Feedforward_N-Cases-Solution

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1. Your commented, working code.Comments should explain what is going on in the algorithm.
2. Demonstrations of your code results including:

a. An evaluation of your NN accuracy; how well does it predict the observed targets based on the features as inputs.
b. A demonstration of the how the loss function decreases with each iteration (epoch). Plot a graph of loss function versus iteration. Do this for three different learning rates to show how convergence depends on learning rate.

Answers:

1. Code commented

2. a. I noticed that the initial predicted_targets are bad (before training). After training, I noticed that the higher the epoch is, the more consistent the targets predicted get to the targets observed. The lower the epoch, the worse the targets predicted compare to the targets observed.

2. b. After the 3 tests at 100, 500 and 1000 epoch I can see that the convergence of the loss function gets quicker and smooths out faster. The 3 graphs are at the end of each section of code.

EPOCH 100

[1]:
```
#importing libraries
import autograd.numpy as np
from autograd import grad
import matplotlib.pyplot as plt

def sigmoid(x): #Creating a definition for the sigmoid function
    return 1.0/(1+np.exp(-1.0*x)) #This is the sigmoid function. We are using␣
 ↪this because we are looking at a logistic model of an NN (only having 2␣
 ↪solutions).

def feed_forward(features,w1,b1,w2,b2,w3,b3): #Creating a definition for␣
 ↪"feed_foward". Basically the features,weights and biases going through the␣
 ↪NN starting from the first 5 features going to the final 2.
    #Calculating Hidden Layer 1
```

```python
    HL1 = np.matmul(w1,features) #multiplying our weights and features. Where the weights are a [4 x 5] and the the features are a [5 x 22] creating a [4 x 22] new matrix.
    HL1_with_bias = np.add(HL1,b1) #Adding the HL1 matrix (weights * features) which is a [4 x 22] to the biases which are also a [4 x 22].

    # Implement RELU activation (max(0,x))
    HL1_with_bias_and_activation = np.maximum(np.zeros((4,1)),HL1_with_bias) #We need to find the RELU to squish the numbers down to keep the numbers managable.
    HL2 = np.matmul(w2,HL1_with_bias_and_activation) #multiplying our weights and features. Where the weights are a [3 x 4] and the the features are a [4 x 22] creating a [3 x 22] new matrix.
    HL2_with_bias = np.add(HL2,b2) #Adding the HL1 matrix (weights * features) which is a [3 x 22] to the biases which are also a [3 x 22].

    # Implement RELU activation
    HL2_with_bias_and_activation = np.maximum(HL2_with_bias,np.zeros((3,1))) #We need to find the RELU to squish the numbers down to keep the numbers managable.
    targets_predicted = np.matmul(w3,HL2_with_bias_and_activation) #multiplying our weights and features. Where the weights are a [2 x 3] and the the features are a [3 x 22] creating a [2 x 22] new matrix.
    targets_predicted = np.add(targets_predicted,b3) #Adding the HL1 matrix (weights * features) which is a [2 x 22] to the biases which are also a [2 x 22].

    # Use sigmoid for the output activation
    targets_predicted = sigmoid(targets_predicted) #Calling the sigmoid on the targets predicted to get them to become "squished" in between 0 and 1.
    return targets_predicted #prints out the targets predicted.

def loss(features,w1,b1,w2,b2,w3,b3,targets_observed): #A method of evaluating how well your algorithm models your dataset. Greater is bad and lower is good.
    targets_predicted = feed_forward(features,w1,b1,w2,b2,w3,b3) #Getting the targets predicted to put into the loss function
    return np.sum((targets_predicted-targets_observed)**2) #Gives the loss function answer. The closer the sum is to 0, the closer the NN is to achieving the bests SSR.
#======================================================

print('Starting ...')

## Set up training data
## Each row is a case
```

```python
## Columns 0-4 are features
## Columns 5 & 6 are targets

#22 x 7 matrix
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 (to create randomness)
np.random.shuffle(features_and_targets)

# Need to transpose to get them as 5 X N matrices
features = np.transpose(features_and_targets[:,0:5]) #Tranposes the matrix to 5␣
 ↪x 22. Picking up the 0-4 index.
print(features) #prints the features in the array

# Need to transpose to get the 2 x N matrices
targets_observed = np.transpose(features_and_targets[:,5:7]) #Transposing the␣
 ↪last 2 columns from N x 2 to a 2 x N. Picking up the 5 and 6 index
number_of_features,number_of_cases = features.shape #[5,22] (creating tuple␣
 ↪(unchangable))
print(number_of_features) #prints the number of features in the array
print(number_of_cases) #prints the number of cases in the array

#Set initial weights and biases
```

```
weights_1 = np.random.rand(4,5) #Setting the dimensions of the matrix for our␣
↪random weights (rows by columns)
biases_1 = np.random.rand(4,number_of_cases) #Setting the dimensions of the␣
↪matrix for our baises (rows by columns)

weights_2 = np.random.rand(3,4) #Setting the dimensions of the matrix for our␣
↪random weights (rows by columns)
biases_2 = np.random.rand(3,number_of_cases) #Setting the dimensions of the␣
↪matrix for our baises (rows by columns)

weights_3 = np.random.rand(2,3) #Setting the dimensions of the matrix for our␣
↪random weights (rows by columns)
biases_3 = np.random.rand(2,number_of_cases) #Setting the dimensions of the␣
↪matrix for our baises (rows by columns)

Targets_Predicted =␣
↪feed_forward(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3)␣
↪#Targets_Predicted before Epoch (before training is initialized)

#Printing the results to the following below:
print(' Features : ',features)
print(' Targets : ', targets_observed)
print(' Targets predicted : ', Targets_Predicted)

#Learning rate gives the rate of speed where the gradient moves during gradient␣
↪descent. Setting it too high would make your path instable, too low would␣
↪make convergence slow. Put it to zero means your model isn't learning␣
↪anything from the gradients.

learning_rate = 0.01 #The amount of change to the model during each iterations

# Find slope functions using autograd
d_by_w1 = grad(loss,1) #create the derivative/gradient --> stored d_by_w1,␣
↪(equation(loss), index=1 (weights_1))
d_by_b1 = grad(loss,2) #create the derivative/gradient --> stored d_by_b1,␣
↪(equation(loss), index=2 (biases_1))
d_by_w2 = grad(loss,3) #create the derivative/gradient --> stored d_by_w2,␣
↪(equation(loss), index=3 (weights_2))
d_by_b2 = grad(loss,4) #create the derivative/gradient --> stored d_by_b2,␣
↪(equation(loss), index=4 (biases_2))
d_by_w3 = grad(loss,5) #create the derivative/gradient --> stored d_by_w3,␣
↪(equation(loss), index=5 (weights_3))
d_by_b3 = grad(loss,6) #create the derivative/gradient --> stored d_by_b3,␣
↪(equation(loss), index=6 (biases_3))

epoch_list1 = [] #creating list for epoch iterations
```

```
lost1 = [] #creating list for loss fucntion results

#Setting the iteration (making higher helps making the loss function look␣
↪better)
for epoch in range(100):

    #At each iteration update weights and biases by subtracting
    #learning_rate times slope
    #Changing the random weights and random biases updating each of them after␣
↪each iteration according to range(X)
    weights_1 -=␣
↪learning_rate*d_by_w1(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    biases_1 -=␣
↪learning_rate*d_by_b1(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    weights_2 -=␣
↪learning_rate*d_by_w2(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    biases_2 -=␣
↪learning_rate*d_by_b2(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    weights_3 -=␣
↪learning_rate*d_by_w3(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    biases_3 -=␣
↪learning_rate*d_by_b3(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar

    #Print out the latest value of the loss
    #We would expect this to go down with each iteration
    #This shows how good of a test it was to get to the desired the results
    #The closer to 0, the better the NN is learning <- This is what the loss␣
↪function is doing in the equation.
   ␣
↪print(epoch,loss(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,targets_

    epoch_list1.append(epoch) #epoch list adding the iterations
    lost1.
↪append(loss(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,targets_obser
↪#loss function list adding for each iteration

Targets_Predicted =␣
↪feed_forward(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3)␣
↪#Targets_Predicted after Epoch (After training is complete)

#Printing the results to the following below:
print(' Features : ',features)
print(' Targets : ', targets_observed)
print(' Targets predicted : ', Targets_Predicted)

N = 22
```

```python
target1_predicted = Targets_Predicted[0,:] #The target we are trying to achieve
target2_predicted = Targets_Predicted[1,:] #The target we are trying to achieve
target1_observed = targets_observed[0,:] #The target we want to achieve (what␣
 ↪the targets should be)
target2_observed = targets_observed[1,:] #The target we want to achieve (what␣
 ↪the targets should be)

ind = np.arange(N) #Return evenly spaced values within a given interval (N=22)
width = 0.35 #creating width to add distance between the 2 different bar graphs
plt.subplot(2,1,1) #creating first graph
plt.bar(ind, target1_predicted, width, label='Predicted') #Plotting the bar␣
 ↪graph of the predicted answers (First set)
plt.bar(ind + width, target1_observed, width,label='Observed') #Plotting the␣
 ↪bar graph of the observed answers (First set)
plt.ylabel('Targets 0 or 1') #y label
plt.title('Closeness of predicted targets for 22 cases') #title
plt.xticks(ind + width / 2, ind) #tick mark indicator
plt.legend(loc='best') #legend (automatically put in best location)
plt.subplot(2,1,2) #creating first graph
plt.bar(ind, target2_predicted, width, label='Predicted') #Plotting the bar␣
 ↪graph of the predicted answers (Second set)
plt.bar(ind + width, target2_observed, width,label='Observed') #Plotting the␣
 ↪bar graph of the observed answers (Second set)
plt.ylabel('Targets 0 or 1') #y label
plt.title('Closeness of predicted targets for 22 cases') #title
plt.xticks(ind + width / 2, ind) #tick mark indicator
plt.legend(loc='best') #legend (automatically put in best location)

plt.show() #display graphs
```

```
Starting …
[[0. 1. 1. 0. 1. 1. 1. 0. 1. 0. 0. 1. 0. 1. 1. 1. 1. 1. 1. 0. 1. 1.]
 [1. 0. 1. 0. 1. 0. 0. 0. 1. 0. 1. 1. 0. 1. 1. 0. 1. 0. 0. 0. 0. 1.]
 [1. 1. 0. 1. 0. 0. 1. 1. 0. 0. 0. 1. 0. 1. 1. 0. 0. 1. 0. 0. 0. 1.]
 [1. 1. 0. 0. 1. 1. 0. 1. 1. 0. 1. 1. 1. 0. 0. 0. 0. 1. 1. 0. 0. 1.]
 [1. 1. 0. 1. 0. 1. 1. 1. 1. 0. 1. 0. 1. 1. 0. 0. 1. 0. 0. 1. 1. 1.]]
5
22
 Features :  [[0. 1. 1. 0. 1. 1. 1. 0. 1. 0. 0. 1. 0. 1. 1. 1. 1. 1. 1. 0. 1.
1.]
 [1. 0. 1. 0. 1. 0. 0. 0. 1. 0. 1. 1. 0. 1. 1. 0. 1. 0. 0. 0. 0. 1.]
 [1. 1. 0. 1. 0. 0. 1. 1. 0. 0. 0. 1. 0. 1. 1. 0. 0. 1. 0. 0. 0. 1.]
 [1. 1. 0. 0. 1. 1. 0. 1. 1. 0. 1. 1. 1. 0. 0. 0. 0. 1. 1. 0. 0. 1.]
 [1. 1. 0. 1. 0. 1. 1. 1. 1. 0. 1. 0. 1. 1. 0. 0. 1. 0. 0. 1. 1. 1.]]
 Targets :  [[0. 1. 0. 0. 0. 1. 1. 0. 1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 0. 0. 1. 1.]
 [1. 0. 1. 1. 1. 0. 0. 1. 0. 1. 1. 1. 1. 0. 1. 1. 0. 1. 1. 1. 0. 0.]]
 Targets predicted :  [[0.99974552 0.99988233 0.99749198 0.98078918 0.99953068
```

```
0.99757348
  0.99961542 0.99924565 0.99983496 0.91088518 0.99835383 0.99907217
  0.99870431 0.99923959 0.99621789 0.99383098 0.998461   0.99922085
  0.99812055 0.97990719 0.99667477 0.99990526]
 [0.99953253 0.99954935 0.99591068 0.98030925 0.99850222 0.99760332
  0.99950385 0.99907038 0.999784   0.94481755 0.99732611 0.99889225
  0.9969958  0.99957247 0.99776471 0.988292   0.99803953 0.9988391
  0.99729983 0.96122579 0.99708802 0.99975973]]
0 21.68207917476477
1 21.66442147177232
2 21.644685013499593
3 21.62246341448813
4 21.597233560792183
5 21.568309736850857
6 21.534774122869976
7 21.49536812135138
8 21.448316124899858
9 21.391027262635838
10 21.319564451979215
11 21.22763998836021
12 21.104569197198632
13 20.930699448552
14 20.665946676258045
15 20.21655667159152
16 19.321640093649727
17 17.17097293463046
18 13.68018417526595
19 13.519778701641883
20 13.470551969176135
21 13.446892545263719
22 13.423704928576155
23 13.400974040098554
24 13.378442947869686
25 13.356144805498978
26 13.334051211169578
27 13.312152736717321
28 13.290434841955445
29 13.268884584144146
30 13.247488597358256
31 13.226233603663621
32 13.205106176667003
33 13.184092717818707
34 13.16317935900798
35 13.142351874900955
36 13.121595577210634
37 13.10089519610039
38 13.080234743147265
39 13.059597352656613
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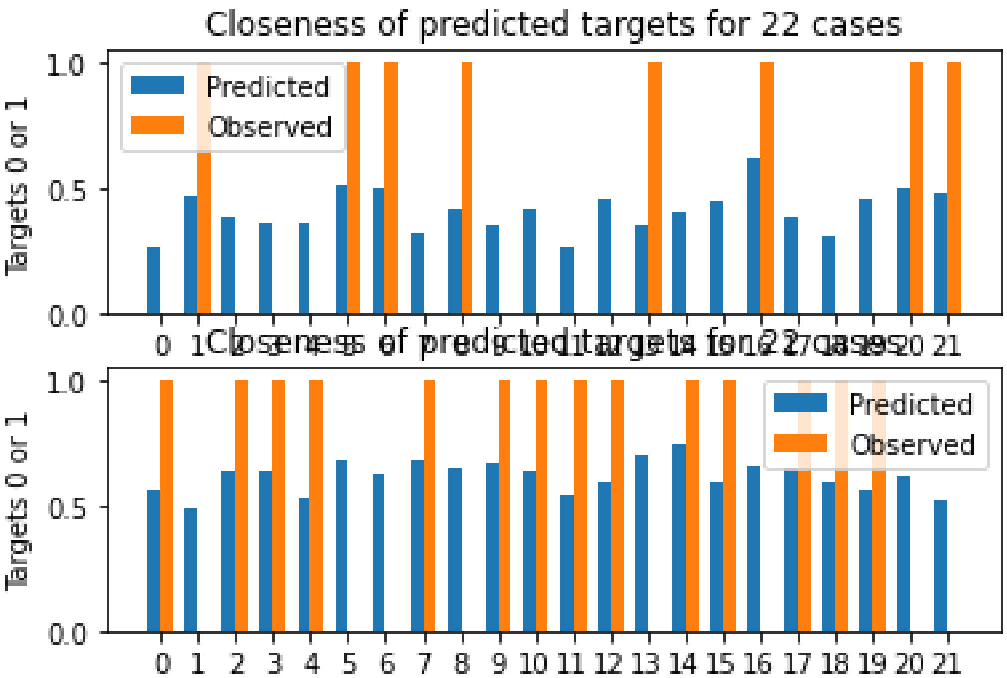
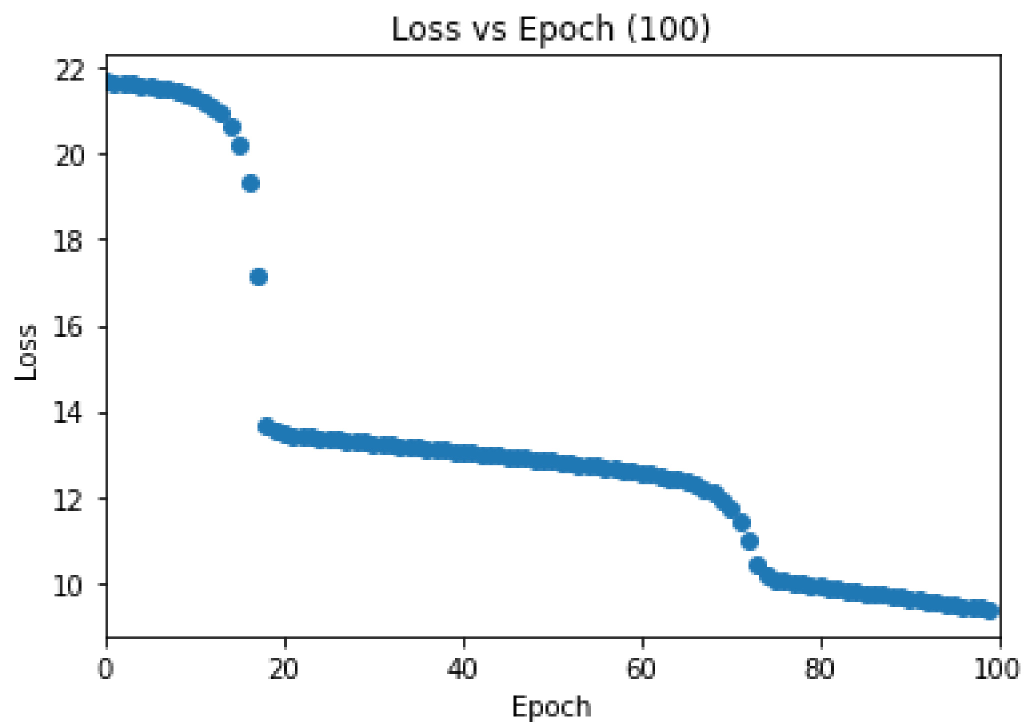
40 13.038965096198616
41 13.018318764298801
42 12.997637607522869
43 12.976899027139321
44 12.956078202794114
45 12.935147641004399
46 12.914076623427412
47 12.892830527320147
48 12.871369981699164
49 12.849649810454062
50 12.827617696615434
51 12.805212477966226
52 12.782361949940599
53 12.758980002243632
54 12.73496284298257
55 12.710183955819208
56 12.684487271470108
57 12.657677781307411
58 12.629508421297311
59 12.599661411354864
60 12.56772117542871
61 12.533134177064625
62 12.49514789760469
63 12.452715635823601
64 12.404343609079255
65 12.347837554670845
66 12.279868730906134
67 12.19520653256608
68 12.085328689025632
69 11.935913410847334
70 11.722748080845694
71 11.408323688756097
72 10.95937461419137
73 10.45291479946377
74 10.157049387404655
75 10.085060509528743
76 10.051161178611746
77 10.018944613779938
78 9.987144711106204
79 9.95570413018283
80 9.9246008033664
81 9.893815796778224
82 9.863331202063636
83 9.833129916352155
84 9.803195578001604
85 9.773512517518608
86 9.744065712089732
87 9.714840742652287

```
88 9.6858237532715
89 9.65700141266436
90 9.628360877725779
91 9.599889758922535
92 9.571576087429799
93 9.543408283893337
94 9.515375128708646
95 9.487465733715279
96 9.4596695152118
97 9.431976168202944
98 9.404375641796452
99 9.376858115672626
 Features :  [[0. 1. 1. 0. 1. 1. 1. 0. 1. 0. 0. 1. 0. 1. 1. 1. 1. 1. 1. 0. 1.
1.]
 [1. 0. 1. 0. 1. 0. 0. 0. 1. 0. 1. 1. 0. 1. 1. 0. 1. 0. 0. 0. 0. 1.]
 [1. 1. 0. 1. 0. 0. 1. 1. 0. 0. 0. 1. 0. 1. 1. 0. 0. 1. 0. 0. 0. 1.]
 [1. 1. 0. 0. 1. 1. 0. 1. 1. 0. 1. 1. 1. 0. 0. 0. 0. 1. 1. 0. 0. 1.]
 [1. 1. 0. 1. 0. 1. 1. 1. 1. 0. 1. 0. 1. 1. 0. 0. 1. 0. 0. 1. 1. 1.]]
 Targets :  [[0. 1. 0. 0. 0. 1. 1. 0. 1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 0. 0. 1. 1.]
 [1. 0. 1. 1. 1. 0. 0. 1. 0. 1. 1. 1. 1. 0. 1. 1. 0. 1. 1. 1. 0. 0.]]
 Targets predicted :  [[0.26917312 0.47480888 0.38383005 0.36702548 0.36847297
0.51495017
  0.50149954 0.32170939 0.41312076 0.34995368 0.42156213 0.26369194
  0.46186874 0.35517612 0.40653479 0.44888257 0.61773094 0.38692549
  0.31206891 0.46131229 0.50265826 0.48393133]
 [0.55865654 0.48808607 0.63371977 0.63643014 0.53366288 0.6752366
  0.62461212 0.67735273 0.6462287  0.66861434 0.63973254 0.53953301
  0.59130755 0.69949288 0.74351365 0.59103464 0.6579599  0.64864999
  0.59302691 0.56007428 0.61609115 0.52254045]]
```



[2]:
```
plt.scatter(x=epoch_list1,y=lost1)
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.xlim(0,100)
plt.title('Loss vs Epoch (100)')
```

[2]:
```
Text(0.5, 1.0, 'Loss vs Epoch (100)')
```



EPOCH 500

[3]:
```
def sigmoid(x): #Creating a definition for the sigmoid function
    return 1.0/(1+np.exp(-1.0*x)) #This is the sigmoid function. We are using
 ↪this because we are looking at a logistic model of an NN (only having 2
 ↪solutions).

def feed_forward(features,w1,b1,w2,b2,w3,b3): #Creating a definition for
 ↪"feed_foward". Basically the features,weights and biases going through the
 ↪NN starting from the first 5 features going to the final 2.
    #Calculating Hidden Layer 1
    HL1 = np.matmul(w1,features) #multiplying our weights and features. Where
 ↪the weights are a [4 x 5] and the the features are a [5 x 22] creating a [4
 ↪x 22] new matrix.
    HL1_with_bias = np.add(HL1,b1) #Adding the HL1 matrix (weights * features)
 ↪which is a [4 x 22] to the biases which are also a [4 x 22].

    # Implement RELU activation (max(0,x))
    HL1_with_bias_and_activation = np.maximum(np.zeros((4,1)),HL1_with_bias)
 ↪#We need to find the RELU to squish the numbers down to keep the numbers
 ↪managable.
```

```
    HL2 = np.matmul(w2,HL1_with_bias_and_activation) #multiplying our weights␣
↪and features. Where the weights are a [3 x 4] and the the features are a [4␣
↪x 22] creating a [3 x 22] new matrix.
    HL2_with_bias = np.add(HL2,b2) #Adding the HL1 matrix (weights * features)␣
↪which is a [3 x 22] to the biases which are also a [3 x 22].

    # Implement RELU activation
    HL2_with_bias_and_activation = np.maximum(HL2_with_bias,np.zeros((3,1)))␣
↪#We need to find the RELU to squish the numbers down to keep the numbers␣
↪managable.
    targets_predicted = np.matmul(w3,HL2_with_bias_and_activation) #multiplying␣
↪our weights and features. Where the weights are a [2 x 3] and the the␣
↪features are a [3 x 22] creating a [2 x 22] new matrix.
    targets_predicted = np.add(targets_predicted,b3) #Adding the HL1 matrix␣
↪(weights * features) which is a [2 x 22] to the biases which are also a [2 x␣
↪22].

    # Use sigmoid for the output activation
    targets_predicted = sigmoid(targets_predicted) #Calling the sigmoid on the␣
↪targets predicted to get them to become "squished" in between 0 and 1.
    return targets_predicted #prints out the targets predicted.

def loss(features,w1,b1,w2,b2,w3,b3,targets_observed): #A method of evaluating␣
↪how well your algorithm models your dataset. Greater is bad and lower is␣
↪good.
    targets_predicted = feed_forward(features,w1,b1,w2,b2,w3,b3) #Getting the␣
↪targets predicted to put into the loss function
    return np.sum((targets_predicted-targets_observed)**2) #Gives the loss␣
↪function answer. The closer the sum is to 0, the closer the NN is to␣
↪achieving the bests SSR.
#======================================================
print('Starting ...')

## Set up training data
## Each row is a case
## Columns 0-4 are features
## Columns 5 & 6 are targets

#22 x 7 matrix
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],
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                                    [1, 1, 1, 1, 1, 1, 0],
                                    [1, 0, 0, 1, 1, 1, 0]  ]
                          , dtype=float)

# shuffle our cases (to create randomness)
np.random.shuffle(features_and_targets)

# Need to transpose to get them as 5 X N matrices
features = np.transpose(features_and_targets[:,0:5]) #Tranposes the matrix to 5␣
 ↪x 22. Picking up the 0-4 index.
print(features) #prints the features in the array

# Need to transpose to get the 2 x N matrices
targets_observed = np.transpose(features_and_targets[:,5:7]) #Transposing the␣
 ↪last 2 columns from N x 2 to a 2 x N. Picking up the 5 and 6 index
number_of_features,number_of_cases = features.shape #[5,22] (creating tuple␣
 ↪(unchangable))
print(number_of_features) #prints the number of features in the array
print(number_of_cases) #prints the number of cases in the array

#Set initial weights and biases

weights_1 = np.random.rand(4,5) #Setting the dimensions of the matrix for our␣
 ↪random weights (rows by columns)
biases_1 = np.random.rand(4,number_of_cases) #Setting the dimensions of the␣
 ↪matrix for our baises (rows by columns)

weights_2 = np.random.rand(3,4) #Setting the dimensions of the matrix for our␣
 ↪random weights (rows by columns)
biases_2 = np.random.rand(3,number_of_cases) #Setting the dimensions of the␣
 ↪matrix for our baises (rows by columns)
```

```python
weights_3 = np.random.rand(2,3) #Setting the dimensions of the matrix for our random weights (rows by columns)
biases_3 = np.random.rand(2,number_of_cases) #Setting the dimensions of the matrix for our baises (rows by columns)

Targets_Predicted = feed_forward(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3) #Targets_Predicted before Epoch (before training is initialized)

#Printing the results to the following below:
print(' Features : ',features)
print(' Targets : ', targets_observed)
print(' Targets predicted : ', Targets_Predicted)

#Learning rate gives the rate of speed where the gradient moves during gradient descent. Setting it too high would make your path instable, too low would make convergence slow. Put it to zero means your model isn't learning anything from the gradients.

learning_rate = 0.01 #The amount of change to the model during each iterations

# Find slope functions using autograd
d_by_w1 = grad(loss,1) #create the derivative/gradient --> stored d_by_w1, (equation(loss), index=1 (weights_1))
d_by_b1 = grad(loss,2) #create the derivative/gradient --> stored d_by_b1, (equation(loss), index=2 (biases_1))
d_by_w2 = grad(loss,3) #create the derivative/gradient --> stored d_by_w2, (equation(loss), index=3 (weights_2))
d_by_b2 = grad(loss,4) #create the derivative/gradient --> stored d_by_b2, (equation(loss), index=4 (biases_2))
d_by_w3 = grad(loss,5) #create the derivative/gradient --> stored d_by_w3, (equation(loss), index=5 (weights_3))
d_by_b3 = grad(loss,6) #create the derivative/gradient --> stored d_by_b3, (equation(loss), index=6 (biases_3))

epoch_list2 = [] #creating list for epoch iterations
lost2 = [] #creating list for loss fucntion results

#Setting the iteration (making higher helps making the loss function look better)
for epoch in range(500):

    #At each iteration update weights and biases by subtracting
    #learning_rate times slope
    #Changing the random weights and random biases updating each of them after each iteration according to range(X)
```

```
    weights_1 -=
↪learning_rate*d_by_w1(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    biases_1 -=
↪learning_rate*d_by_b1(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    weights_2 -=
↪learning_rate*d_by_w2(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    biases_2 -=
↪learning_rate*d_by_b2(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    weights_3 -=
↪learning_rate*d_by_w3(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    biases_3 -=
↪learning_rate*d_by_b3(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar

    #Print out the latest value of the loss
    #We would expect this to go down with each iteration
    #This shows how good of a test it was to get to the desired the results
    #The closer to 0, the better the NN is learning <- This is what the loss
↪function is doing in the equation.

↪print(epoch,loss(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,targets_

    epoch_list2.append(epoch) #epoch list adding the iterations
    lost2.
↪append(loss(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,targets_obser
↪#loss function list adding for each iteration

Targets_Predicted =
↪feed_forward(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3)
↪#Targets_Predicted after Epoch (After training is complete)

#Printing the results to the following below:
print(' Features : ',features)
print(' Targets : ', targets_observed)
print(' Targets predicted : ', Targets_Predicted)

N = 22
target1_predicted = Targets_Predicted[0,:] #The target we are trying to achieve
target2_predicted = Targets_Predicted[1,:] #The target we are trying to achieve
target1_observed = targets_observed[0,:] #The target we want to achieve (what
↪the targets should be)
target2_observed = targets_observed[1,:] #The target we want to achieve (what
↪the targets should be)

ind = np.arange(N) #Return evenly spaced values within a given interval (N=22)
width = 0.35 #creating width to add distance between the 2 different bar graphs
plt.subplot(2,1,1) #creating first graph
```

```
plt.bar(ind, target1_predicted, width, label='Predicted') #Plotting the bar␣
 ↪graph of the predicted answers (First set)
plt.bar(ind + width, target1_observed, width,label='Observed') #Plotting the␣
 ↪bar graph of the observed answers (First set)
plt.ylabel('Targets 0 or 1') #y label
plt.title('Closeness of predicted targets for 22 cases') #title
plt.xticks(ind + width / 2, ind) #tick mark indicator
plt.legend(loc='best') #legend (automatically put in best location)
plt.subplot(2,1,2) #creating first graph
plt.bar(ind, target2_predicted, width, label='Predicted') #Plotting the bar␣
 ↪graph of the predicted answers (Second set)
plt.bar(ind + width, target2_observed, width,label='Observed') #Plotting the␣
 ↪bar graph of the observed answers (Second set)
plt.ylabel('Targets 0 or 1') #y label
plt.title('Closeness of predicted targets for 22 cases') #title
plt.xticks(ind + width / 2, ind) #tick mark indicator
plt.legend(loc='best') #legend (automatically put in best location)

plt.show() #display graphs
```

```
Starting …
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22
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 Targets predicted :  [[0.99971564 0.99984954 0.99715073 0.99970074 0.99987584
0.9996942
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  0.96678248 0.99982654 0.99998842 0.99996984]
 [0.99999461 0.99999822 0.99968697 0.99999067 0.99999152 0.99999628
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  0.98086104 0.99999483 0.99999996 0.99999917]]
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```

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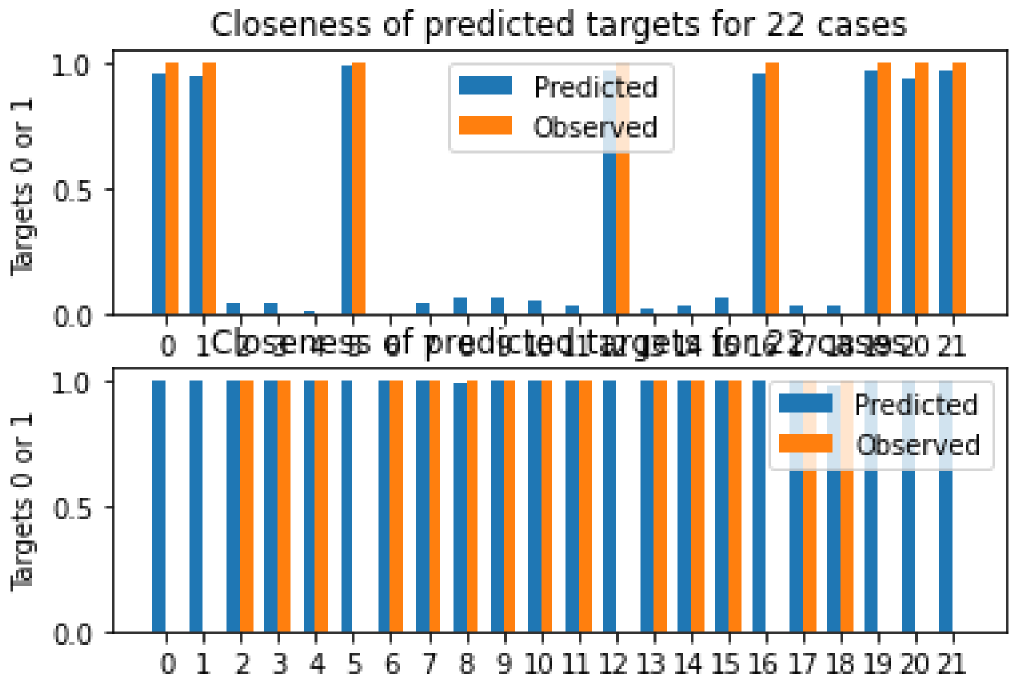
408	8.068805570296673
409	8.0680678823808
410	8.067337769293703
411	8.0666150414151
412	8.065899511775447
413	8.065190995929733
414	8.064489311832325
415	8.063794279712699
416	8.063105721951892
417	8.06242346295949
418	8.061747329050977
419	8.061077148325287
420	8.060412750542334
421	8.059753967000358
422	8.059100630412876
423	8.058452574785022
424	8.057809635289097
425	8.05717164813907
426	8.05653845046382
427	8.055909880178893
428	8.055285775856495
429	8.054665976593478
430	8.054050321877034
431	8.053438651447836
432	8.05283080516029
433	8.052226622839571

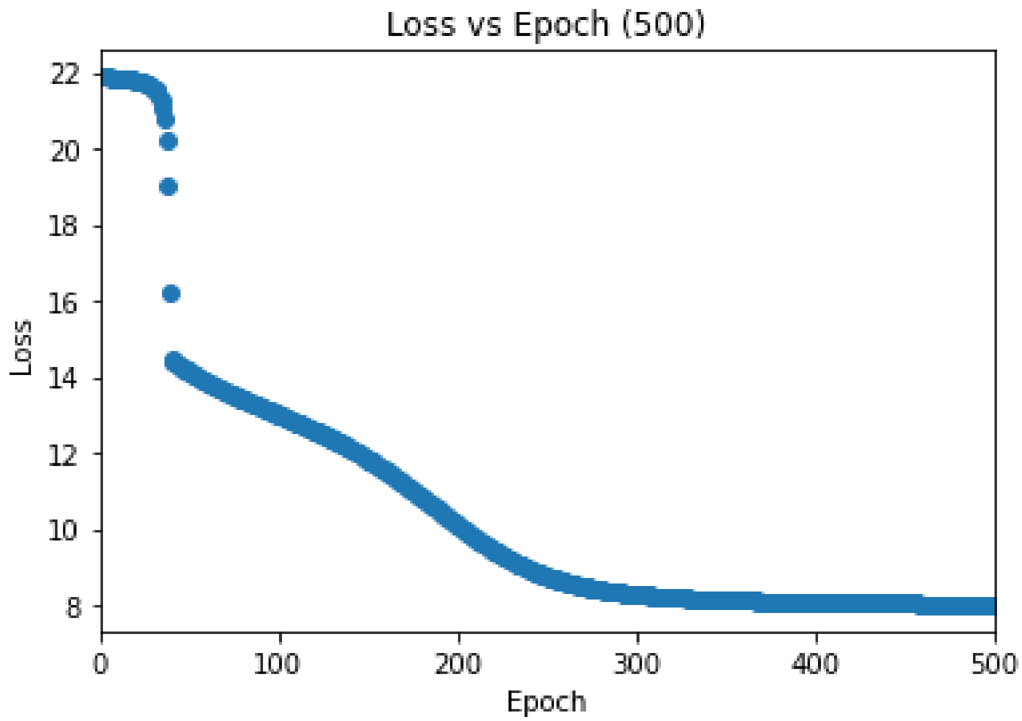
434	8.05162594413517
435	8.051028608370501
436	8.050434454388258
437	8.049843320391094
438	8.049255043777185
439	8.048669460970228
440	8.0480864072434
441	8.047505716536717
442	8.046927221267284
443	8.046350752131787
444	8.045776137900628
445	8.045203205202984
446	8.044631778302065
447	8.044061678859746
448	8.043492725689763
449	8.042924734498474
450	8.042357517612242
451	8.041790883690314
452	8.041224637422037
453	8.040658579207127
454	8.040092504817615
455	8.039526205039948
456	8.038959465295633
457	8.038392065238623
458	8.037823778327505
459	8.037254371370373
460	8.03668360404009
461	8.036111228357374
462	8.035536988138936
463	8.03496061840769
464	8.034381844761613
465	8.033800382697674
466	8.033215936886737
467	8.03262820039506
468	8.032036853847439
469	8.031441564526668
470	8.030841985403272
471	8.03023775408896
472	8.029628491706461
473	8.02901380166762
474	8.02839326835071
475	8.02776645566695
476	8.027132905504985
477	8.026492136040886
478	8.025843639899648
479	8.025186882152573
480	8.024521298133001
481	8.023846291050686

```
482 8.023161229382652
483 8.02246544401553
484 8.02175822511122
485 8.02103881866389
486 8.020306422712215
487 8.019560183165787
488 8.018799189198868
489 8.01802246815834
490 8.01722897992484
491 8.01641761065737
492 8.015587165841369
493 8.014736362547993
494 8.013863820798491
495 8.012968053910635
496 8.012047457684773
497 8.011100298263777
498 8.010124698473682
499 8.009118622419036
 Features :  [[1. 1. 0. 1. 1. 1. 0. 1. 0. 1. 1. 0. 1. 0. 1. 0. 1. 1. 0. 1. 1.
1.]
 [0. 1. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0. 1. 1. 1. 1. 0. 1. 0. 1. 1. 0.]
 [0. 0. 1. 1. 1. 1. 1. 0. 0. 0. 0. 0. 1. 1. 0. 0. 0. 1. 0. 0. 1. 1.]
 [0. 1. 0. 1. 0. 0. 1. 0. 0. 0. 1. 1. 0. 1. 1. 1. 1. 1. 0. 0. 1. 1.]
 [1. 1. 1. 0. 0. 1. 1. 0. 1. 0. 0. 1. 1. 1. 0. 1. 1. 0. 0. 1. 1. 1.]]
 Targets :  [[1. 1. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 1. 1. 1.]
 [0. 0. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 0. 1. 1. 0. 0. 0.]]
 Targets predicted :  [[0.95397716 0.94232141 0.04547998 0.04365808 0.01521292
0.98717156
  0.00620891 0.04397697 0.07064264 0.06299677 0.05774408 0.02870492
  0.96911034 0.02569967 0.03133324 0.0652091  0.95814137 0.02997042
  0.03658198 0.96752578 0.93976454 0.96483633]
 [0.99795514 0.99824149 0.99501073 0.99954984 0.9994411  0.99759924
  0.99961974 0.99193798 0.9900403  0.99758663 0.99869867 0.99892031
  0.99931879 0.99958783 0.99968673 0.99832409 0.99499548 0.99925003
  0.97017541 0.99614899 0.99986195 0.99903435]]
```



[4]:
```
plt.scatter(x=epoch_list2,y=lost2)
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.xlim(0,500)
plt.title('Loss vs Epoch (500)')
```

[4]: Text(0.5, 1.0, 'Loss vs Epoch (500)')



EPOCH 1000

```
[5]: def sigmoid(x): #Creating a definition for the sigmoid function
         return 1.0/(1+np.exp(-1.0*x)) #This is the sigmoid function. We are using␣
      ↪this because we are looking at a logistic model of an NN (only having 2␣
      ↪solutions).

     def feed_forward(features,w1,b1,w2,b2,w3,b3): #Creating a definition for␣
      ↪"feed_foward". Basically the features,weights and biases going through the␣
      ↪NN starting from the first 5 features going to the final 2.
         #Calculating Hidden Layer 1
         HL1 = np.matmul(w1,features) #multiplying our weights and features. Where␣
      ↪the weights are a [4 x 5] and the the features are a [5 x 22] creating a [4␣
      ↪x 22] new matrix.
         HL1_with_bias = np.add(HL1,b1) #Adding the HL1 matrix (weights * features)␣
      ↪which is a [4 x 22] to the biases which are also a [4 x 22].

         # Implement RELU activation (max(0,x))
         HL1_with_bias_and_activation = np.maximum(np.zeros((4,1)),HL1_with_bias)␣
      ↪#We need to find the RELU to squish the numbers down to keep the numbers␣
      ↪managable.
```

```python
    HL2 = np.matmul(w2,HL1_with_bias_and_activation) #multiplying our weights␣
↪and features. Where the weights are a [3 x 4] and the the features are a [4␣
↪x 22] creating a [3 x 22] new matrix.
    HL2_with_bias = np.add(HL2,b2) #Adding the HL1 matrix (weights * features)␣
↪which is a [3 x 22] to the biases which are also a [3 x 22].

    # Implement RELU activation
    HL2_with_bias_and_activation = np.maximum(HL2_with_bias,np.zeros((3,1)))␣
↪#We need to find the RELU to squish the numbers down to keep the numbers␣
↪managable.
    targets_predicted = np.matmul(w3,HL2_with_bias_and_activation) #multiplying␣
↪our weights and features. Where the weights are a [2 x 3] and the the␣
↪features are a [3 x 22] creating a [2 x 22] new matrix.
    targets_predicted = np.add(targets_predicted,b3) #Adding the HL1 matrix␣
↪(weights * features) which is a [2 x 22] to the biases which are also a [2 x␣
↪22].

    # Use sigmoid for the output activation
    targets_predicted = sigmoid(targets_predicted) #Calling the sigmoid on the␣
↪targets predicted to get them to become "squished" in between 0 and 1.
    return targets_predicted #prints out the targets predicted.

def loss(features,w1,b1,w2,b2,w3,b3,targets_observed): #A method of evaluating␣
↪how well your algorithm models your dataset. Greater is bad and lower is␣
↪good.
    targets_predicted = feed_forward(features,w1,b1,w2,b2,w3,b3) #Getting the␣
↪targets predicted to put into the loss function
    return np.sum((targets_predicted-targets_observed)**2) #Gives the loss␣
↪function answer. The closer the sum is to 0, the closer the NN is to␣
↪achieving the bests SSR.
#=======================================================
print('Starting ...')

## Set up training data
## Each row is a case
## Columns 0-4 are features
## Columns 5 & 6 are targets

#22 x 7 matrix
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 (to create randomness)
np.random.shuffle(features_and_targets)

# Need to transpose to get them as 5 X N matrices
features = np.transpose(features_and_targets[:,0:5]) #Tranposes the matrix to 5 x 22. Picking up the 0-4 index.
print(features) #prints the features in the array

# Need to transpose to get the 2 x N matrices
targets_observed = np.transpose(features_and_targets[:,5:7]) #Transposing the last 2 columns from N x 2 to a 2 x N. Picking up the 5 and 6 index
number_of_features,number_of_cases = features.shape #[5,22] (creating tuple (unchangable))
print(number_of_features) #prints the number of features in the array
print(number_of_cases) #prints the number of cases in the array

#Set initial weights and biases

weights_1 = np.random.rand(4,5) #Setting the dimensions of the matrix for our random weights (rows by columns)
biases_1 = np.random.rand(4,number_of_cases) #Setting the dimensions of the matrix for our baises (rows by columns)

weights_2 = np.random.rand(3,4) #Setting the dimensions of the matrix for our random weights (rows by columns)
biases_2 = np.random.rand(3,number_of_cases) #Setting the dimensions of the matrix for our baises (rows by columns)
```

```
weights_3 = np.random.rand(2,3) #Setting the dimensions of the matrix for our␣
 ↪random weights (rows by columns)
biases_3 = np.random.rand(2,number_of_cases) #Setting the dimensions of the␣
 ↪matrix for our baises (rows by columns)

Targets_Predicted =␣
 ↪feed_forward(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3)␣
 ↪#Targets_Predicted before Epoch (before training is initialized)

#Printing the results to the following below:
print(' Features : ',features)
print(' Targets : ', targets_observed)
print(' Targets predicted : ', Targets_Predicted)

#Learning rate gives the rate of speed where the gradient moves during gradient␣
 ↪descent. Setting it too high would make your path instable, too low would␣
 ↪make convergence slow. Put it to zero means your model isn't learning␣
 ↪anything from the gradients.

learning_rate = 0.01 #The amount of change to the model during each iterations

# Find slope functions using autograd
d_by_w1 = grad(loss,1) #create the derivative/gradient --> stored d_by_w1,␣
 ↪(equation(loss), index=1 (weights_1))
d_by_b1 = grad(loss,2) #create the derivative/gradient --> stored d_by_b1,␣
 ↪(equation(loss), index=2 (biases_1))
d_by_w2 = grad(loss,3) #create the derivative/gradient --> stored d_by_w2,␣
 ↪(equation(loss), index=3 (weights_2))
d_by_b2 = grad(loss,4) #create the derivative/gradient --> stored d_by_b2,␣
 ↪(equation(loss), index=4 (biases_2))
d_by_w3 = grad(loss,5) #create the derivative/gradient --> stored d_by_w3,␣
 ↪(equation(loss), index=5 (weights_3))
d_by_b3 = grad(loss,6) #create the derivative/gradient --> stored d_by_b3,␣
 ↪(equation(loss), index=6 (biases_3))

epoch_list3 = [] #creating list for epoch iterations
lost3 = [] #creating list for loss fucntion results

#Setting the iteration (making higher helps making the loss function look␣
 ↪better)
for epoch in range(1000):

    #At each iteration update weights and biases by subtracting
    #learning_rate times slope
    #Changing the random weights and random biases updating each of them after␣
 ↪each iteration according to range(X)
```

```
    weights_1 -=␣
↪learning_rate*d_by_w1(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    biases_1 -=␣
↪learning_rate*d_by_b1(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    weights_2 -=␣
↪learning_rate*d_by_w2(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    biases_2 -=␣
↪learning_rate*d_by_b2(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    weights_3 -=␣
↪learning_rate*d_by_w3(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar
    biases_3 -=␣
↪learning_rate*d_by_b3(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,tar

    #Print out the latest value of the loss
    #We would expect this to go down with each iteration
    #This shows how good of a test it was to get to the desired the results
    #The closer to 0, the better the NN is learning <- This is what the loss␣
↪function is doing in the equation.
  ␣
↪print(epoch,loss(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,targets_

    epoch_list3.append(epoch) #epoch list adding the iterations
    lost3.
↪append(loss(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3,targets_obser
↪#loss function list adding for each iteration

Targets_Predicted =␣
↪feed_forward(features,weights_1,biases_1,weights_2,biases_2,weights_3,biases_3)␣
↪#Targets_Predicted after Epoch (After training is complete)

#Printing the results to the following below:
print(' Features : ',features)
print(' Targets : ', targets_observed)
print(' Targets predicted : ', Targets_Predicted)

N = 22
target1_predicted = Targets_Predicted[0,:] #The target we are trying to achieve
target2_predicted = Targets_Predicted[1,:] #The target we are trying to achieve
target1_observed = targets_observed[0,:] #The target we want to achieve (what␣
↪the targets should be)
target2_observed = targets_observed[1,:] #The target we want to achieve (what␣
↪the targets should be)

ind = np.arange(N) #Return evenly spaced values within a given interval (N=22)
width = 0.35 #creating width to add distance between the 2 different bar graphs
plt.subplot(2,1,1) #creating first graph
```

```
plt.bar(ind, target1_predicted, width, label='Predicted') #Plotting the bar␣
↪graph of the predicted answers (First set)
plt.bar(ind + width, target1_observed, width,label='Observed') #Plotting the␣
↪bar graph of the observed answers (First set)
plt.ylabel('Targets 0 or 1') #y label
plt.title('Closeness of predicted targets for 22 cases') #title
plt.xticks(ind + width / 2, ind) #tick mark indicator
plt.legend(loc='best') #legend (automatically put in best location)
plt.subplot(2,1,2) #creating first graph
plt.bar(ind, target2_predicted, width, label='Predicted') #Plotting the bar␣
↪graph of the predicted answers (Second set)
plt.bar(ind + width, target2_observed, width,label='Observed') #Plotting the␣
↪bar graph of the observed answers (Second set)
plt.ylabel('Targets 0 or 1') #y label
plt.title('Closeness of predicted targets for 22 cases') #title
plt.xticks(ind + width / 2, ind) #tick mark indicator
plt.legend(loc='best') #legend (automatically put in best location)

plt.show() #display graphs
```

```
Starting …
[[0. 1. 0. 0. 1. 1. 1. 1. 1. 0. 1. 1. 1. 0. 0. 1. 1. 1. 1. 1. 1. 0.]
 [0. 1. 1. 0. 0. 1. 1. 1. 0. 0. 0. 1. 1. 0. 0. 1. 0. 0. 0. 1. 0. 1.]
 [0. 0. 1. 0. 1. 0. 1. 1. 0. 1. 1. 1. 0. 1. 0. 0. 0. 0. 0. 1. 1. 0.]
 [1. 1. 1. 0. 0. 1. 0. 1. 0. 0. 1. 0. 0. 1. 0. 0. 1. 1. 0. 1. 1. 1.]
 [1. 0. 1. 1. 1. 1. 0. 0. 1. 1. 1. 1. 0. 1. 0. 1. 1. 0. 0. 1. 0. 1.]]
5
22
 Features :  [[0. 1. 0. 0. 1. 1. 1. 1. 1. 0. 1. 1. 1. 0. 0. 1. 1. 1. 1. 1. 1.
0.]
 [0. 1. 1. 0. 0. 1. 1. 1. 0. 0. 0. 1. 1. 0. 0. 1. 0. 0. 0. 1. 0. 1.]
 [0. 0. 1. 0. 1. 0. 1. 1. 0. 1. 1. 1. 0. 1. 0. 0. 0. 0. 0. 1. 1. 0.]
 [1. 1. 1. 0. 0. 1. 0. 1. 0. 0. 1. 0. 0. 1. 0. 0. 1. 1. 0. 1. 1. 1.]
 [1. 0. 1. 1. 1. 1. 0. 0. 1. 1. 1. 1. 0. 1. 0. 1. 1. 0. 0. 1. 0. 1.]]
 Targets :  [[0. 0. 0. 0. 1. 1. 0. 0. 1. 0. 1. 1. 0. 0. 0. 1. 1. 0. 0. 1. 0. 0.]
 [1. 1. 1. 1. 0. 0. 1. 1. 0. 1. 0. 0. 1. 1. 1. 0. 0. 1. 1. 0. 1. 1.]]
 Targets predicted :  [[0.98363339 0.99553079 0.99934737 0.95257727 0.99826303
0.99871201
  0.98919614 0.99883202 0.99019502 0.99429307 0.99930612 0.99882063
  0.98690107 0.99763554 0.91307719 0.99684356 0.99773331 0.9872429
  0.95902614 0.99951054 0.99423249 0.99719311]
 [0.98294772 0.99131575 0.99972275 0.97727298 0.99827293 0.99725721
  0.98934977 0.99933964 0.99375122 0.9937413  0.99947837 0.99917346
  0.98143573 0.99738043 0.89345232 0.99566856 0.99757773 0.98383728
  0.9305845  0.9994398  0.9963027  0.99625893]]
0 21.427371018966134
1 21.3474094713935
```

2 21.23944055301944
3 21.085622384920093
4 20.849554186748573
5 20.445855189275537
6 19.632560816547052
7 17.584083618323618
8 13.971302786030119
9 13.898346346726067
10 13.854165176504155
11 13.828339020977296
12 13.801772625452505
13 13.775879938524328
14 13.74926387334698
15 13.7222930281838
16 13.694676534891187
17 13.666406338760885
18 13.637326742309508
19 13.607310670283926
20 13.576169411471536
21 13.543674699032449
22 13.509523104533184
23 13.473313363115718
24 13.434497390747548
25 13.392308787266195
26 13.345642055051163
27 13.292846744125653
28 13.231356756072053
29 13.15698740320604
30 13.06251650454815
31 12.934614772764126
32 12.746718008635485
33 12.441747708599728
34 11.895722213774802
35 10.944049266957688
36 10.121822219055709
37 10.038709993044993
38 9.977475706395708
39 9.9147218215284
40 9.851744306131895
41 9.786939306395862
42 9.72064942688359
43 9.652630665187061
44 9.582877732213559
45 9.511263305979222
46 9.437729113281355
47 9.36219500860357
48 9.284590239822666
49 9.204840072129429

50 9.122872295146935
51 9.038614905110272
52 8.951997877563326
53 8.862953162157748
54 8.771415600020898
55 8.677323517376992
56 8.580619581647262
57 8.481251646215933
58 8.379173713936996
59 8.274346954509156
60 8.16674080089883
61 8.056334102232537
62 7.943116328943379
63 7.8270888111315635
64 7.7082659920336525
65 7.586676670889057
66 7.462365205859085
67 7.3353926418266795
68 7.205837723551595
69 7.073797750317664
70 6.939389225347856
71 6.802748251790676
72 6.664030627866606
73 6.523411597103519
74 6.381085216044521
75 6.237263311588089
76 6.092174013336031
77 5.946059862723004
78 5.799175519727154
79 5.658527851840609
80 5.523576500902635
81 5.388274709400487
82 5.252954832738647
83 5.1177884220953045
84 4.982958275072221
85 4.848640205429011
86 4.715009359256866
87 4.5822355763763944
88 4.450484059784387
89 4.3199138926903
90 4.190677750582578
91 4.062921360451568
92 3.93678329971714
93 3.8123948697722634
94 3.689880108909555
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98 3.220789815394682
99 3.109256852758329
100 3.000194779332662
101 2.893679008840442
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106 2.401410709244293
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116 1.6279934229807698
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0.]
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2.28900877e-02
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 1.69296566e-02 6.94858781e-03 1.06918635e-02 9.87097884e-01
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 2.10342920e-02 9.85004188e-01 1.51119780e-02 1.44702433e-02
 9.81214052e-01 9.89702164e-01 9.94275506e-01 9.25890113e-03
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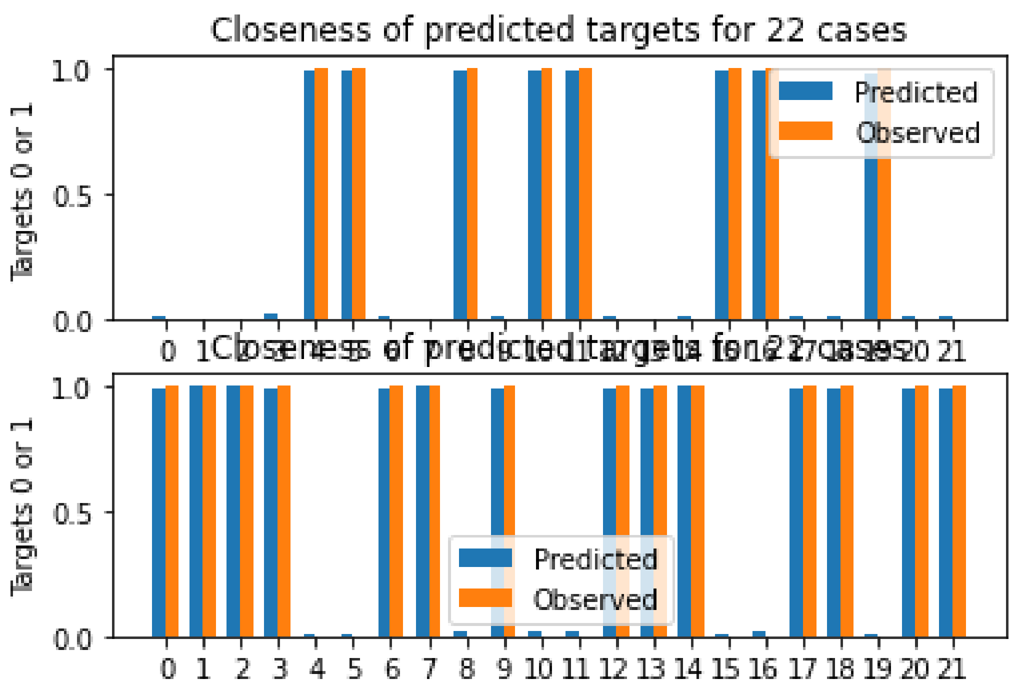
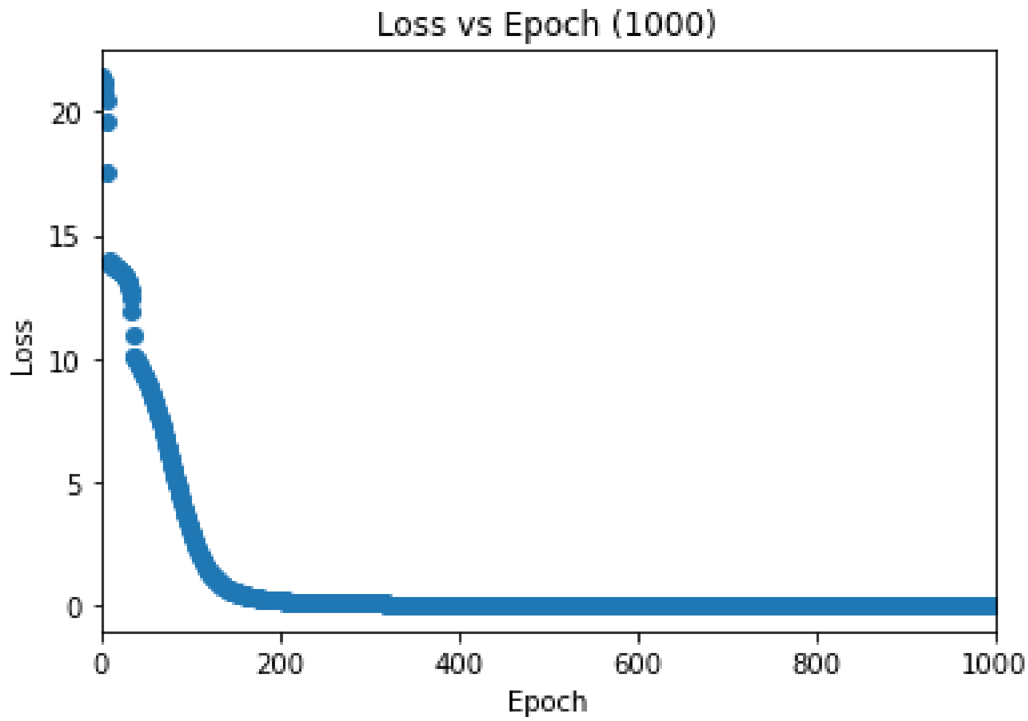



```
[6]: plt.scatter(x=epoch_list3,y=lost3)
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.xlim(0,1000)
plt.title('Loss vs Epoch (1000)')
```

```
[6]: Text(0.5, 1.0, 'Loss vs Epoch (1000)')
```


Loss vs Epoch (1000)
Loss
20
15
10
5
0
0
200
400
600
800
1000
Epoch