Layered Neural Network

In [ ]:
```
import numpy as np
```

In [ ]:
```
input_size = 2
layers = [4,3]
output_size = 2
```

In [ ]:
```
def softmax(a):
    ea = np.exp(a)
    ans = ea/np.sum(ea,axis=1,keepdims=True) # To preserves the dimensions
    return ans
```

In [ ]:
```
a = np.array([[20,30],[20,20]])
a_ = softmax(a)
print(a_)
```

```
[[4.53978687e-05 9.99954602e-01]
 [5.00000000e-01 5.00000000e-01]]
```

In [ ]:
```
class NeuralNetwork:
    def __init__(self, input_size, layers, output_size):
        np.random.seed(0)

        model = {}

        model['W1'] = np.random.randn(input_size, layers[0])
        model['b1'] = np.zeros((1,layers[0]))
        model['W2'] = np.random.randn(layers[0], layers[1])
        model['b2'] = np.zeros((1,layers[1]))
        model['W3'] = np.random.randn(layers[1], output_size)
        model['b3'] = np.zeros((1,output_size))

        self.model = model
        self.activation_outputs = None

    def forward(self,x):
        W1,W2,W3 = self.model['W1'],self.model['W2'],self.model['W3']
        b1,b2,b3 = self.model['b1'],self.model['b2'],self.model['b3']

        z1 = np.dot(x,W1) + b1
        a1 = np.tanh(z1)

        z2 = np.dot(a1,W2) + b2
        a2 = np.tanh(z2)

        z3 = np.dot(a2,W3) + b3
        y_ = softmax(z3)

        self.activation_outputs = (a1,a2,y_)
        return y_
```

```
    def backward(self,x,y,learning_rate=0.001):
        W1,W2,W3 = self.model['W1'],self.model['W2'],self.model['W3']
        b1,b2,b3 = self.model['b1'],self.model['b2'],self.model['b3']

        a1,a2,y_ = self.activation_outputs

        m = x.shape[0]

        delta3 = y_-y
        dw3 = np.dot(a2.T,delta3)
        db3 = np.sum(delta3,axis=0)

        delta2 = (1-np.square(a2))*np.dot(delta3,W3.T)
        dw2 = np.dot(a1.T,delta2)
        db2 = np.sum(delta2,axis=0)

        delta1 = (1-np.square(a1))*np.dot(delta2,W2.T)
        dw1 = np.dot(x.T,delta1)
        db1 = np.sum(delta1,axis=0)

        self.model["W1"] -= learning_rate*dw1
        self.model["b1"] -= learning_rate*db1

        self.model["W2"] -= learning_rate*dw2
        self.model["b2"] -= learning_rate*db2

        self.model["W3"] -= learning_rate*dw3
        self.model["b3"] -= learning_rate*db3

    def predict(self,x):
        y_out = self.forward(x)
        return np.argmax(y_out,axis=1)
    def summary(self):
        W1,W2,W3 = self.model['W1'],self.model['W2'],self.model['W3']
        a1,a2,y_ = self.activation_outputs

        print("W1 ",W1.shape)
        print("A1 ",a1.shape)

        print("W2 ",W2.shape)
        print("A2 ",a2.shape)

        print("W3 ",W3.shape)
        print("Y_ ",y_.shape)
```

In [ ]:

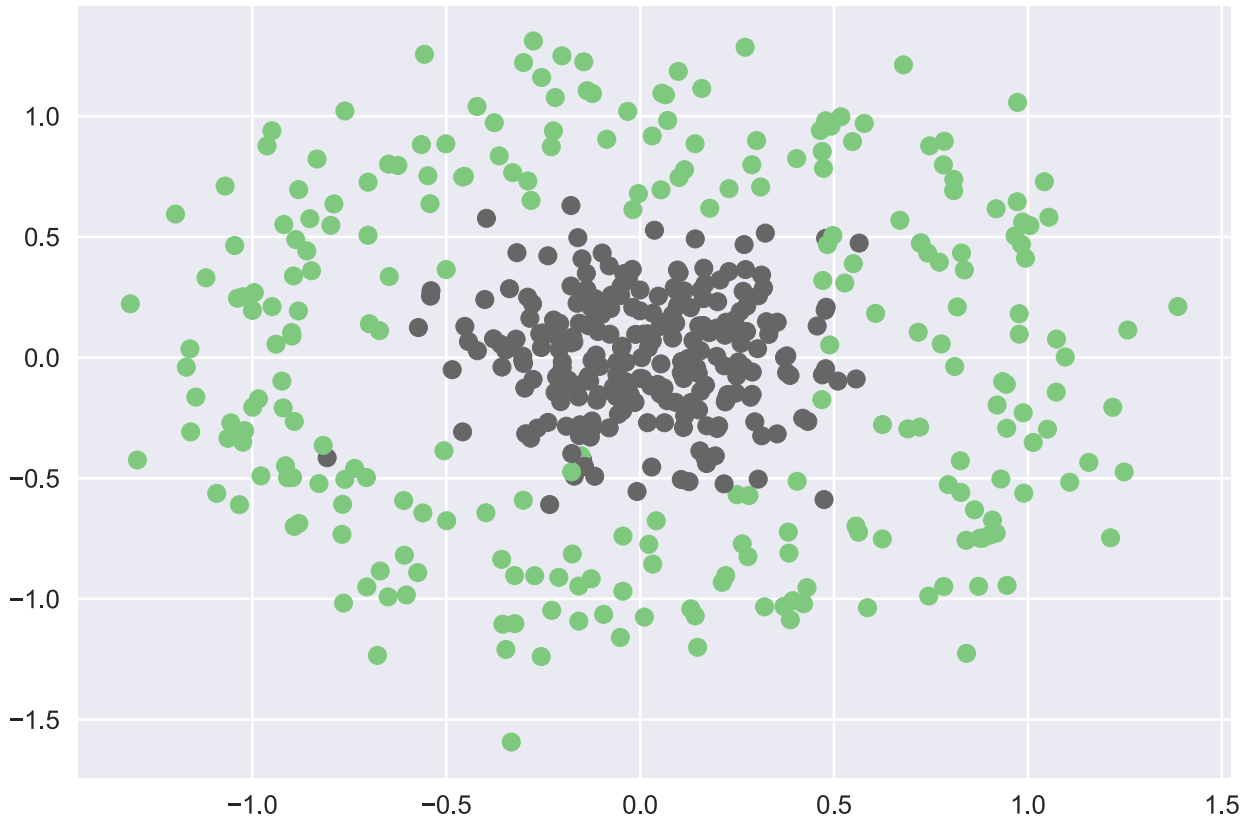
```
def loss(y_oht, p):
    l = -np.mean(y_oht*np.log(p))
    return l

def one_hot(y,depth):
    m = y.shape[0]
    y_oht = np.zeros((m,depth))
    y_oht[np.arange(m),y] = 1

    return y_oht
```

In [ ]:

```
from sklearn.datasets import make_circles
import matplotlib.pyplot as plt
```

In [ ]:
```
x,y = make_circles(n_samples=500, shuffle=True, noise=0.2, random_state=1, factor=0.2)
```

In [ ]:
```
plt.style.use('seaborn')
plt.scatter(x[:,0],x[:,1],c=y,cmap=plt.cm.Accent)
plt.show()
```



In [ ]:
```
model = NeuralNetwork(input_size=2,layers=[10,5],output_size=2)
```

In [ ]:
```
model.forward(x)
```

Out[ ]:
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       [0.51067345, 0.48932655],
       [0.5736724 , 0.4263276 ],
       [0.5642692 , 0.4357308 ]])
```

In [ ]:

```
model.summary()
```

```
W1  (2, 10)
```

```
A1  (500, 10)
W2  (10, 5)
A2  (500, 5)
W3  (5, 2)
Y_  (500, 2)
```

In [ ]:

```
# y_oht = one_hot(y,2)
# print(y_oht)
```

In [ ]:

```
def train(X,Y,model,epochs,learning_rate,logs=True):
    training_loss = []

    classes = 2
    Y_OHT = one_hot(Y,classes)

    for ix in range(epochs):

        Y_ = model.forward(X)
        l = loss(Y_OHT,Y_)
        training_loss.append(l)
        model.backward(X,Y_OHT,learning_rate)

        if(logs):
            print("Epoch %d Loss %.4f"%(ix,l))


    return training_loss
```

In [ ]:

```
losses = train(x,y,model,500,0.001)
```

```
Epoch 0 Loss 0.3571
Epoch 1 Loss 0.3554
Epoch 2 Loss 0.2593
Epoch 3 Loss 0.2407
Epoch 4 Loss 0.2258
Epoch 5 Loss 0.2132
Epoch 6 Loss 0.2020
Epoch 7 Loss 0.1919
Epoch 8 Loss 0.1827
Epoch 9 Loss 0.1742
Epoch 10 Loss 0.1664
Epoch 11 Loss 0.1593
Epoch 12 Loss 0.1527
Epoch 13 Loss 0.1467
Epoch 14 Loss 0.1411
Epoch 15 Loss 0.1360
Epoch 16 Loss 0.1313
Epoch 17 Loss 0.1270
Epoch 18 Loss 0.1230
Epoch 19 Loss 0.1193
Epoch 20 Loss 0.1159
Epoch 21 Loss 0.1127
Epoch 22 Loss 0.1098
Epoch 23 Loss 0.1070
Epoch 24 Loss 0.1045
Epoch 25 Loss 0.1021
Epoch 26 Loss 0.0999
```

```
Epoch 27 Loss 0.0978
Epoch 28 Loss 0.0958
Epoch 29 Loss 0.0940
Epoch 30 Loss 0.0922
Epoch 31 Loss 0.0906
Epoch 32 Loss 0.0891
Epoch 33 Loss 0.0876
Epoch 34 Loss 0.0862
Epoch 35 Loss 0.0849
Epoch 36 Loss 0.0837
Epoch 37 Loss 0.0825
Epoch 38 Loss 0.0814
Epoch 39 Loss 0.0803
Epoch 40 Loss 0.0793
Epoch 41 Loss 0.0783
Epoch 42 Loss 0.0774
Epoch 43 Loss 0.0765
Epoch 44 Loss 0.0756
Epoch 45 Loss 0.0748
Epoch 46 Loss 0.0740
Epoch 47 Loss 0.0732
Epoch 48 Loss 0.0725
Epoch 49 Loss 0.0718
Epoch 50 Loss 0.0711
Epoch 51 Loss 0.0705
Epoch 52 Loss 0.0699
Epoch 53 Loss 0.0693
Epoch 54 Loss 0.0687
Epoch 55 Loss 0.0681
Epoch 56 Loss 0.0676
Epoch 57 Loss 0.0671
Epoch 58 Loss 0.0666
Epoch 59 Loss 0.0661
Epoch 60 Loss 0.0656
Epoch 61 Loss 0.0651
Epoch 62 Loss 0.0647
Epoch 63 Loss 0.0643
Epoch 64 Loss 0.0638
Epoch 65 Loss 0.0634
Epoch 66 Loss 0.0630
Epoch 67 Loss 0.0627
Epoch 68 Loss 0.0623
Epoch 69 Loss 0.0619
Epoch 70 Loss 0.0616
Epoch 71 Loss 0.0612
Epoch 72 Loss 0.0609
Epoch 73 Loss 0.0606
Epoch 74 Loss 0.0602
Epoch 75 Loss 0.0599
Epoch 76 Loss 0.0596
Epoch 77 Loss 0.0593
Epoch 78 Loss 0.0591
Epoch 79 Loss 0.0588
Epoch 80 Loss 0.0585
Epoch 81 Loss 0.0582
Epoch 82 Loss 0.0580
Epoch 83 Loss 0.0577
Epoch 84 Loss 0.0575
Epoch 85 Loss 0.0572
Epoch 86 Loss 0.0570
Epoch 87 Loss 0.0568
```

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Epoch 88 Loss 0.0565
Epoch 89 Loss 0.0563
Epoch 90 Loss 0.0561
Epoch 91 Loss 0.0559
Epoch 92 Loss 0.0557
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Epoch 149 Loss 0.0484
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```

```
Epoch 454 Loss 0.0399
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Epoch 497 Loss 0.0394
Epoch 498 Loss 0.0394
Epoch 499 Loss 0.0394
```
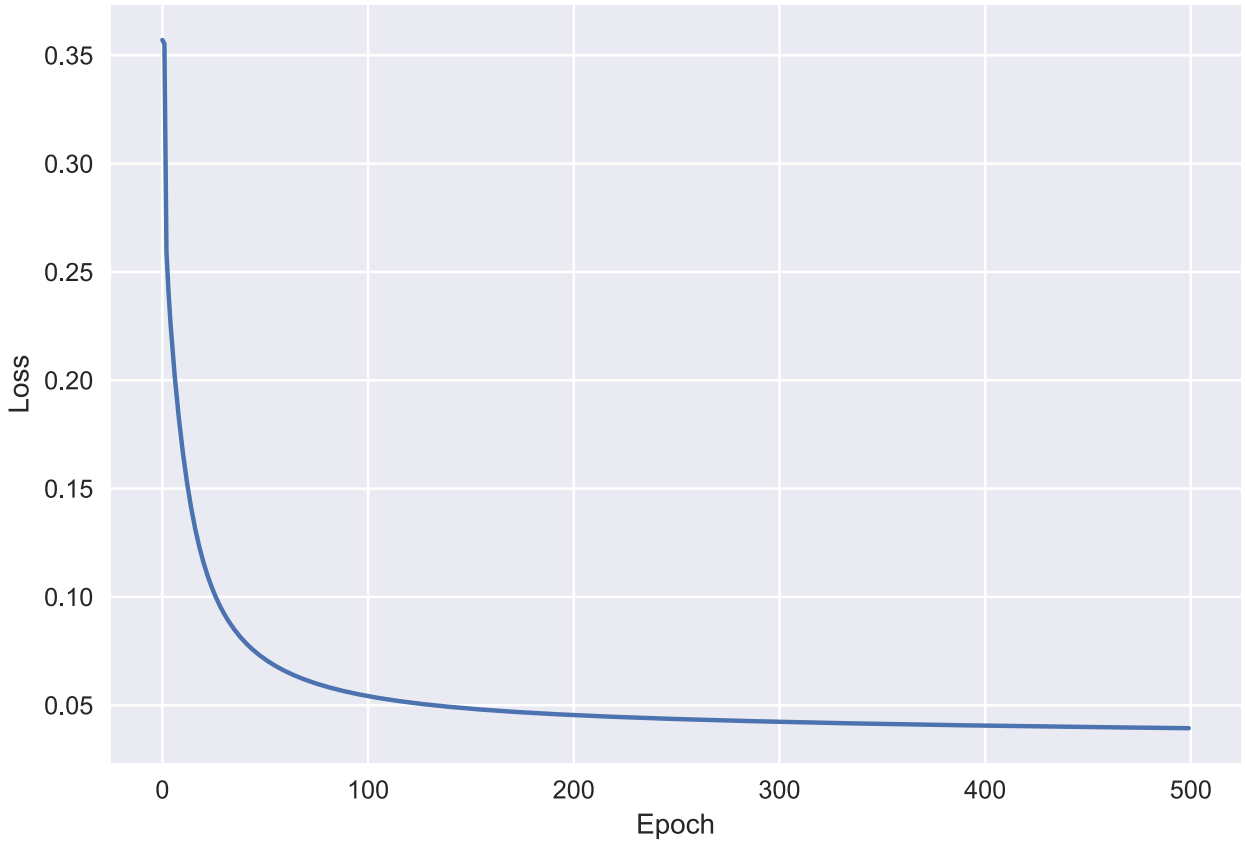
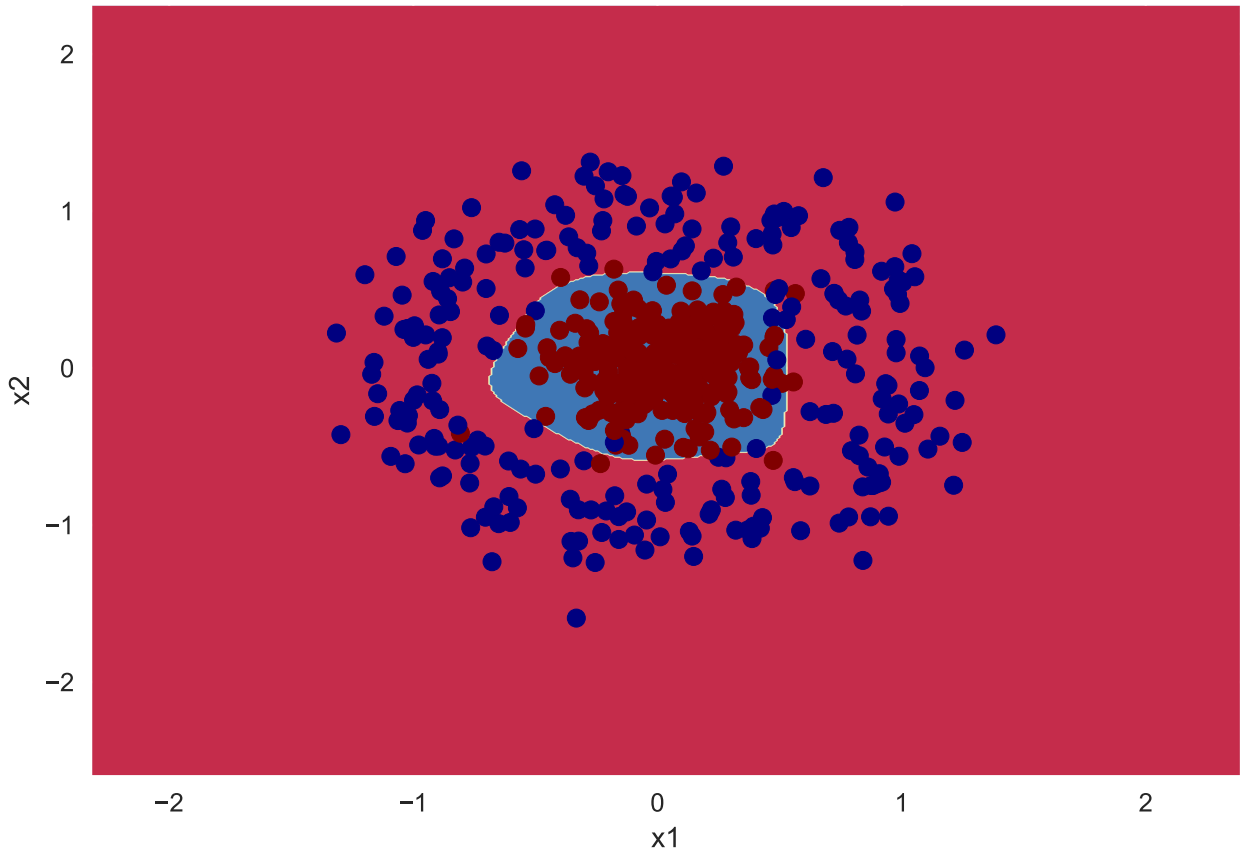

In [ ]:

```
plt.plot(losses)
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.show()
```



In [ ]:
```
## Find Accuracy
from visualize import plot_decision_boundary
```

In [ ]:
```
plot_decision_boundary(lambda X:model.predict(X),x,y)
```



In [ ]:
```
outputs = model.predict(x)
```

In [ ]:
```
training_accuracy = np.sum(outputs==y)/y.shape[0]
print("Training Accuracy %.4f"%(training_accuracy*100))
```

```
Training Accuracy 97.0000
```

Other Data Sets

In [ ]:
```
model  = NeuralNetwork(input_size=2,layers=[10,5],output_size=2)
```

XOR Data Set

In [ ]:
```
X = np.array([[0,0],
              [0,1],
              [1,0],
              [1,1]
             ])

Y = np.array([0,1,1,0])
```

In [ ]:
```
losses = train(X,Y,model,300,0.1)
```

```
Epoch 0 Loss 0.3427
```

```
Epoch 1 Loss 0.2543
Epoch 2 Loss 0.2126
Epoch 3 Loss 0.1926
Epoch 4 Loss 0.1778
Epoch 5 Loss 0.1639
Epoch 6 Loss 0.1493
Epoch 7 Loss 0.1346
Epoch 8 Loss 0.1207
Epoch 9 Loss 0.1089
Epoch 10 Loss 0.1008
Epoch 11 Loss 0.1004
Epoch 12 Loss 0.1244
Epoch 13 Loss 0.1949
Epoch 14 Loss 0.3900
Epoch 15 Loss 0.1355
Epoch 16 Loss 0.0958
Epoch 17 Loss 0.0762
Epoch 18 Loss 0.0636
Epoch 19 Loss 0.0552
Epoch 20 Loss 0.0492
Epoch 21 Loss 0.0447
Epoch 22 Loss 0.0412
Epoch 23 Loss 0.0384
Epoch 24 Loss 0.0361
Epoch 25 Loss 0.0341
Epoch 26 Loss 0.0323
Epoch 27 Loss 0.0307
Epoch 28 Loss 0.0293
Epoch 29 Loss 0.0281
Epoch 30 Loss 0.0269
Epoch 31 Loss 0.0258
Epoch 32 Loss 0.0248
Epoch 33 Loss 0.0239
Epoch 34 Loss 0.0231
Epoch 35 Loss 0.0223
Epoch 36 Loss 0.0215
Epoch 37 Loss 0.0208
Epoch 38 Loss 0.0202
Epoch 39 Loss 0.0196
Epoch 40 Loss 0.0190
Epoch 41 Loss 0.0184
Epoch 42 Loss 0.0179
Epoch 43 Loss 0.0174
Epoch 44 Loss 0.0170
Epoch 45 Loss 0.0165
Epoch 46 Loss 0.0161
Epoch 47 Loss 0.0157
Epoch 48 Loss 0.0153
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Epoch 51 Loss 0.0143
Epoch 52 Loss 0.0139
Epoch 53 Loss 0.0136
Epoch 54 Loss 0.0133
Epoch 55 Loss 0.0131
Epoch 56 Loss 0.0128
Epoch 57 Loss 0.0125
Epoch 58 Loss 0.0123
Epoch 59 Loss 0.0120
Epoch 60 Loss 0.0118
Epoch 61 Loss 0.0116
```

```
Epoch 62 Loss 0.0114
Epoch 63 Loss 0.0112
Epoch 64 Loss 0.0110
Epoch 65 Loss 0.0108
Epoch 66 Loss 0.0106
Epoch 67 Loss 0.0104
Epoch 68 Loss 0.0102
Epoch 69 Loss 0.0100
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Epoch 299 Loss 0.0019
```
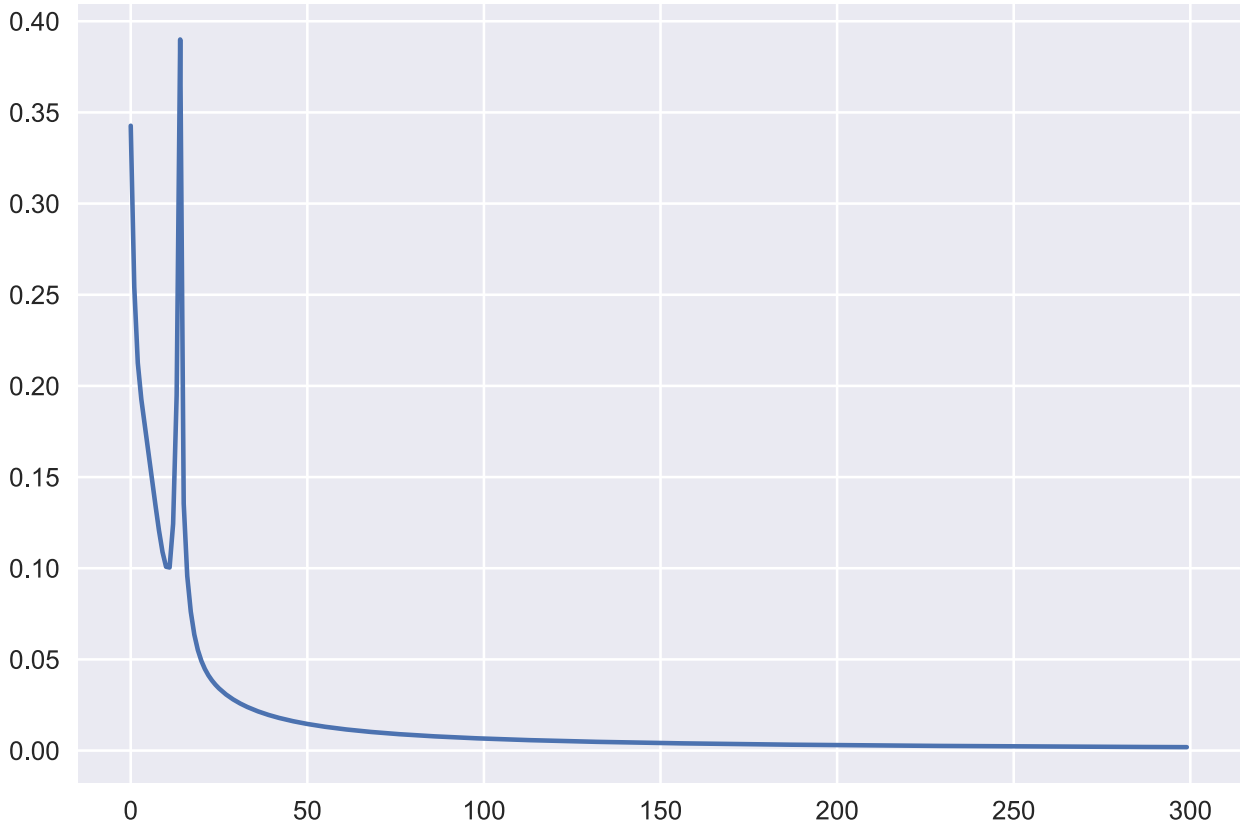
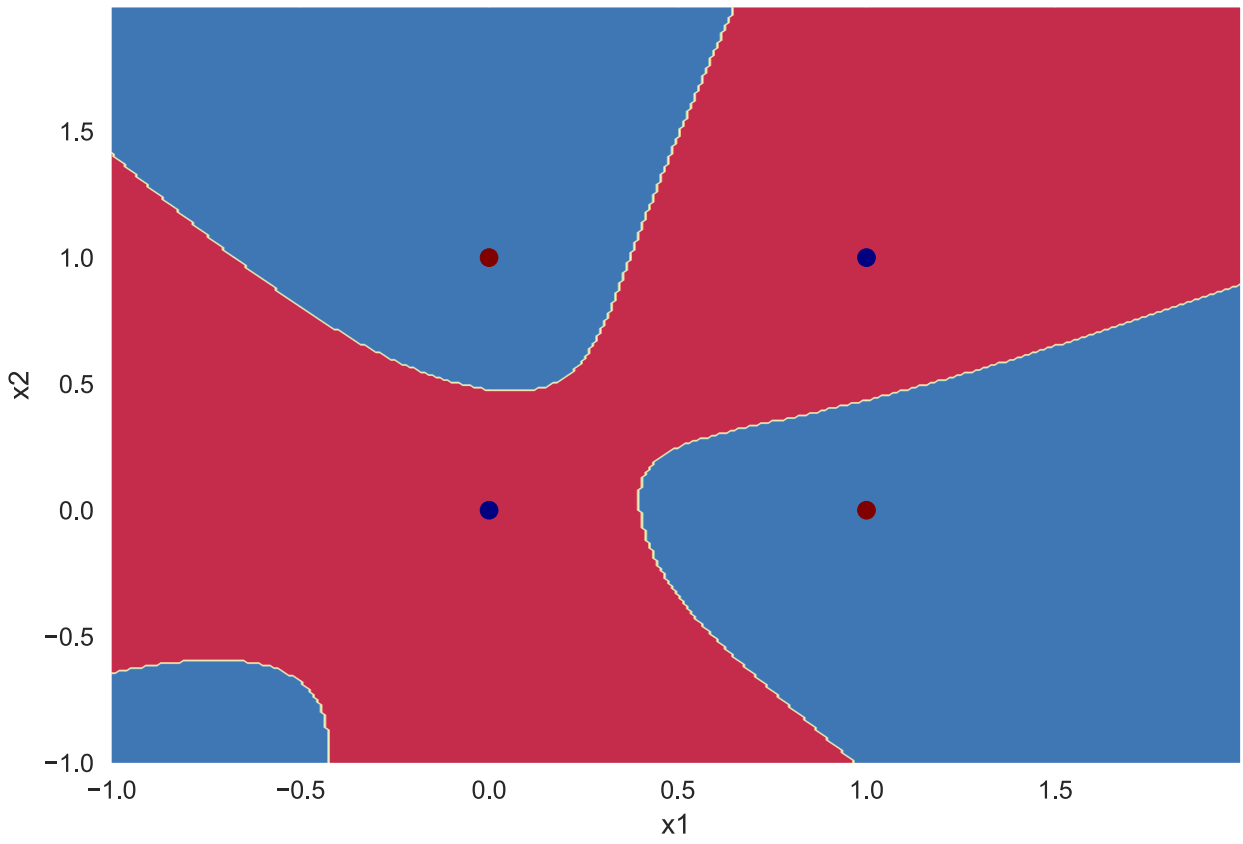

In [ ]:

```
plt.plot(losses)
plt.show()
```



In [ ]:
```
plot_decision_boundary(lambda x:model.predict(x),X,Y)
```



In [ ]:
```
from sklearn.datasets import make_moons,make_circles,make_classification
```

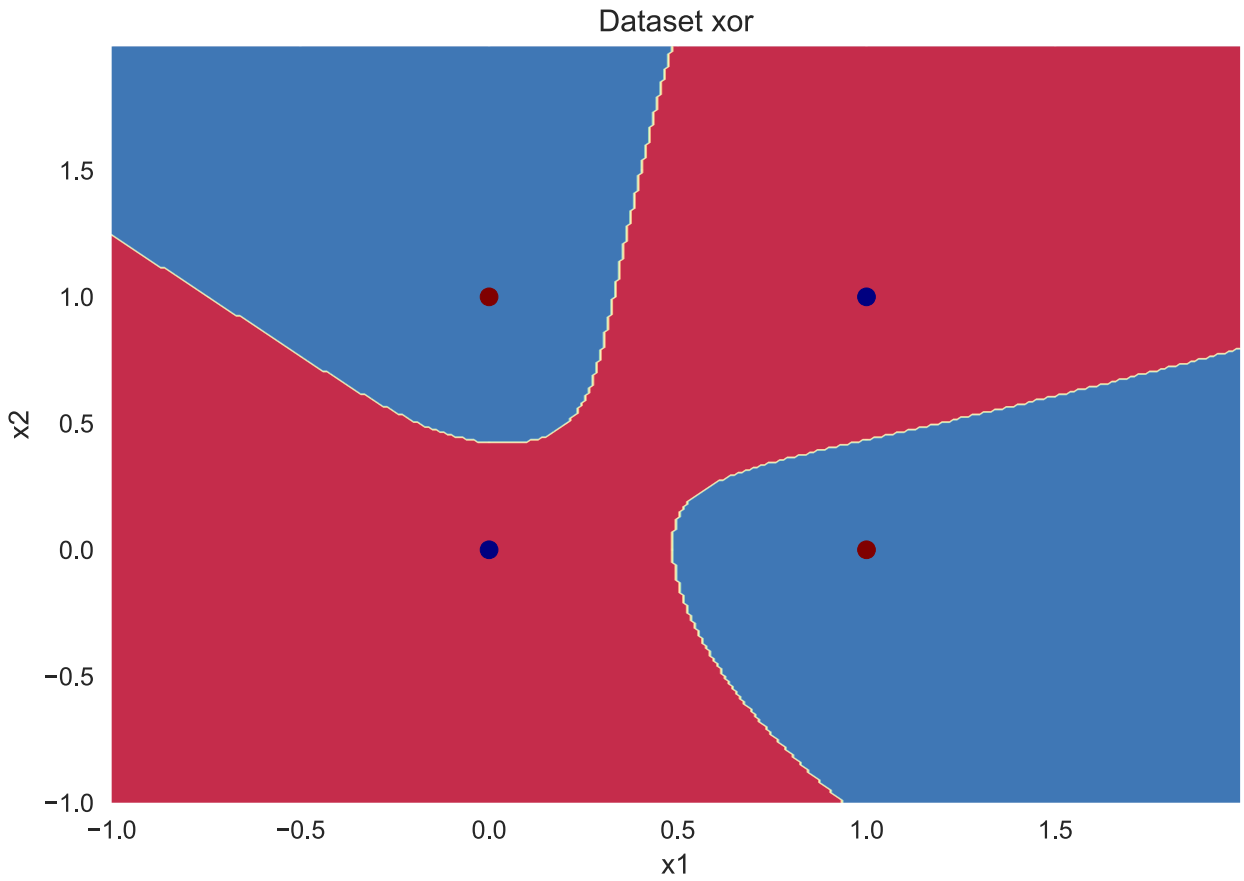
In [ ]:

```
def load_dataset(dataset):
    if dataset=='moons':
        X,Y = make_moons(n_samples=500,noise=0.2,random_state=1) #Perceptron
    elif dataset=='circles':
        X,Y = make_circles(n_samples=500, shuffle=True, noise=0.2, random_state=1, fact
    elif dataset=='classification':
        X,Y = make_classification(n_samples=500,n_classes=2,n_features=2,n_informative=
    else:
        #Create XOR Dataset
        X = np.array([[0,0],
                      [0,1],
                      [1,0],
                      [1,1]])
        Y = np.array([0,1,1,0])

    return X,Y
```

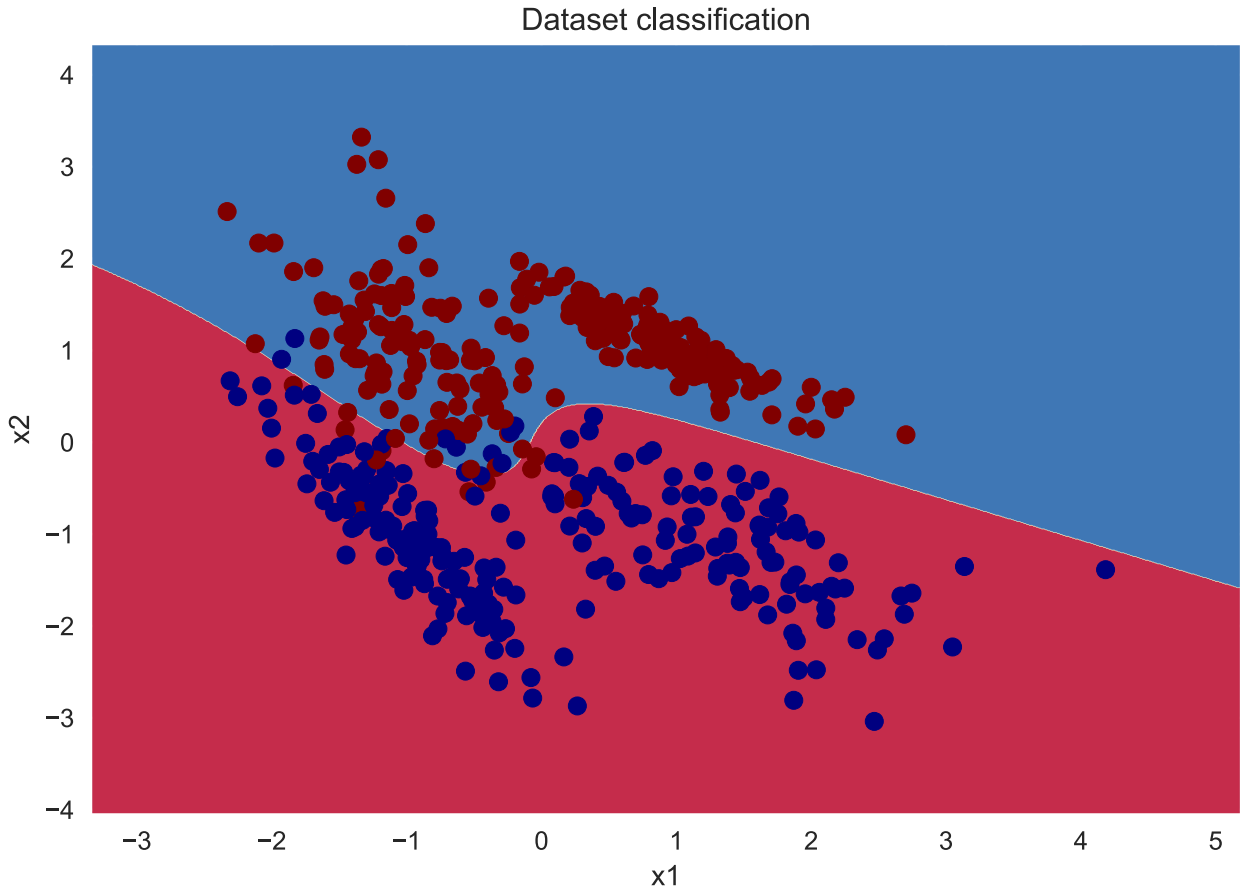
In [ ]:

```
datasets = ["xor","classification","moons","circles"]

for d in datasets:
    model = NeuralNetwork(input_size=2,layers=[4,3],output_size=2)
    X,Y  = load_dataset(d)
    train(X,Y,model,1000,0.001,logs=False)
    outputs = model.predict(X)

    training_accuracy = np.sum(outputs==Y)/Y.shape[0]
    print("Training Acc %.4f"%training_accuracy)

    plt.title("Dataset "+d)
    plot_decision_boundary(lambda x:model.predict(x),X,Y)
    plt.show()
```

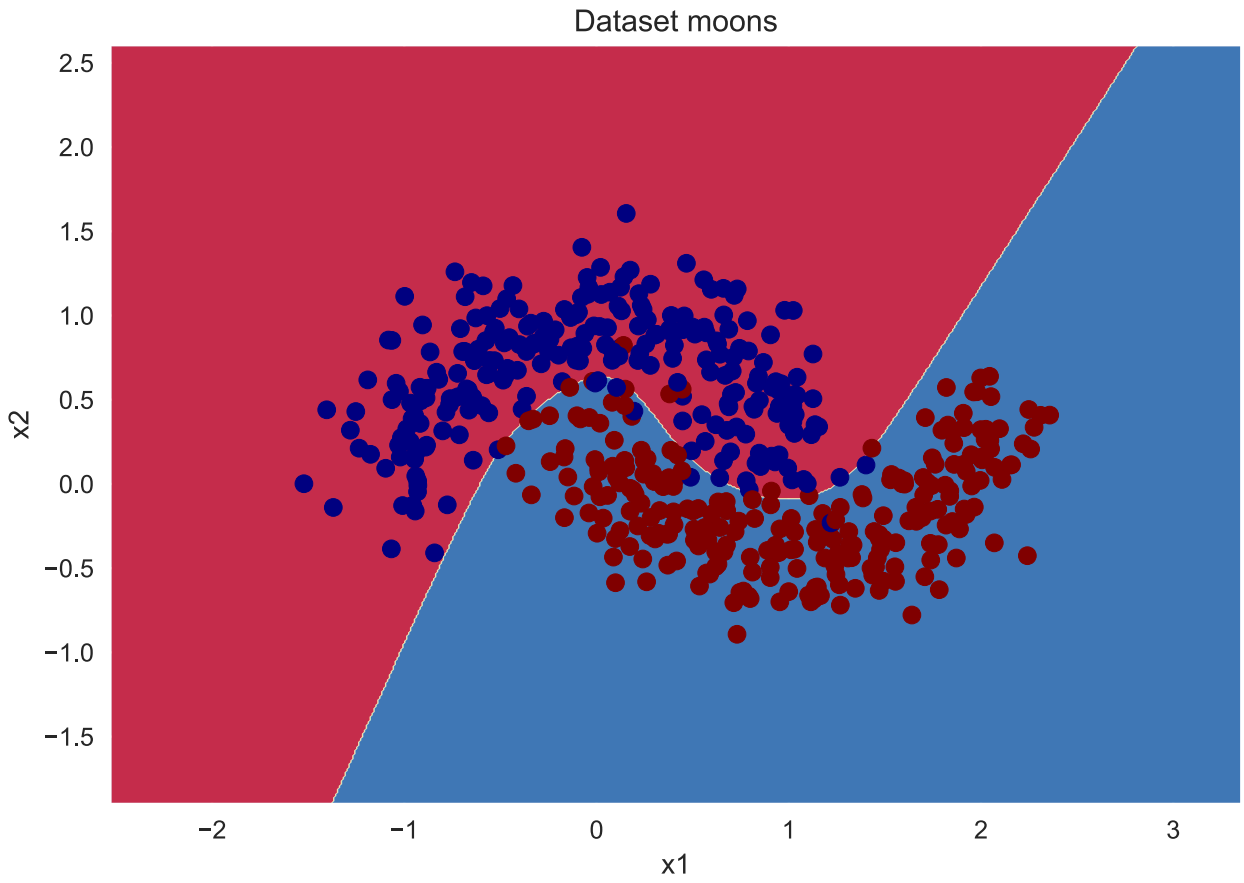
```
Training Acc 1.0000
```



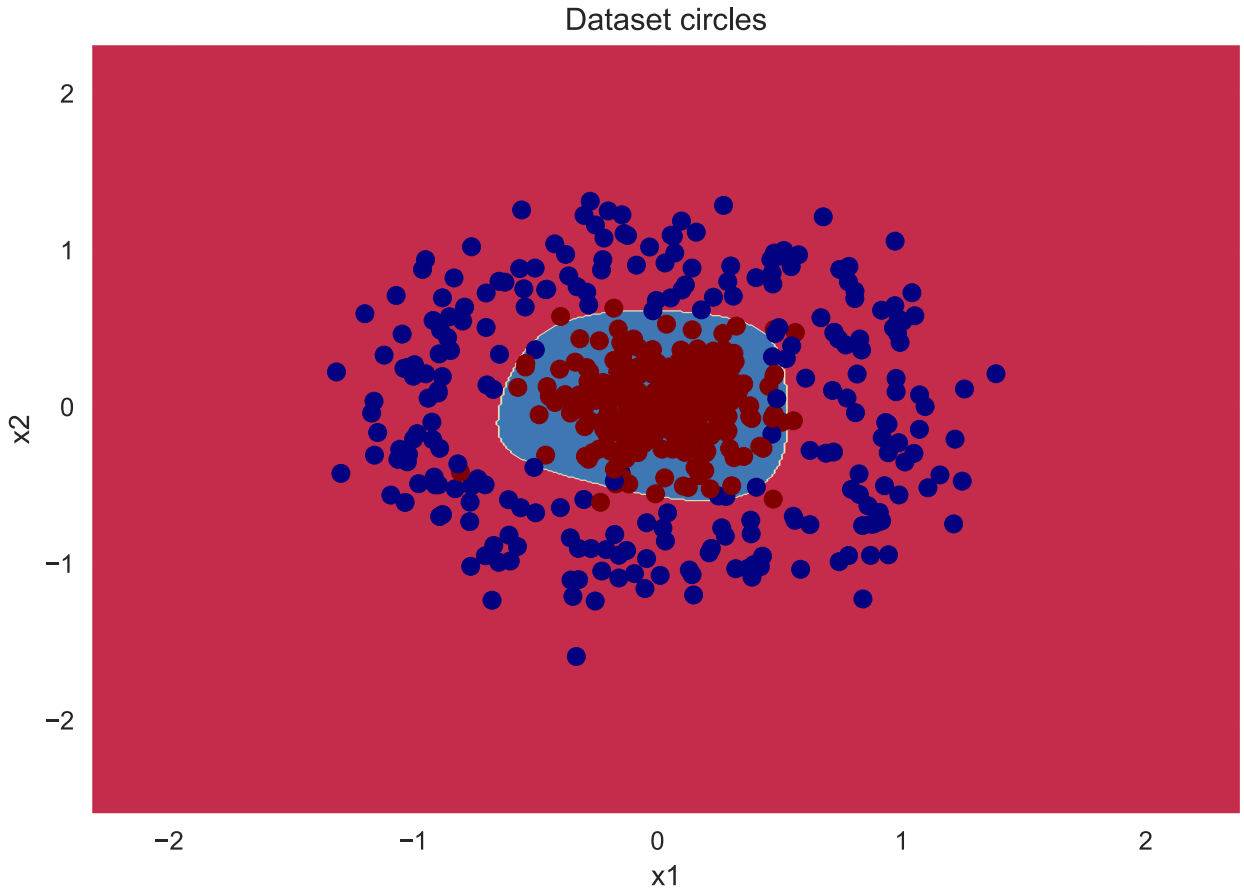

```
Training Acc 0.9600
```




```
Training Acc 0.9740
```




```
Training Acc 0.9640
```



In [ ]: