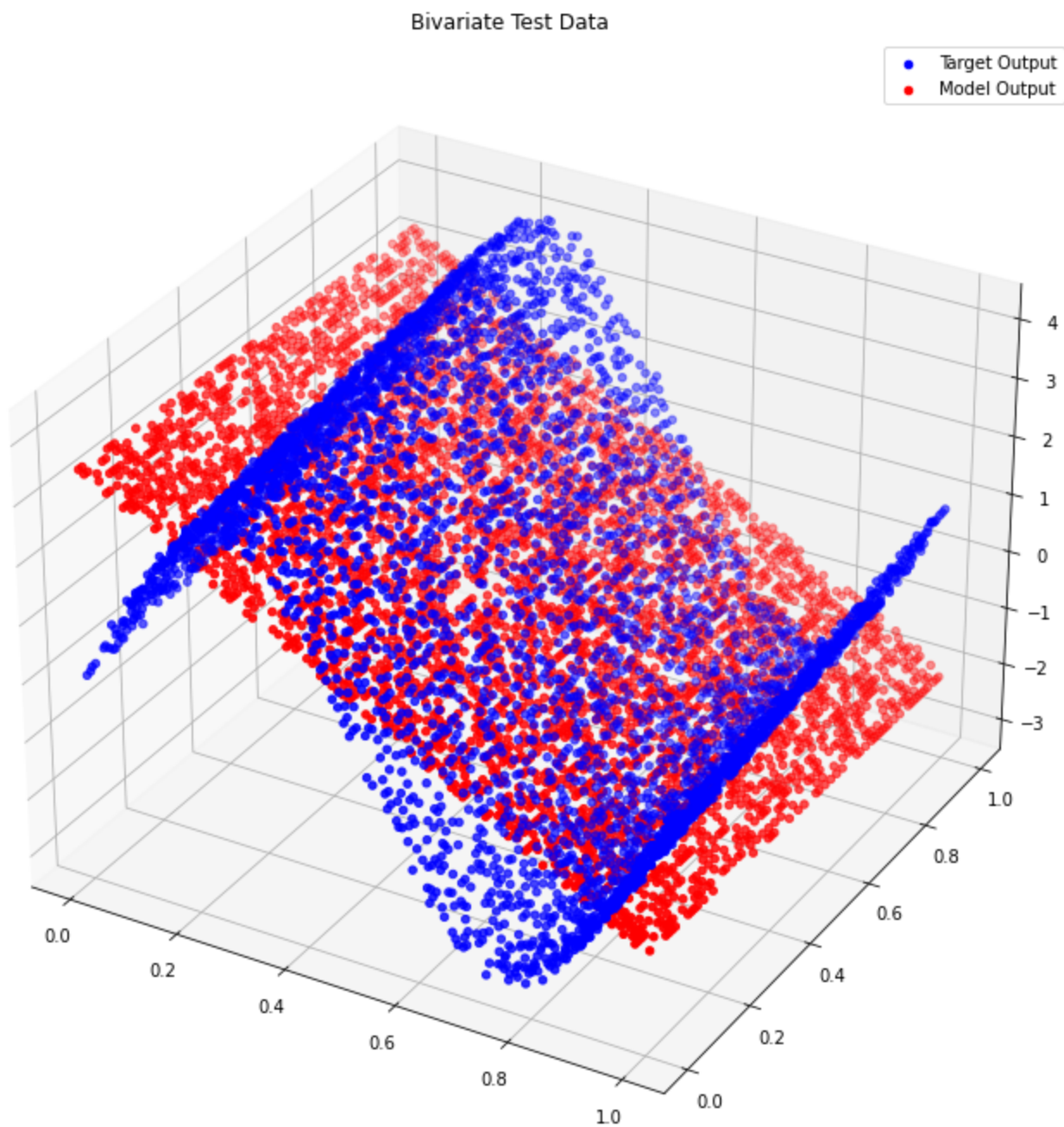


Bivariate Train Data



Bivariate Train Data

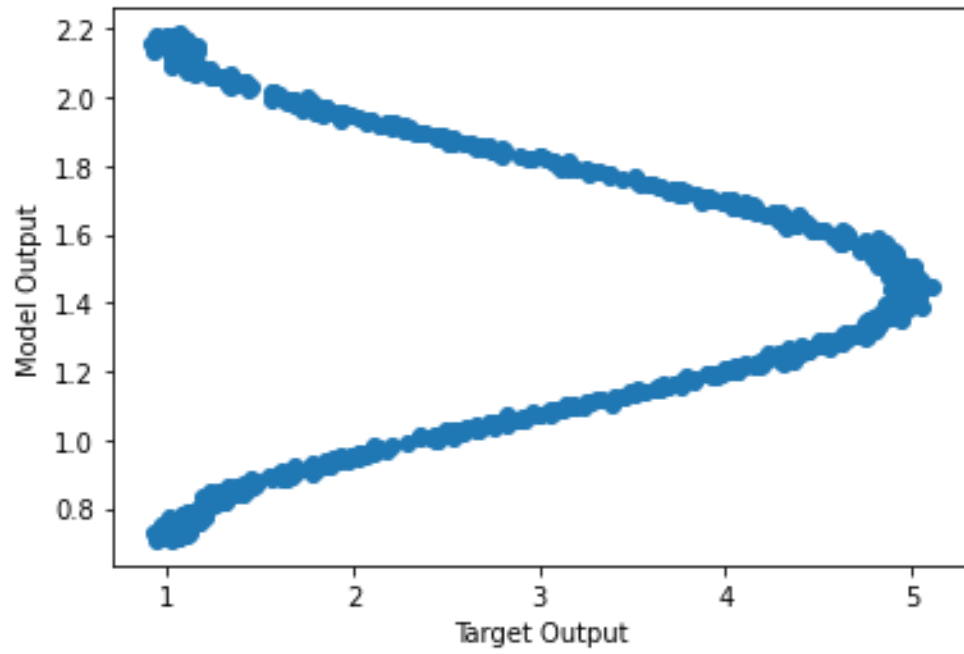




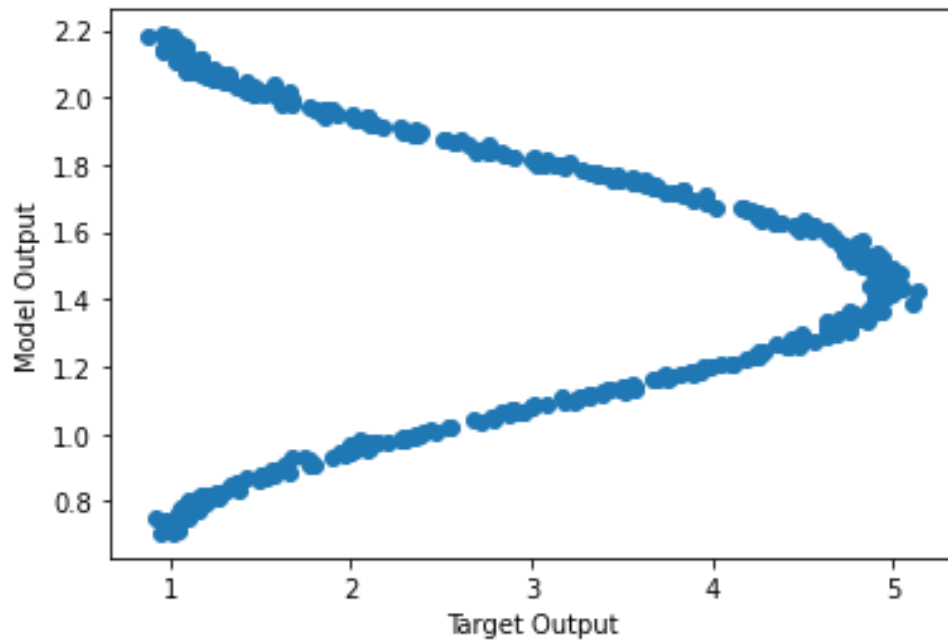
**Q4 Model Output vs Target Output**

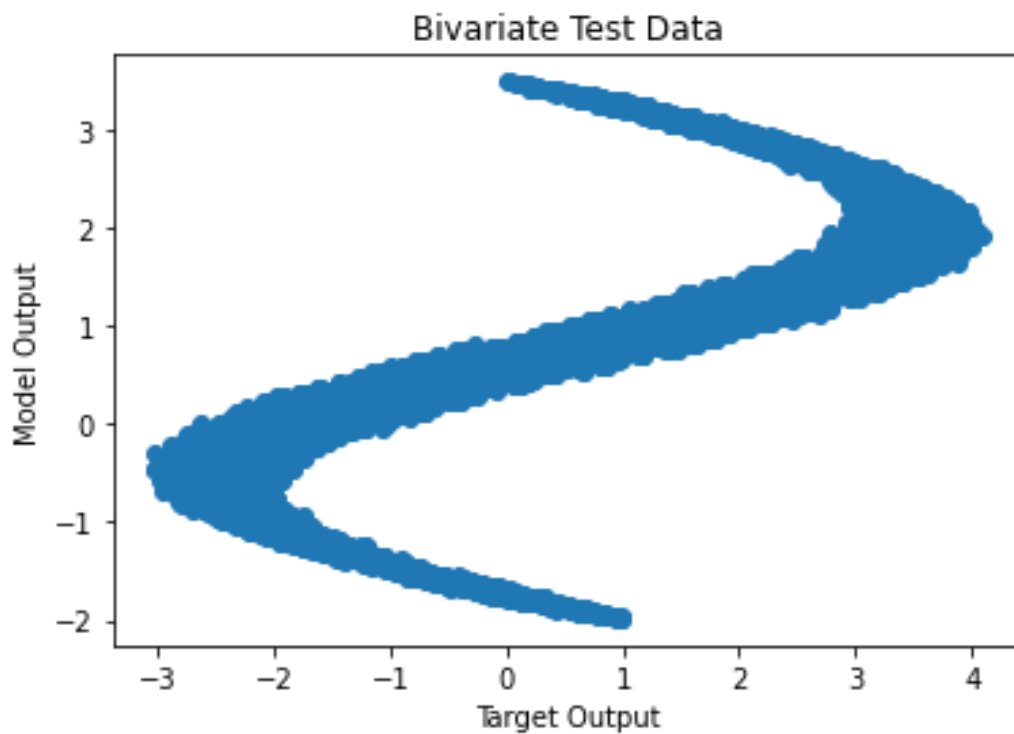
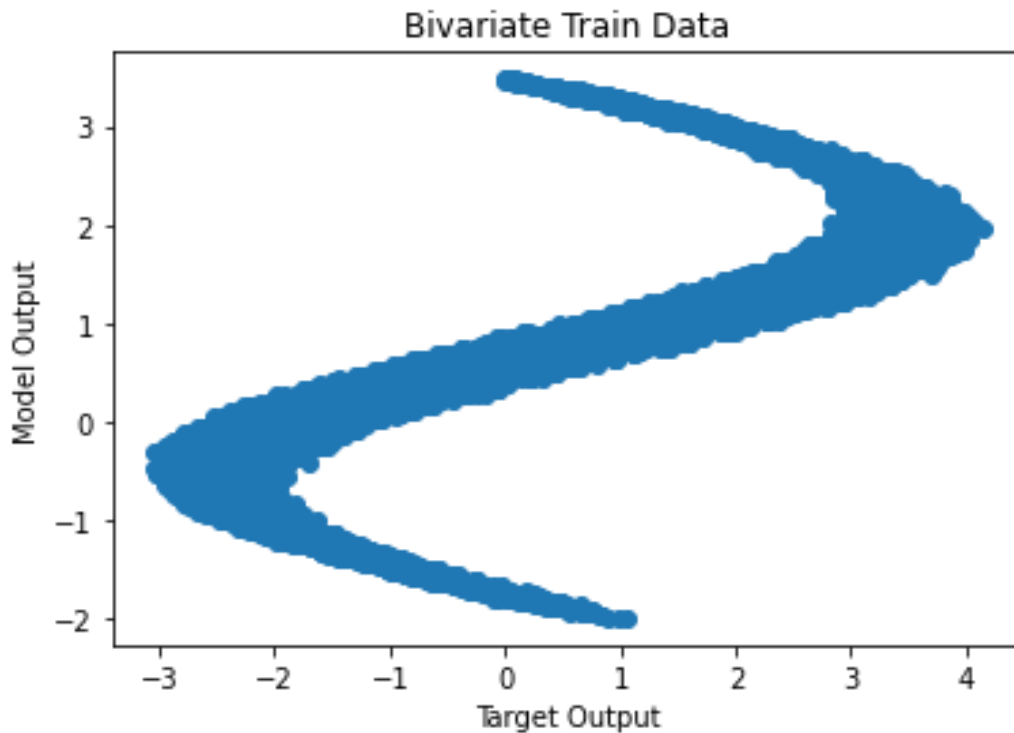


Univariate Train Data



Univariate Test Data





### FCNN

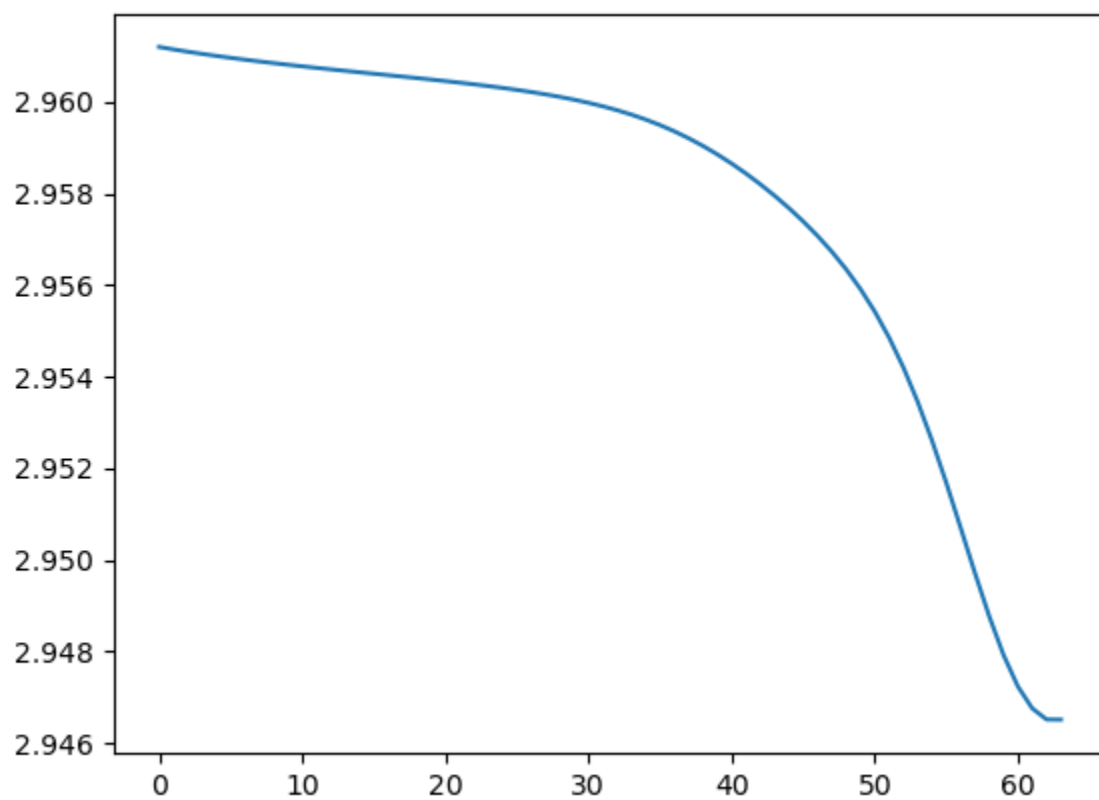
We implemented multi layer perceptron with 1 hidden layer for univariate data.

Parameters for this model were set as:

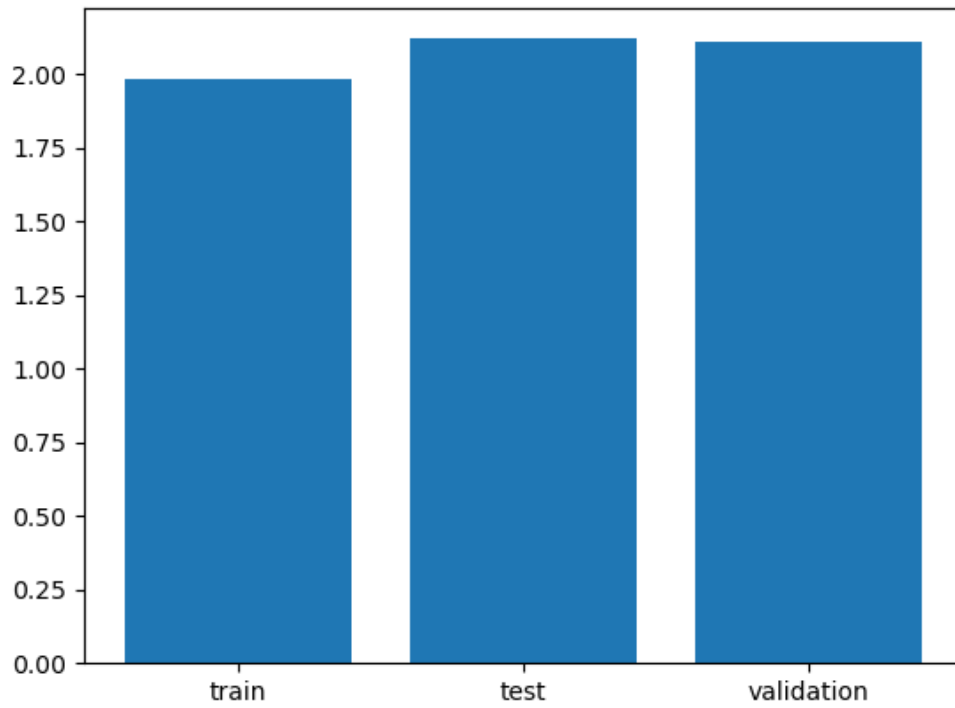
- 1) Eta = 0.01
- 2) Number of nodes in the hidden layer ( $n_{\text{hidden}}$ ) = 4



**Plot of average error vs epochs**

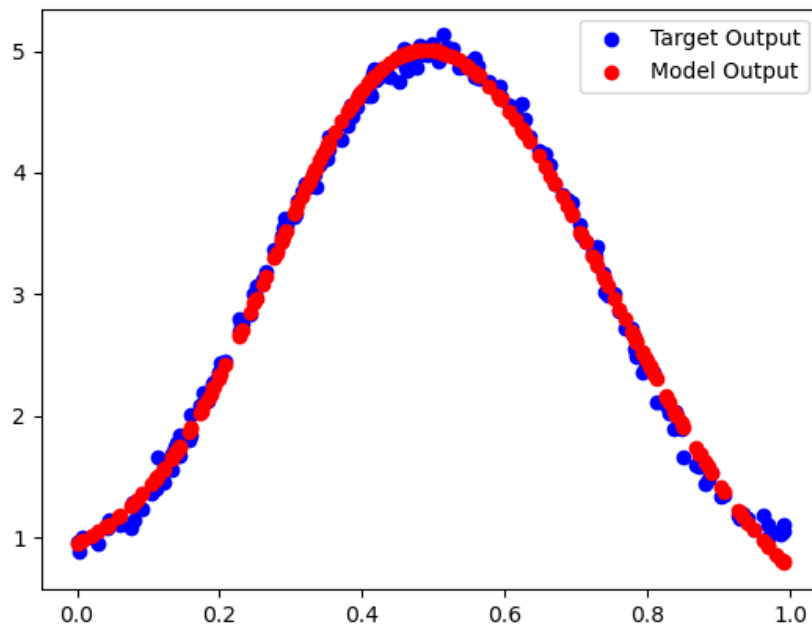


## Plots of MSE

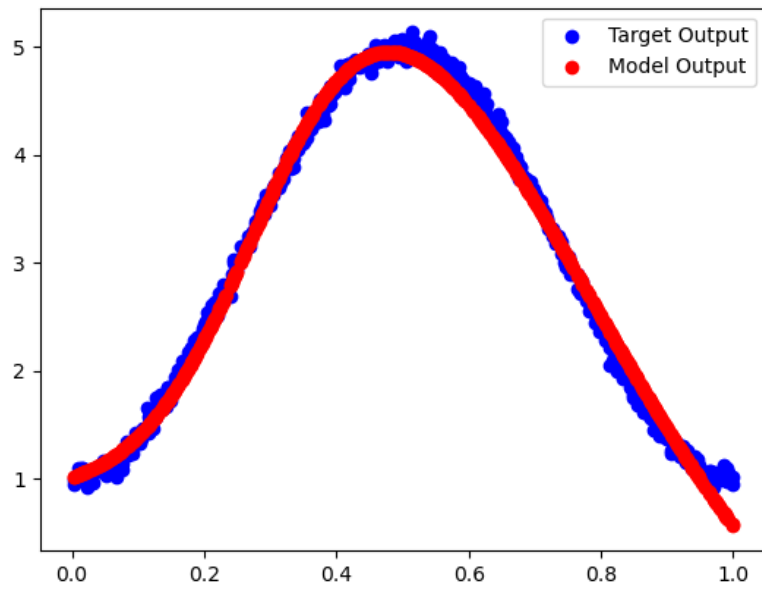
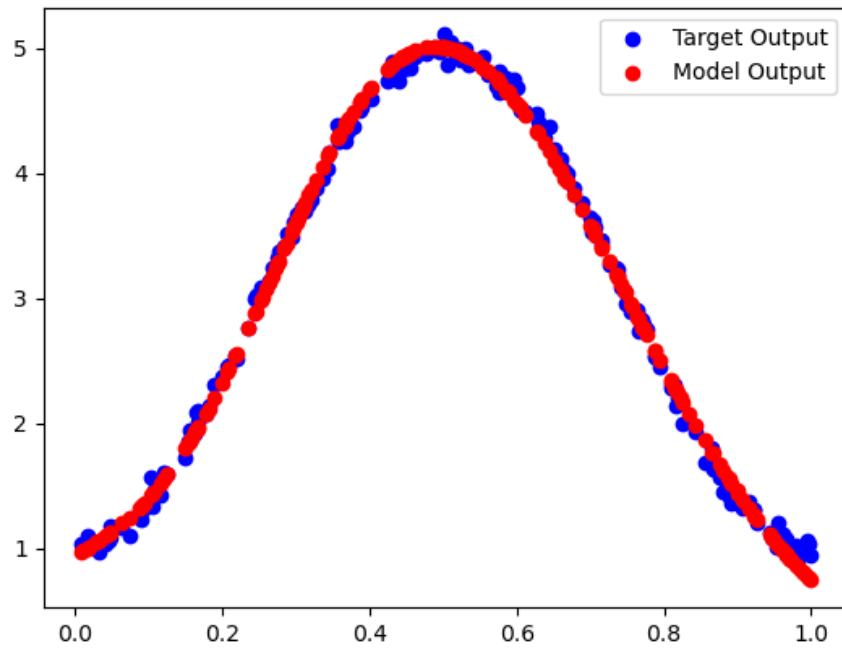


Q3.

## Validation data



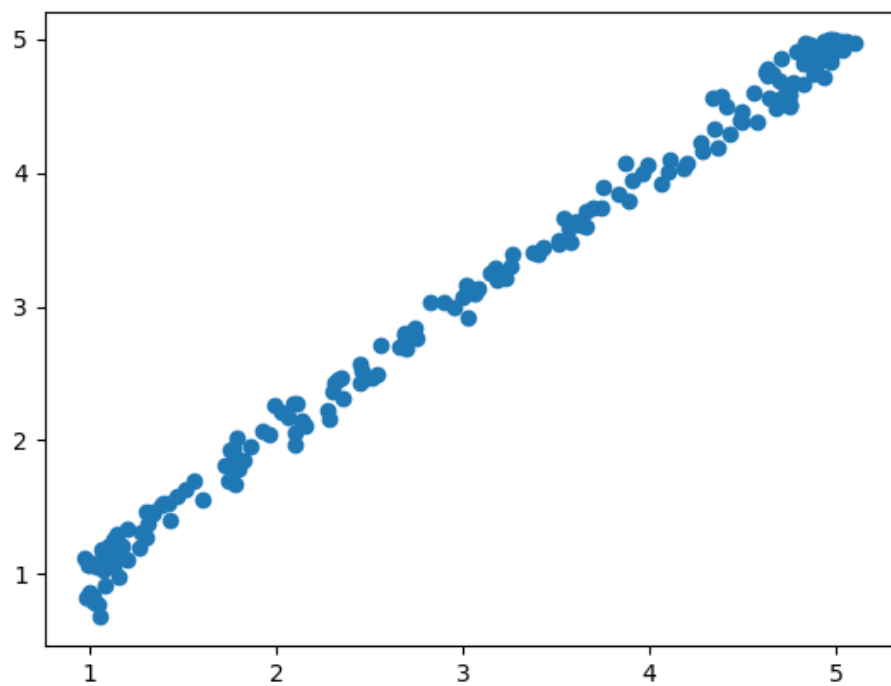
## Test data



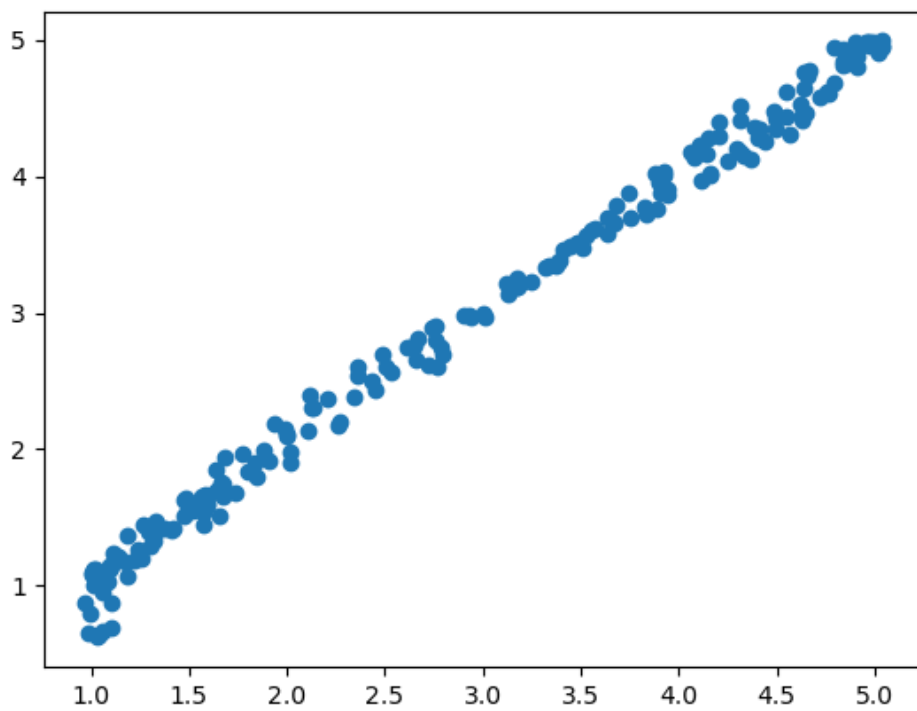
## Training data

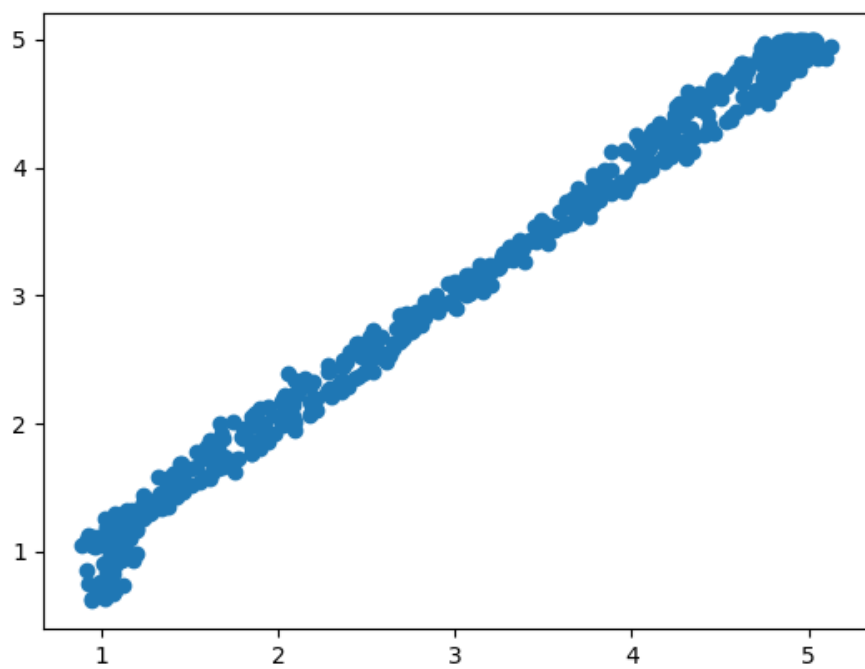
Q4.

Validation data



Test data





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Training data

Que 6.

$$\Delta w_{jk}^{(0)} = n \delta_{nk}^{(0)} h_{nj}$$

$$\text{where } \delta_{nk}^{(0)} = (y_{nk} - \hat{y}_{nk}) \frac{\partial f(a_{nk}^{(0)})}{\partial a_{nk}^{(0)}}$$

$$\Delta w_{ij}^{(h)} = -n \frac{\partial E_n}{\partial w_{ij}^{(h)}}$$

$$= n \delta_{nj}^{(h)} x_i$$

$$\text{where } \delta_{nj}^{(h)} = \left[ \sum_{k=1}^K \delta_{nk}^{(0)} w_{jk}^{(0)} \right] \frac{\partial g(a_{nj})}{\partial a_{nj}}$$

Expression for 1 hidden layer

$$\frac{\partial E_n}{\partial w_{ij}} = \frac{1}{2} \frac{\partial \sum_{k=1}^K (y_{nk} - \hat{y}_{nk})^2}{\partial w_{ij}^{(h_1)}}$$

$$= - \sum_{k=1}^K (y_{nk} - \hat{y}_{nk}) \times \frac{\partial f(a_{nk})}{\partial (a_{nk})}$$

$$\times \sum_{l=0}^L w_{lk}^{(0)} \times \left[ \frac{\partial h_{2nl}}{\partial w_{ij}^{(h_1)}} \right]$$

↓

$$\frac{\partial g(a_{nl})}{\partial a_{nl}} \times w_{jl} \times \frac{\partial f(a_{nj})}{\partial (a_{nj})}$$

$$\times \kappa_{ni}$$

Expression for 2 hidden layers