Daniel W. Anner
Deep Learning
Project 1 Report

Commented Working Code:

```
import autograd.numpy as np
from autograd import grad
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure


#Simple loop to have user select which version to run
while True:
    select = input("Please enter 'relu' or 'sigmoid' or 'combo' for RELU or Sigmo
id or Combo of both respectively \n")
    if select in ["relu", "sigmoid", "combo"]:
        print("Running %s" % select)
        break


def feed_forward(features, w1, b1, w2, b2, w3, b3, select):
    #my Sigmoid functions
    def sigmoid(x):
        return 1/(1+np.exp(-x))

    #my RELU function
    def relu(x):
        return np.maximum(x, 0)

    #run Relu, Sigmoid, or Combo depending on the user input
    #activation function gets ran on every layer
    if select == "sigmoid":
        #sigmoid
        #hidden layer 1
        hl1 = (np.matmul(w1, features))
        hl1_bias = np.add(hl1, b1)
        hl1_act = sigmoid(hl1_bias)
        #hidden layer 2
        hl2 = (np.matmul(w2, hl1_act))
        hl2_bias = np.add(hl2, b2)
        hl2_act = sigmoid(hl2_bias)
        #output layer
        output = (np.matmul(w3, hl2_act))
        targets_predicted = np.add(output, b3)
        targets_predicted = sigmoid(targets_predicted)
    elif select == "relu":
        #relu
        #hidden layer 1
```

```
        hl1 = (np.matmul(w1, features))
        hl1_bias = np.add(hl1, b1)
        hl1_act = relu(hl1_bias)
        #hidden layer 2
        hl2 = (np.matmul(w2, hl1_act))
        hl2_bias = np.add(hl2, b2)
        hl2_act = relu(hl2_bias)
        #output layer
        output = (np.matmul(w3, hl2_act))
        targets_predicted = np.add(output, b3)
        targets_predicted = relu(targets_predicted)
    else: #combo function
        #relu
        #hidden layer 1
        hl1 = (np.matmul(w1, features))
        hl1_bias = np.add(hl1, b1)
        hl1_act = relu(hl1_bias)
        #relu
        #hidden layer 2
        hl2 = (np.matmul(w2, hl1_act))
        hl2_bias = np.add(hl2, b2)
        hl2_act = relu(hl2_bias)
        #sigmoid
        #output layer
        output = (np.matmul(w3, hl2_act))
        targets_predicted = np.add(output, b3)
        targets_predicted = sigmoid(targets_predicted)
    return targets_predicted


def loss(features, w1, b1, w2, b2, w3, b3, targets_observed, select):
    '''
    w1 is weights matrix for transition from input to first hidden layer
    b1 is the biases added at the first hidden layer
    w2 is weights matrix for transition from hidden layer 1 to hidden layer 2
    b2 is the biases added to the second hidden layer
    w3 is weights matrix for transition from hidden layer 2 to output layer
    b3 is the biases added to the output layer
    Usage: Calculate the sum of square residuals of the feed forward function
    '''
    #Loss function to
    Targets_Predicted = feed_forward(features, w1, b1, w2, b2, w3, b3, select)
    return np.sum((Targets_Predicted - targets_observed) ** 2)


print('You selected: ' + select)
```

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```
print('Engines Starting ...')
print('Hold Tight Running Epochs')

#set up training datam
#each row is a case
#columns 0-4 are features
#columns 5 & 6 are targets
features_and_targets = np.array(
                                   [[0, 0, 0, 0, 0, 0, 1],
                                    [0, 0, 0, 0, 1, 0, 1],
                                    [0, 0, 0, 1, 1, 0, 1],
                                    [0, 0, 1, 1, 1, 0, 1],
                                    [0, 1, 1, 1, 1, 0, 1],
                                    [1, 1, 1, 1, 0, 0, 1],
                                    [1, 1, 1, 0, 0, 0, 1],
                                    [1, 1, 0, 0, 0, 0, 1],
                                    [1, 0, 0, 0, 0, 0, 1],
                                    [1, 0, 0, 1, 0, 0, 1],
                                    [1, 0, 1, 1, 0, 0, 1],
                                    [1, 1, 0, 1, 0, 0, 1],
                                    [0, 1, 0, 1, 1, 0, 1],
                                    [0, 0, 1, 0, 1, 0, 1],
                                    [1, 0, 1, 1, 1, 1, 0],
                                    [1, 1, 0, 1, 1, 1, 0],
                                    [1, 0, 1, 0, 1, 1, 0],
                                    [1, 0, 0, 0, 1, 1, 0],
                                    [1, 1, 0, 0, 1, 1, 0],
                                    [1, 1, 1, 0, 1, 1, 0],
                                    [1, 1, 1, 1, 1, 1, 0],
                                    [1, 0, 0, 1, 1, 1, 0]], dtype=float)

#shuffle our cases
np.random.shuffle(features_and_targets)

#transpose Matrix for mat mul in feed forward
features = np.transpose(features_and_targets[:, 0:5])
targets_observed = np.transpose(features_and_targets[:, 5:7])
number_of_features, number_of_cases = features.shape
print('Number of Features:', number_of_features)
print('Number of Cases:', number_of_cases)


#set initial weights and biases
#use a seed so others can replicate results
np.random.seed(912312)
```

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```
losses = []
weights_1 = np.random.rand(4, 5)
biases_1 = np.random.rand(4, number_of_cases)
weights_2 = np.random.rand(3, 4)
biases_2 = np.random.rand(3, number_of_cases)
weights_3 = np.random.rand(2, 3)
biases_3 = np.random.rand(2, number_of_cases)

#set our learning rate
lr = 0.00001



#find slope
#grad loss, variable you want to look at
d_loss_by_d_w1 = grad(loss, 1)  # w1
d_loss_by_d_b1 = grad(loss, 2)  # b1
d_loss_by_d_w2 = grad(loss, 3)  # w2
d_loss_by_d_b2 = grad(loss, 4)  # b2
d_loss_by_d_w3 = grad(loss, 5)  # w3
d_loss_by_d_b3 = grad(loss, 6)  # b3


#create epoch for our back tracking.
#backpropagate to calculate the gradient for each weight
epochs = 10000

for epoch in range(epochs):
    weights_1 -= lr * d_loss_by_d_w1(features, weights_1, biases_1, weights_2,
                                     biases_2, weights_3, biases_3,
                                     targets_observed, select)
    biases_1 -= lr * d_loss_by_d_b1(features, weights_1, biases_1, weights_2,
                                    biases_2, weights_3, biases_3,
                                    targets_observed, select)
    weights_2 -= lr * d_loss_by_d_w2(features, weights_1, biases_1, weights_2,
                                     biases_2, weights_3, biases_3,
                                     targets_observed, select)
    biases_2 -= lr * d_loss_by_d_b2(features, weights_1, biases_1, weights_2,
                                    biases_2, weights_3, biases_3,
                                    targets_observed, select)
    weights_3 -= lr * d_loss_by_d_w3(features, weights_1, biases_1, weights_2,
                                     biases_2, weights_3, biases_3,
                                     targets_observed, select)
    biases_3 -= lr * d_loss_by_d_b3(features, weights_1, biases_1, weights_2,
                                    biases_2, weights_3, biases_3,
```

```
                                    targets_observed, select)
    losses.append(loss(features, weights_1, biases_1, weights_2,
                       biases_2, weights_3, biases_3,
                       targets_observed, select))

    #used for testing purposes. If you want to see how the
    #loss backpropagate is calculating a lower gradient uncomment this
    print(epoch, loss(features, weights_1, biases_1, weights_2, biases_2,
                      weights_3, biases_3, targets_observed, select))


#run feed forward
Targets_Predicted = feed_forward(features, weights_1, biases_1, weights_2,
                                 biases_2, weights_3, biases_3, select)



'''
Code to show line graph of the Epochs vs Observed
'''
print('Features : \n', features)
print(' Targets : \n', targets_observed)
print(' Targets predicted : \n', Targets_Predicted)
figure(figsize=(10,8), dpi=120)
plt.plot(losses) #plot losses
plt.xlabel('Epochs')  #add x label name
plt.title('Learning Curve using %s Activation Function LR 0.00001' % select) #set
 title
plt.ylabel('Observed') #add y label name

plt.savefig('%s_line.png' % select) #save figure
plt.show() #show plot and clear object


'''
Code to show observed vs predicted
'''
N = 22
target1_predicted = Targets_Predicted[0, ]
target2_predicted = Targets_Predicted[1, :]
target1_observed = targets_observed[0, :]
target2_observed = targets_observed[1, :]

ind = np.arange(N)
width = 0.35
```

```
figure(figsize=(10,8), dpi=120) #set fig size and dpi
plt.subplot(2, 1, 1) #create subplot
plt.bar(ind, target1_predicted, width, label='Predicted') #create predicted bar
plt.bar(ind + width, target1_observed, width, label='Observed') #create observed bar
plt.ylabel('Targets 0 or 1') #set y label
plt.title('Closeness of predicted targets for 22 cases - %s' % select) #set title
plt.xticks(ind + width / 2, ind)
plt.legend(loc='best') #set legend place to best/show legend
plt.subplot(2, 1, 2) #set subplot 2 generation
plt.bar(ind, target2_predicted, width, label='Predicted') #create predicted bar
plt.bar(ind + width, target2_observed, width, label='Observed') #create observed bar
plt.ylabel('Targets 0 or 1') #set y label
plt.title('Closeness of predicted targets for 22 cases - %s' % select) #set title
plt.xticks(ind + width / 2, ind)
plt.legend(loc='best') #set legend place to best/show legend
plt.savefig('%s_observation.png' % select) #save figure
plt.show() #show plot
```

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Results:

```
Running combo
```

```
You selected: combo
```

```
Running Epochs
```

```
Number of Features: 5
```

```
Number of Cases: 22
```

```
Features : [[1. 1. 1. 0. 1. 1. 0. 0. 1. 1. 1. 0. 1. 0. 1. 1. 1. 0. 1. 0. 1. 1.]
[0. 1. 1. 0. 0. 0. 1. 1. 0. 0. 1. 0. 1. 0. 0. 1. 1. 0. 1. 0. 1. 0.] [0. 0. 1. 1.
0. 1. 0. 1. 1. 0. 1. 0. 0. 1. 0. 1. 0. 0. 1. 0. 0. 1.] [0. 0. 1. 0. 1. 1. 1. 1.
0. 1. 0. 0. 0. 1. 0. 1. 1. 1. 0. 0. 1. 1.] [0. 0. 0. 1. 1. 0. 1. 1. 1. 0. 1. 0.
1. 1. 1. 1. 1. 1. 0. 1. 0. 1.]]
```

```
Targets : [[0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 1. 0. 1. 0. 1. 1. 1. 0. 0. 0. 0. 1.]
[1. 1. 1. 1. 0. 1. 1. 1. 0. 1. 0. 1. 0. 1. 0. 0. 0. 1. 1. 1. 1. 0.]]
```

```
Targets predicted : [[0.65868495 0.38649967 0.41891895 0.46514931 0.51455131
0.4113774 0.32321588 0.44122416 0.46998526 0.44530997 0.44698204 0.5589786
0.5082679 0.44510287 0.43494124 0.23755726 0.29606325 0.58786062 0.30466912
0.41789123 0.33784127 0.30221717] [0.99665597 0.99996727 0.99999862 0.99946364
0.99998046 0.99997463 0.99968205 0.99996127 0.9999633 0.99993821 0.9999941
0.98550738 0.99991716 0.99993456 0.99993102 0.99999977 0.9999922 0.9990635
0.999993 0.99551305 0.99999134 0.99999597]]
```

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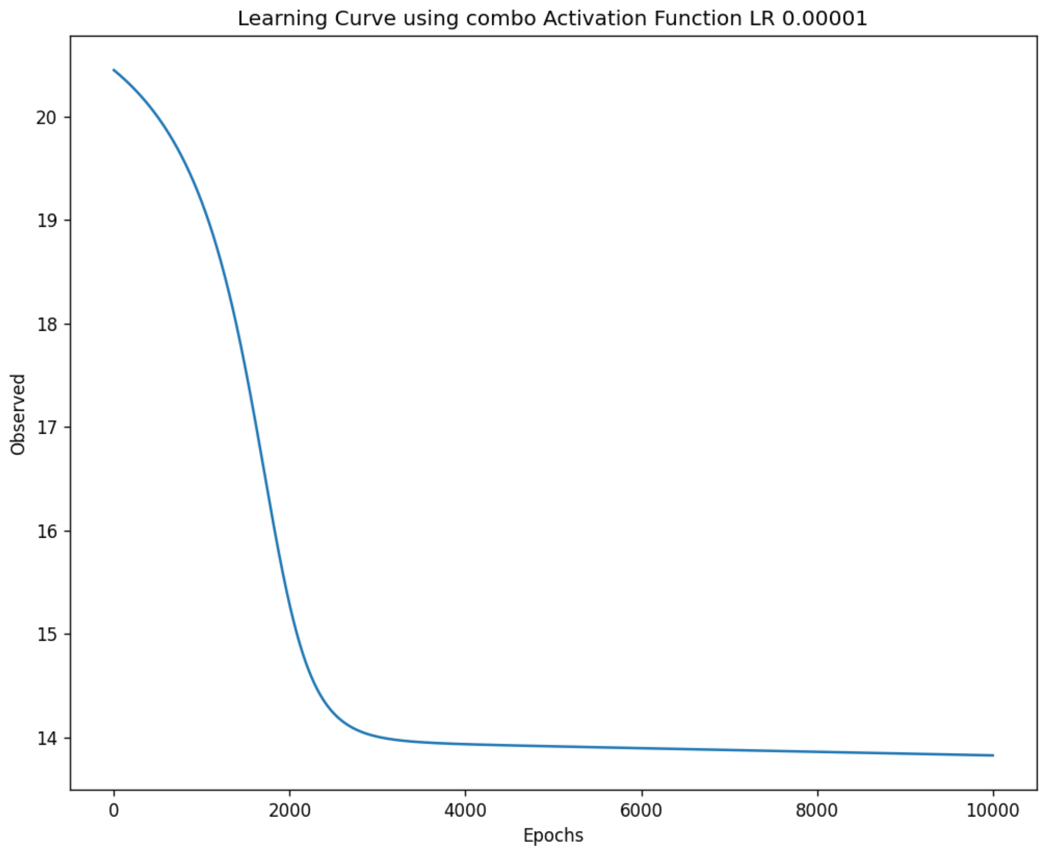
Graphs:



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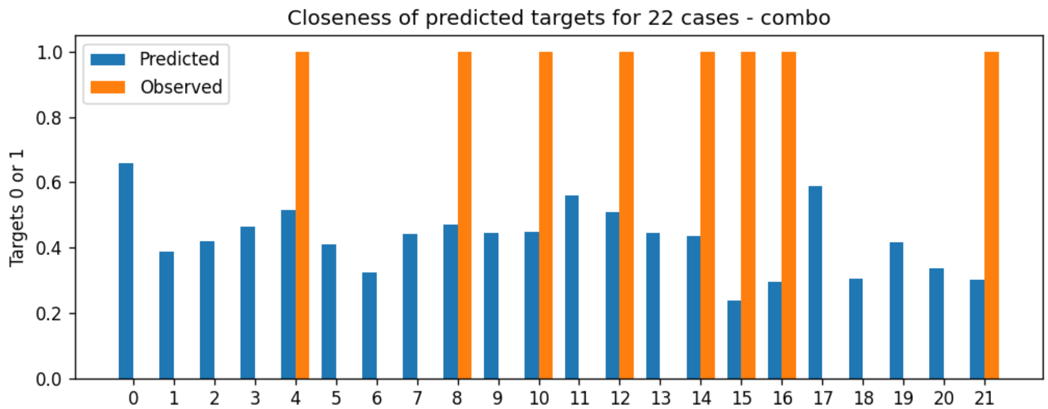

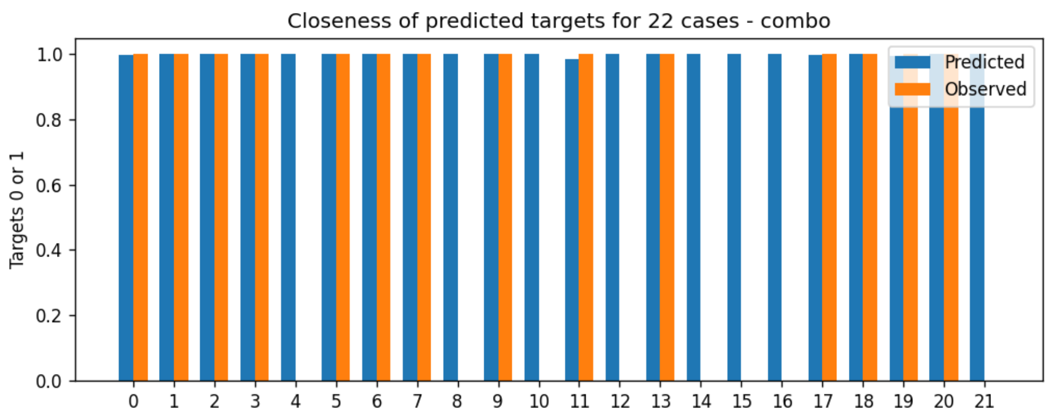

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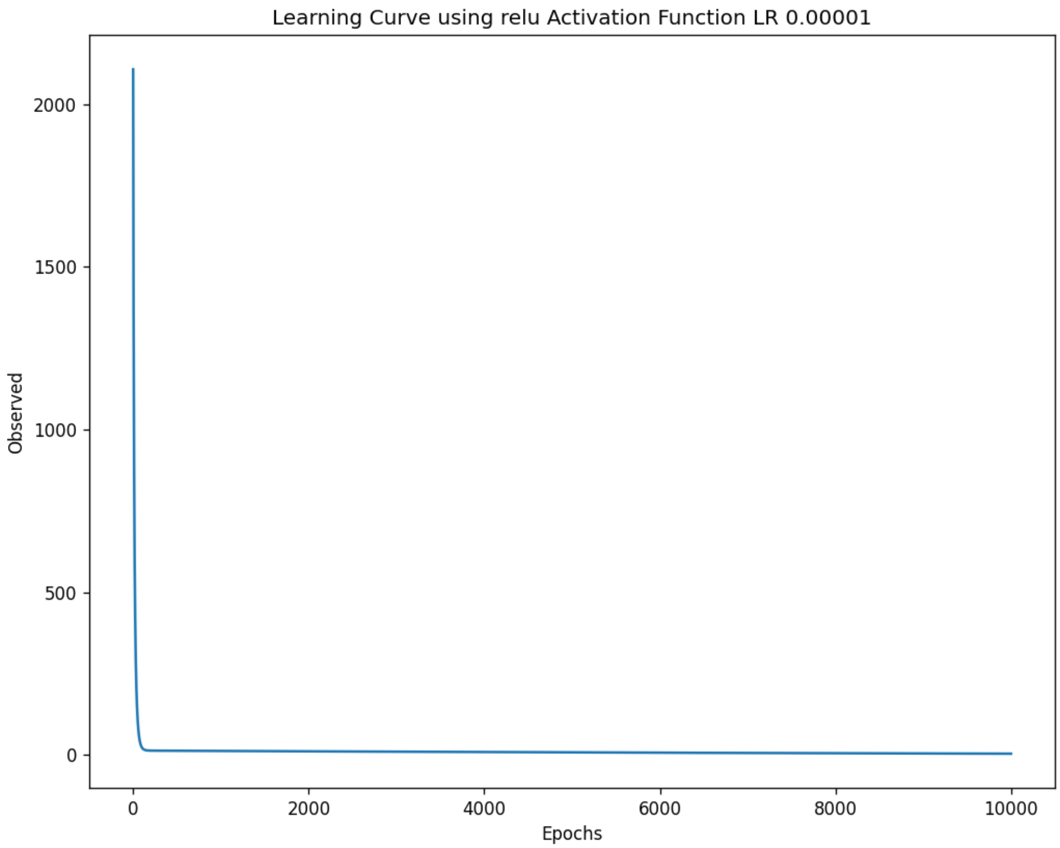

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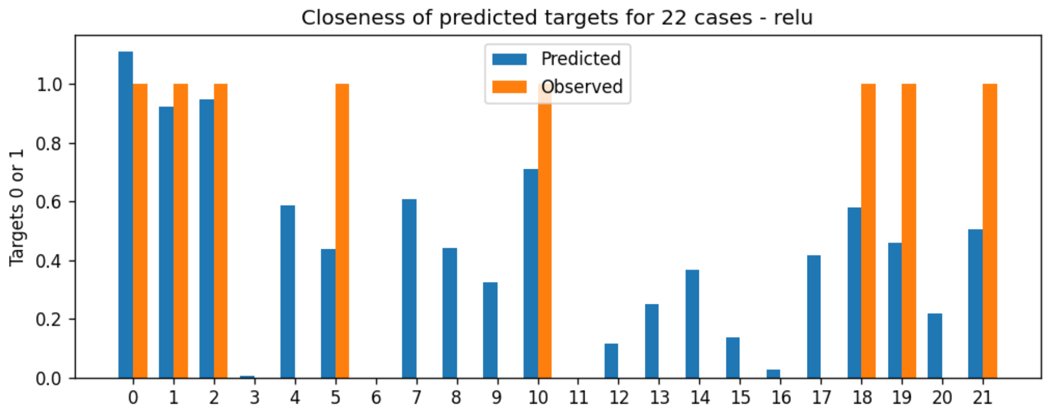

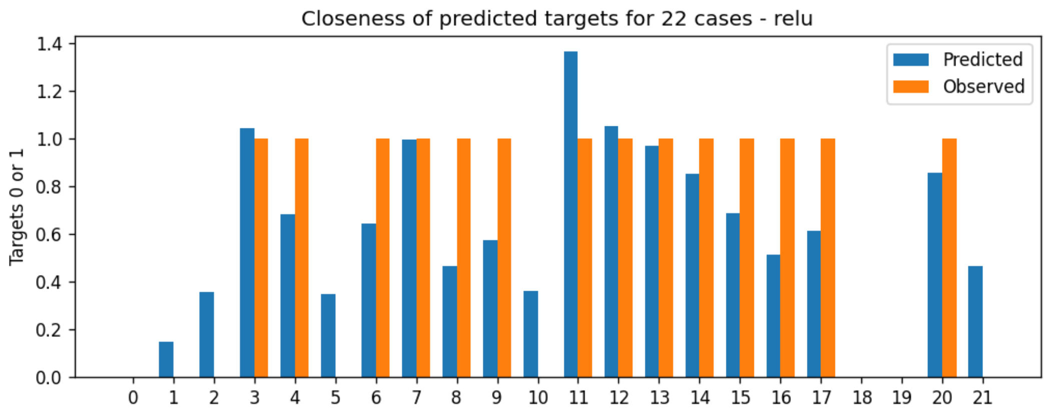

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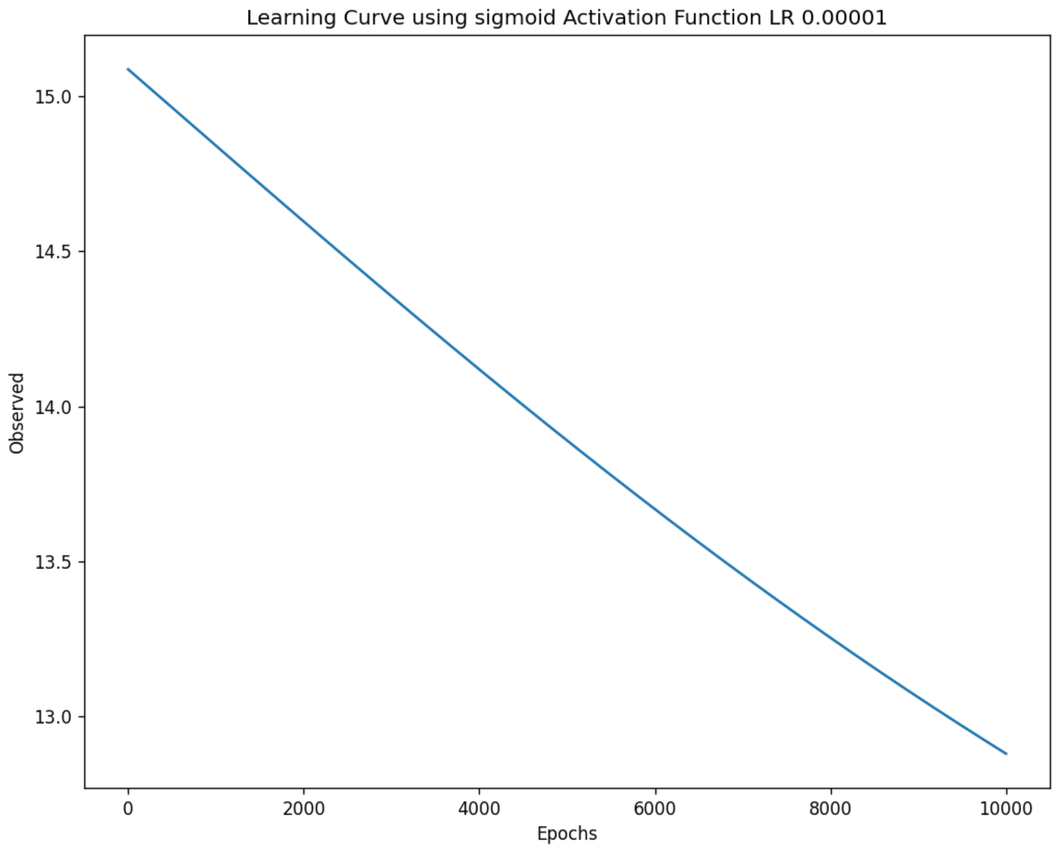

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