```
import numpy as np
In [2]:
         import pandas as pd
         from math import exp
         from sklearn.metrics import confusion matrix
         from sklearn.metrics import cohen kappa score
         import numpy as np
         import csv
         import matplotlib.pyplot as plt
In [3]: | cd /Users/jithu/Documents/Notes
        /Users/jithu/Documents/Notes
        dataset = pd.read_csv('data.csv')
In [4]:
In [5]:
         # Backprop on the Vowel Dataset
         from random import seed
         from random import randrange
         from random import random
         from csv import reader
         from math import exp
         from sklearn.metrics import confusion matrix
         from sklearn.metrics import cohen_kappa_score
         import numpy as np
         import csv
         # Load a CSV file
         def loadCsv(filename):
                 trainSet = []
                 lines = csv.reader(open(filename, 'r'))
                 dataset = list(lines)
                 for i in range(len(dataset)):
                         for j in range(4):
                                  #print("DATA {}".format(dataset[i]))
                                  dataset[i][j] = float(dataset[i][j])
                         trainSet.append(dataset[i])
                 return trainSet
         def minmax(dataset):
                 minmax = list()
                 stats = [[min(column), max(column)] for column in zip(*dataset)]
                 return stats
         # Rescale dataset columns to the range 0-1
         def normalize(dataset, minmax):
                 for row in dataset:
                         for i in range(len(row)-1):
                                  row[i] = (row[i] - minmax[i][0]) / (minmax[i][1] -
         # Convert string column to float
         def column to float(dataset, column):
                 for row in dataset:
                         trv:
                                  row[column] = float(row[column])
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except ValueError:
                        print("Error with row", column, ":", row[column])
# Convert string column to integer
def column_to_int(dataset, column):
        class_values = [row[column] for row in dataset]
        unique = set(class values)
        lookup = dict()
        for i, value in enumerate(unique):
                lookup[value] = i
        for row in dataset:
                row[column] = lookup[row[column]]
        return lookup
# Find the min and max values for each column
# Split a dataset into k folds
def cross validation split(dataset, n folds):
        dataset split = list()
        dataset copy = list(dataset)
        fold size = int(len(dataset) / n folds)
        for i in range(n_folds):
                fold = list()
                while len(fold) < fold size:</pre>
                        index = randrange(len(dataset_copy))
                        fold.append(dataset_copy.pop(index))
                dataset_split.append(fold)
        return dataset split
# Calculate accuracy percentage
def accuracy met(actual, predicted):
        correct = 0
        for i in range(len(actual)):
                if actual[i] == predicted[i]:
                        correct += 1
        return correct / float(len(actual)) * 100.0
# Evaluate an algorithm usimport pandas as pd
def run algorithm(dataset, algorithm, n folds, *args):
        folds = cross validation split(dataset, n folds)
        #for fold in folds:
                #print("Fold {} \n \n".format(fold))
        scores = list()
        for fold in folds:
                #print("Test Fold {} \n \n".format(fold))
                train_set = list(folds)
                train_set.remove(fold)
                train_set = sum(train_set, [])
                test set = list()
                for row in fold:
                        row_copy = list(row)
                        test set.append(row copy)
                        row_copy[-1] = None
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predicted = algorithm(train_set, test_set, *args)
                actual = [row[-1] for row in fold]
                accuracy = accuracy met(actual, predicted)
                cm = confusion matrix(actual, predicted)
                print('\n'.join([''.join(['{:4}'.format(item) for item in :
                #confusionmatrix = np.matrix(cm)
                FP = cm.sum(axis=0) - np.diag(cm)
                FN = cm.sum(axis=1) - np.diag(cm)
                TP = np.diag(cm)
                TN = cm.sum() - (FP + FN + TP)
                print('False Positives\n {}'.format(FP))
                print('False Negetives\n {}'.format(FN))
                print('True Positives\n {}'.format(TP))
                print('True Negetives\n {}'.format(TN))
                TPR = TP/(TP+FN)
                print('Sensitivity \n {}'.format(TPR))
                TNR = TN/(TN+FP)
                print('Specificity \n {}'.format(TNR))
                Precision = TP/(TP+FP)
                print('Precision \n {}'.format(Precision))
                Recall = TP/(TP+FN)
                print('Recall \n {}'.format(Recall))
                Acc = (TP+TN)/(TP+TN+FP+FN)
                print('Accuracy \n{}'.format(Acc))
                Fscore = 2*(Precision*Recall)/(Precision+Recall)
                print('FScore \n{}'.format(Fscore))
                k=cohen_kappa_score(actual, predicted)
                print('Çohen Kappa \n{}'.format(k))
                scores.append(accuracy)
        return scores
# Calculate neuron activation for an input
def activate(weights, inputs):
        activation = weights[-1]
        for i in range(len(weights)-1):
                activation += weights[i] * inputs[i]
        return activation
# Transfer neuron activation
def transfer(activation):
        return 1.0 / (1.0 + exp(-activation))
# Forward propagate input to a network output
def forward propagate(network, row):
        inputs = row
        for layer in network:
                new inputs = []
                for neuron in layer:
                        activation = activate(neuron['weights'], inputs)
                        neuron['output'] = transfer(activation)
                        new inputs.append(neuron['output'])
                inputs = new inputs
        return inputs
# Calculate the derivative of an neuron output
def transfer_derivative(output):
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return output * (1.0 - output)
# Backpropagate error and store in neurons
def backward_propagate_error(network, expected):
        for i in reversed(range(len(network))):
                layer = network[i]
                errors = list()
                if i != len(network)-1:
                        for j in range(len(layer)):
                                error = 0.0
                                for neuron in network[i + 1]:
                                        error += (neuron['weights'][j] * ne
                                errors.append(error)
                else:
                        for j in range(len(layer)):
                                neuron = layer[j]
                                errors.append(expected[j] - neuron['output
                for j in range(len(layer)):
                        neuron = layer[j]
                        neuron['delta'] = errors[j] * transfer derivative()
# Update network weights with error
def update weights(network, row, l_rate):
        for i in range(len(network)):
                inputs = row[:-1]
                if i != 0:
                        inputs = [neuron['output'] for neuron in network[i
                for neuron in network[i]:
                        for j in range(len(inputs)):
                                temp = 1 rate * neuron['delta'] * inputs[j
                                neuron['weights'][j] += temp
                                #print("neuron weight{} \n".format(neuron[
                                neuron['prev'][j] = temp
                        temp = 1 rate * neuron['delta'] + mu * neuron['pre'
                        neuron['weights'][-1] += temp
                        neuron['prev'][-1] = temp
# Train a network for a fixed number of epochs
def train_network(network, train, l_rate, n_epoch, n_outputs):
        for epoch in range(n epoch):
                for row in train:
                        outputs = forward propagate(network, row)
                        #print(network)
                        expected = [0 for i in range(n_outputs)]
                        expected[row[-1]] = 1
                        #print("expected row{}\n".format(expected))
                        backward propagate error(network, expected)
                        update_weights(network, row, l_rate)
# Initialize a network
def initialize_network(n_inputs, n_hidden, n_outputs):
        network = list()
        hidden_layer = [{'weights':[random() for i in range(n inputs + 1)]
        network.append(hidden layer)
        hidden_layer = [{'weights':[random() for i in range(n_inputs + 1)]
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network.append(hidden layer)
        output layer = [{'weights':[random() for i in range(n hidden + 1)]
        network.append(output layer)
        #print(network)
        return network
# Make a prediction with a network
def predict(network, row):
        outputs = forward propagate(network, row)
        return outputs.index(max(outputs))
# Backpropagation Algorithm With Stochastic Gradient Descent
def back propagation(train, test, 1 rate, n epoch, n hidden):
        n inputs = len(train[0]) - 1
        n outputs = len(set([row[-1] for row in train]))
        network = initialize_network(n_inputs, n_hidden, n_outputs)
        train_network(network, train, l_rate, n_epoch, n_outputs)
        #print("network {}\n".format(network))
        predictions = list()
        for row in test:
                prediction = predict(network, row)
                predictions.append(prediction)
        return(predictions)
# Test Backprop on Seeds dataset
seed(1)
# load and prepare data
filename = 'data.csv'
dataset = loadCsv(filename)
for i in range(len(dataset[0])-1):
        column to float(dataset, i)
# convert class column to integers
column to int(dataset, len(dataset[0])-1)
# normalize input variables
minmax = minmax(dataset)
normalize(dataset, minmax)
# evaluate algorithm
n folds = 5
1_rate = 0.1
mu = 0.001
n = 20
n hidden = 4
scores = run algorithm(dataset, back propagation, n folds, l rate, n epoch
print('Scores: %s' % scores)
print('Mean Accuracy: %.3f%%' % (sum(scores)/float(len(scores))))
   0
           0
               0
                  17
                       0
   0
      0
          0
               0
                  9
                       0
               0 27
   0
      0
          0
                       0
   0
      0
          0
               0
                 31
                       0
      0
   0
          0
                 47
   0
      Ω
          Ω
               0 43
False Positives
0
              0 127
      0
          0
                        0 1
False Negetives
[17 9 27 31 0 43]
True Positives
```

```
[ 0 0 0 0 47 0]
True Negetives
 [157 165 147 143 0 131]
Sensitivity
[0. 0. 0. 0. 1. 0.]
Specificity
[1. 1. 1. 1. 0. 1.]
Precision
ſ
        nan
               nan
                               nan
                                         nan 0.27011494
                                                                nan]
Recall
 [0. 0. 0. 0. 1. 0.]
Áccuracy
[0.90229885 0.94827586 0.84482759 0.82183908 0.27011494 0.75287356]
FScore
                              nan
                                         nan 0.42533937
        nan
                   nan
                                                               nan]
Çohen Kappa
0.0
<ipython-input-5-70463cd331ec>:116: RuntimeWarning: invalid value encounter
ed in true divide
 Precision = TP/(TP+FP)
          0
   0
      0
               0 17
                       0
   0
       0
           0
               0
                 21
   0
       0
           0
                  40
               0
   0
       0
           0
               0
                  28
                       0
   0
       0
           0
               0
                  39
                       0
   0
       0
           0
               0 29
False Positives
 [ 0 0 0 0 135
                        0]
False Negetives
[17 21 40 28 0 29]
True Positives
[ 0 0 0 0 39 0]
True Negetives
[157 153 134 146 0 145]
Sensitivity
[0. 0. 0. 0. 1. 0.]
Specificity
[1. 1. 1. 1. 0. 1.]
Precision
                               nan
                                        nan 0.22413793
                                                                nan]
ſ
        nan
                    nan
Recall
[0. 0. 0. 0. 1. 0.]
[0.90229885 0.87931034 0.77011494 0.83908046 0.22413793 0.83333333]
FScore
        nan
                   nan
                              nan
                                         nan 0.36619718
                                                               nan]
Çohen Kappa
0.0
   0
           0
               0
                 12
                       0
       0
   0
                  18
       0
           0
               0
                       0
   0
       0
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               0
                  45
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           0
               0
                  28
                       0
   0
       0
           0
               0
                  37
                       0
   0
       0
           0
               0
                  34
False Positives
 0 0 ]
          0 0 137
                        0]
False Negetives
[12 18 45 28 0 34]
True Positives
 [ 0 0 0 0 37 0]
```

```
True Negetives
 [162 156 129 146 0 140]
Sensitivity
 [0. 0. 0. 0. 1. 0.]
Specificity
[1. 1. 1. 1. 0. 1.]
Precision
        nan
                  nan
                               nan
                                         nan 0.21264368
                                                                 nan]
[
Recall
[0. 0. 0. 0. 1. 0.]
Áccuracy
[0.93103448 0.89655172 0.74137931 0.83908046 0.21264368 0.8045977 ]
       nan
                 nan
                           nan
                                     nan 0.3507109
                                                          nan]
Çohen Kappa
0.0
   0
                  10
               0
   0
       0
           0
               0
                  22
                       0
   0
       0
           0
               0
                  31
                       0
   0
       0
           0
               0
                  35
   0
       0
           0
               0
                  40
                       0
   0
               0 36
                       0
       0
           0
False Positives
0 0
          0
              0 134
                        0 1
False Negetives
 [10 22 31 35 0 36]
True Positives
[ 0 0 0 0 40 0]
True Negetives
 [164 152 143 139 0 138]
Sensitivity
 [0. 0. 0. 0. 1. 0.]
Specificity
[1. 1. 1. 1. 0. 1.]
Precision
                                         nan 0.22988506
        nan
                               nan
                  nan
                                                                 nan]
[
Recall
[0. 0. 0. 0. 1. 0.]
Áccuracy
[0.94252874 0.87356322 0.82183908 0.79885057 0.22988506 0.79310345]
FScore
                              nan
                                         nan 0.37383178
        nan
                   nan
                                                                nan]
Çohen Kappa
0.0
   0
           0
               0
                  16
                       0
       0
           0
               0
                  19
   0
                       0
   0
           0
               0
                  29
       0
                       0
   0
       0
           0
               0
                  29
                       0
   0
       0
               0
                  43
   0
       0
           0
               0
                 38
False Positives
               0 131
[ 0
      0
          0
                        0]
False Negetives
 [16 19 29 29 0 38]
True Positives
[ 0 0 0 0 43 0]
True Negetives
 [158 155 145 145 0 136]
Sensitivity
 [0. 0. 0. 0. 1. 0.]
Specificity
```

```
[1. 1. 1. 1. 0. 1.]
        Precision
                                       nan nan 0.24712644
                 nan
                            nan
                                                                         nanl
         [
        Recall
         [0. 0. 0. 0. 1. 0.]
        Áccuracy
        [0.90804598 0.8908046 0.83333333 0.83333333 0.24712644 0.7816092 ]
        FScore
                nan
                           nan
                                      nan
                                                  nan 0.39631336
                                                                        nan]
        Çohen Kappa
        0.0
        Scores: [27.011494252873565, 22.413793103448278, 21.26436781609195, 22.9885
        05747126435, 24.712643678160921
        Mean Accuracy: 23.678%
        #df = pd.DataFrame(dataset)
In [6]:
         #accuracy = history.history['accuracy']
In [7]:
         #val accuracy = history.history['val accuracy']
         #loss = history.history['loss']
         #val loss = history.history['val loss']
In [9]:
         W1 = np.random.normal(0.1, 0.2, size=(6,3))
         W2 = np.random.normal(0.1, 0.2, size=(3,1))
         epoch = 10
         learning rate = 0.001
         loss_sgd_tr = []
         loss sgd te = []
         epochs = []
         for i in range (epoch):
             loss = 0
             loss1 = 0
             for j in range (len(train)):
                 #forward pass:
                 forward = forward prop1(train[j],train[j],W1,W2)
                 loss += forward['loss']
                 #back pass:
                 w11 , w22 = back_prop1(train[j],W1,W2,forward)
                 #weight updates
                 W1 = W1 - (learning_rate * w11)
                 W2 = W2 - (learning rate * w22)
             for k in range(len(X test)):
                 forward = forward prop1(test[k],test[k],W1,W2)
                 loss1 += forward['loss']
             loss sgd tr.append(loss/len(train))
             loss sgd te.append(loss1/len(test))
             epochs.append(i)
```

	<pre>NameError <ipython-input-9-ce7298dc1969> in <module< th=""><th>•</th><th>all:</th><th>last)</th></module<></ipython-input-9-ce7298dc1969></pre>	•	all:	last)
	NameError: name 'train' is not defined			
In []:				
In []:				
In []:				