backward_bashtovyi

December 1, 2021

[1]:
```
# Import Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

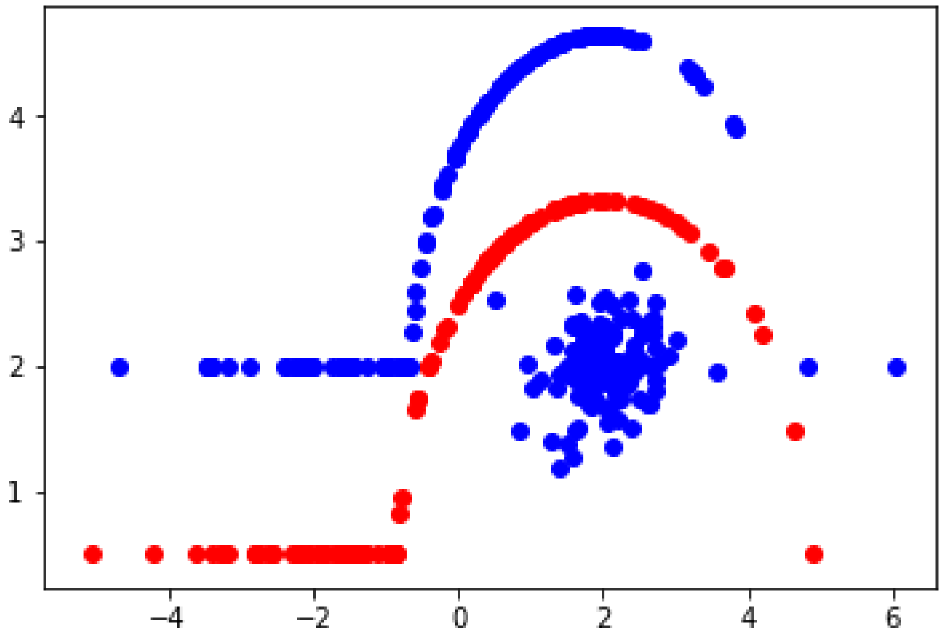
Lets import and visualize our data

[2]:
```
header = ['x1', 'x2', 'y']
dataset = pd.read_csv(r"/Users/andrei/Desktop/KNUProjects/Masters/Neironki/
 ↪master_labs/data/data3.csv", sep=' '
                        , names=header)
X, y = dataset.iloc[:,:2], dataset['y']
print(X.shape)
print(y.shape)
```

```
(360, 2)
(360,)
```

[3]:
```
plt.scatter(dataset['x1'][dataset['y'] == 1], dataset['x2'][dataset['y'] == 1],␣
 ↪c='blue')
plt.scatter(dataset['x1'][dataset['y'] == 0], dataset['x2'][dataset['y'] == 0],␣
 ↪c='red')
```

[3]:
```
<matplotlib.collections.PathCollection at 0x7fed8be255f8>
```



Lets transfor our lables into dummy variables

[4]:
```
# Get dummy variable
y = pd.get_dummies(y).values

y[:2]
```

[4]:
```
array([[0, 1],
       [0, 1]], dtype=uint8)
```

Lets define constants and initialize parametrs for the future network

[22]:
```
# Initialize variables
learning_rate = 0.01
iterations = 50000
N = y.size

# number of input features
input_size = 2

# number of hidden layers neurons
hidden_size = 500

# number of neurons at the output layer
output_size = 2
```

```
results = pd.DataFrame(columns=["mse", "accuracy"])
```

[23]:
```
# Initialize weights
np.random.seed(10)

# initializing weight for the hidden layer
W1 = np.random.normal(scale=0.5, size=(input_size, hidden_size))

# initializing weight for the output layer
W2 = np.random.normal(scale=0.5, size=(hidden_size , output_size))
```

Lets define hellper functions and build forward propagation, metrics calculation, backward propagation and parametr updates

[24]:
```
def sigmoid(x):
    return 1 / (1 + np.exp(-x))

def mean_squared_error(y_pred, y_true):
    return ((y_pred - y_true)**2).sum() / (2*y_pred.size)

def accuracy(y_pred, y_true):
    acc = y_pred.argmax(axis=1) == y_true.argmax(axis=1)
    return acc.mean()
```

[25]:
```
for itr in range(iterations):

    # feedforward propagation
    # on hidden layer
    Z1 = np.dot(X, W1)
    A1 = sigmoid(Z1)

    # on output layer
    Z2 = np.dot(A1, W2)
    A2 = sigmoid(Z2)


    # Calculating error
    mse = mean_squared_error(A2, y)
    acc = accuracy(A2, y)
    results=results.append({"mse":mse, "accuracy":acc},ignore_index=True )

    # backpropagation
    E1 = A2 - y
    dW1 = E1 * A2 * (1 - A2)

    E2 = np.dot(dW1, W2.T)
    dW2 = E2 * A1 * (1 - A1)
```

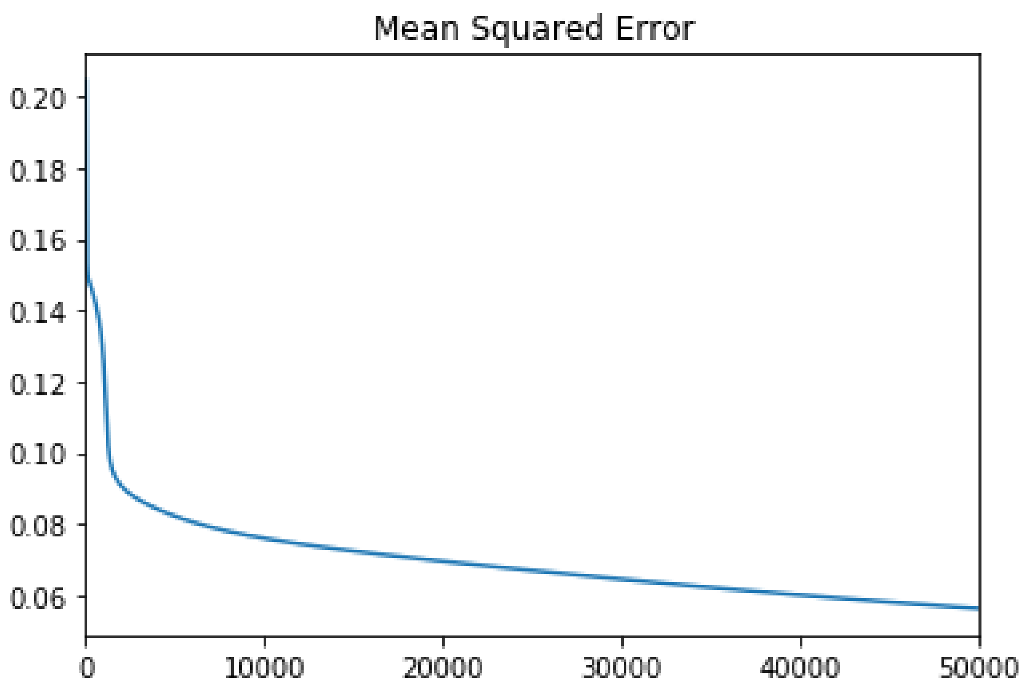
```
    # weight updates
    W2_update = np.dot(A1.T, dW1) / N
    W1_update = np.dot(X.T, dW2) / N

    W2 = W2 - learning_rate * W2_update
    W1 = W1 - learning_rate * W1_update
```

Lets visualize our optimization process

[26]:
```
results.mse.plot(title="Mean Squared Error")
```

[26]: <matplotlib.axes._subplots.AxesSubplot at 0x7fed8c03b0f0>



Lets use our network to predict labels

[27]:
```
# feedforward
Z1 = np.dot(X, W1)
A1 = sigmoid(Z1)

Z2 = np.dot(A1, W2)
A2 = sigmoid(Z2)

acc = accuracy(A2, y)
```

```
print("Accuracy: {}".format(acc))
```

```
Accuracy: 0.8638888888888889
```

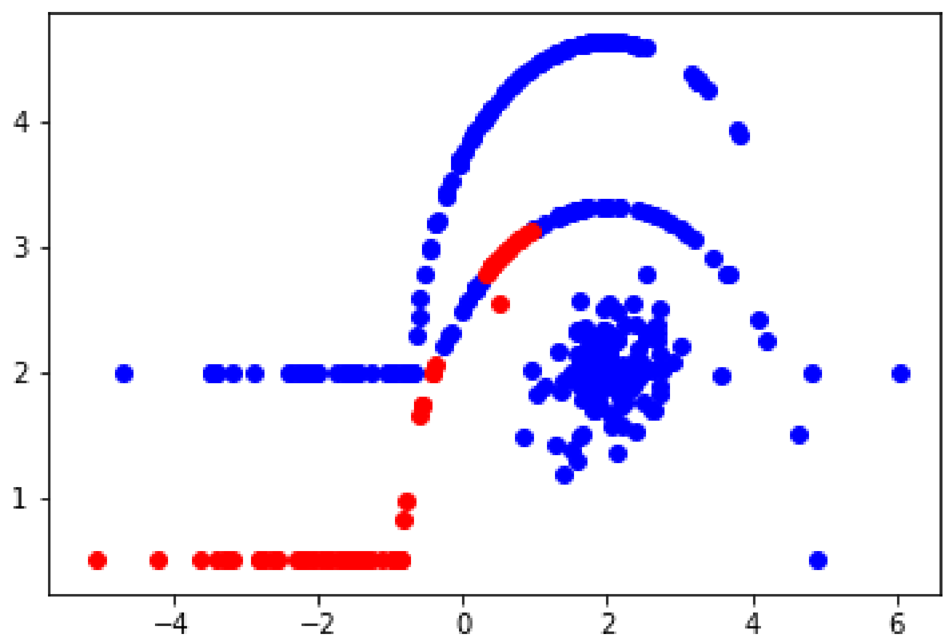
Lets visualize network prediction

```
[28]: z = []
      for i in range(A2.shape[0]):
          if A2[i][0] > A2[i][1]:
              z.append(0)
          else:
              z.append(1)

      dataset['z'] = z
```

```
[29]: plt.scatter(dataset['x1'][dataset['z'] == 1], dataset['x2'][dataset['z'] == 1],␣
       ↪c='blue')
      plt.scatter(dataset['x1'][dataset['z'] == 0], dataset['x2'][dataset['z'] == 0],␣
       ↪c='red')
```

```
[29]: <matplotlib.collections.PathCollection at 0x7fed71b019e8>
```



Conclusion:

Our simple neural network with one hidden layer havent shown best results. A lot of the misclassifications in the “blue” label. To increase classification accuracy more hidden layers should be added.