ASSGN 4 PART 1

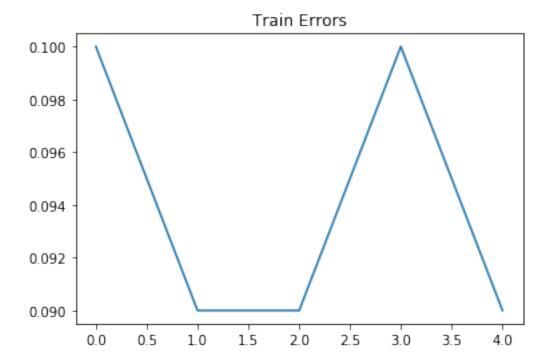
February 25, 2022

```
[1]: # importing modules
    import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    from scipy.io import loadmat
    from sklearn.tree import DecisionTreeClassifier
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.model_selection import cross_val_score
    from sklearn.model_selection import cross_validate
    from sklearn.metrics import accuracy_score
    from sklearn.model_selection import validation_curve
[2]: # loading the mat file
    XR = loadmat('annualrainfall.mat')
[3]: XR = XR["XR"]
[4]: XR.shape
[4]: (357, 118)
[5]: # conversion into dataframe for ease in visualisation
    df = pd.DataFrame(XR.T)
[6]: df.head()
[6]:
            0
                                2
                                                              5
       0.719022 0.799972 1.116379
                                     0.764488 0.923383
                                                         0.961330 0.558784
    1 2.572195 2.358573 3.817571
                                     2.544322 1.777028
                                                        1.908791 0.716344
    2 5.115582 4.459389
                           5.715812 5.017730
                                               3.644102
                                                        3.152490
                                                                  1.511983
    3 0.509786 0.649587
                           1.357004 0.584740 0.878721
                                                         0.927881
                                                                  0.002060
    4 0.600234 1.078375 1.584306 0.753628 1.811034 2.033962 0.332660
            7
                      8
                                9
                                              347
                                                         348
                                                                    349
    0 1.043538
                 2.035055
                           2.412407
                                     ... 13.020404
                                                   12.291794
                                                              12.565416
    1 3.693454 6.151360 4.426207 ... 11.486169
                                                  10.682952
                                                              10.680328
    2 5.075399 7.259941 4.552429
                                         9.685181
                                                    9.213934
                                                               9.213934
```

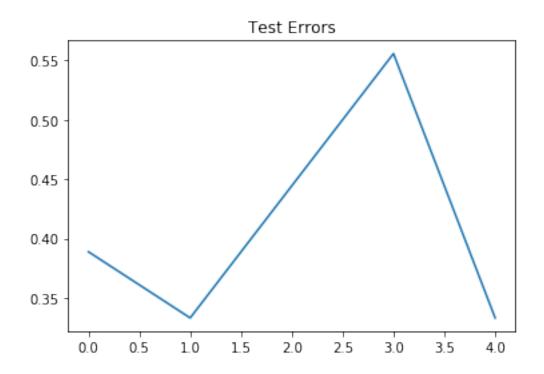
```
3 1.601084 2.431932 2.139452 ... 10.281640
                                                    9.984426
                                                               9.984426
    4 1.851805 3.144972 3.733844 ...
                                        11.919070 11.156557
                                                              11.156557
             350
                        351
                                   352
                                              353
                                                         354
                                                                    355
                                                                               356
    0 12.688719 12.852414 11.667012 12.174392 12.512038 10.399852 11.287784
    1 10.680328 11.080315 10.112830 10.391051
                                                  10.737137
                                                               9.187904
                                                                         9.791919
    2
       9.213934
                 9.445984 8.772028 8.985728
                                                    9.214482
                                                               8.054785
                                                                         8.523733
                                                    9.926839
    3
        9.977869 10.129921 9.474487
                                         9.726133
                                                               8.654893
                                                                          9.182062
    4 11.156557 11.543451 10.539118 10.844063 11.189535
                                                               9.524974 10.185022
    [5 rows x 357 columns]
[7]: # Question 1
    year_totals = np.sum(df,axis=1)
    print("Total over all locations per year\n")
    print(year_totals)
    Total over all locations per year
    0
           2419.465229
    1
           2512.018018
    2
           2667.357994
    3
           2327.246610
           2306.637001
    113
           2320.219852
    114
           2307.336725
    115
           2568.183404
    116
           2575.166233
    117
           2379.061657
    Length: 118, dtype: float64
[8]: # Question 1
    mean = np.mean(year_totals)
    stdev = np.std(year_totals)
    print("Mean :",mean)
    print("Standard Deviation: ",stdev)
    Mean: 2731.5638988707724
    Standard Deviation: 266.89890593445193
[9]: # Question 2
    label = np.where(year_totals>mean+stdev,1,0)
    label = np.where(year_totals<mean-stdev,-1,label)</pre>
    label = label.reshape((-1,1))
```

```
[10]: # labels are added to the dataframe
     df['label'] = label
[11]: df.head()
Γ11]:
                                   2
                                                      4
        0.719022 0.799972
                           1.116379
                                      0.764488 0.923383
                                                         0.961330
                                                                   0.558784
     1 2.572195
                  2.358573 3.817571
                                      2.544322 1.777028 1.908791
                                                                   0.716344
     2 5.115582 4.459389 5.715812 5.017730 3.644102 3.152490 1.511983
     3 0.509786 0.649587 1.357004 0.584740 0.878721
                                                        0.927881 0.002060
     4 0.600234 1.078375 1.584306 0.753628 1.811034 2.033962 0.332660
               7
                         8
                                   9
                                               348
                                                         349
                                                                    350
     0 1.043538
                  2.035055
                            2.412407 ... 12.291794
                                                    12.565416
                                                              12.688719
     1 3.693454 6.151360 4.426207
                                      ... 10.682952
                                                   10.680328
                                                              10.680328
     2 5.075399 7.259941 4.552429
                                         9.213934
                                                    9.213934
                                                               9.213934
     3 1.601084 2.431932 2.139452 ...
                                          9.984426
                                                    9.984426
                                                               9.977869
     4 1.851805 3.144972 3.733844 ... 11.156557
                                                   11.156557
                                                              11.156557
              351
                         352
                                    353
                                               354
                                                         355
                                                                    356
                                                                         label
     0 12.852414 11.667012 12.174392 12.512038
                                                    10.399852
                                                              11.287784
                                                                            -1
     1 11.080315 10.112830 10.391051 10.737137
                                                    9.187904
                                                               9.791919
                                                                             0
     2 9.445984
                  8.772028
                              8.985728
                                         9.214482
                                                    8.054785
                                                               8.523733
                                                                             0
     3 10.129921
                    9.474487
                               9.726133
                                          9.926839
                                                    8.654893
                                                               9.182062
                                                                            -1
     4 11.543451 10.539118 10.844063 11.189535
                                                                            -1
                                                    9.524974 10.185022
     [5 rows x 358 columns]
[12]: X = df.iloc[:,:-1]
     Y = df.iloc[:,-1]
[13]: # preparing the train and test sets using 100 years for train only
     X_train = X.iloc[0:100,:]
     X_test = X.iloc[100:,:]
     Y_train = Y.iloc[0:100]
     Y_{test} = Y.iloc[100:]
     print("X_train shape: ",X_train.shape)
     print("X_test shape: ",X_test.shape)
     X_train shape: (100, 357)
     X_test shape: (18, 357)
[14]: # Question 3
      # Training the decision tree with 5-fold cross validation
     clf = DecisionTreeClassifier(max_depth=10,random_state=0)
```

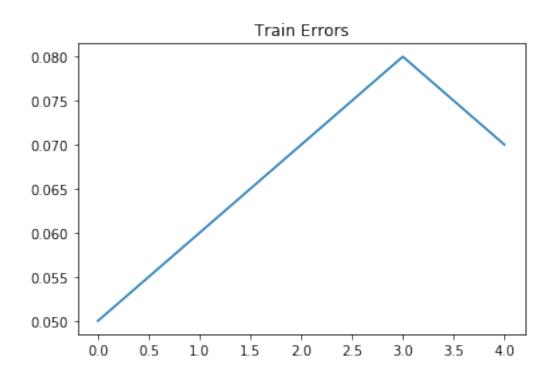
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[16]: plt.plot(train_error)
   plt.title("Train Errors")
   plt.show()
```

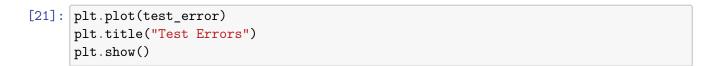


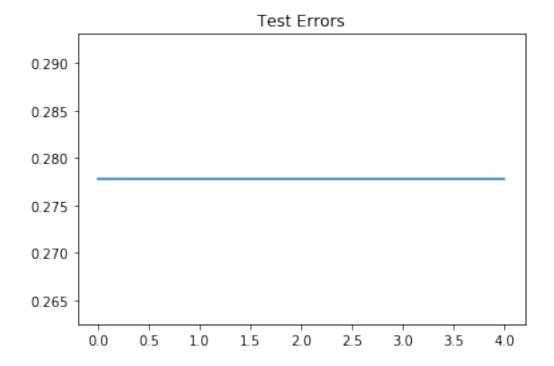
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[17]: plt.plot(test_error)
   plt.title("Test Errors")
   plt.show()
```



```
[18]: # Question 4
      # Training the random forest with 5-fold cross validation
      # Both train and test errors are seen improving
      rfclf = RandomForestClassifier(max_depth=10,random_state=0)
      scores = cross_validate(rfclf, X_train, Y_train, cv=5,return_estimator=True)
      rfclf = rfclf.fit(X_train, Y_train)
[19]: train_error = []
      test_error = []
      for i in range(5):
          train_outputs = scores["estimator"][i].predict(X_train)
          preds = scores["estimator"][i].predict(X_test)
          train_error.append(1-accuracy_score(y_true = Y_train,y_pred =__
       →train_outputs))
          test_error.append(1-accuracy_score(y_true = Y_test,y_pred = preds))
[20]: plt.plot(train_error)
      plt.title("Train Errors")
      plt.show()
```







```
[22]: # Question 5
      location_means = np.mean(df.iloc[:,:-1],axis=0)
      print("Mean Rainfall for locations\n")
      print(location_means)
      location_std = np.std(df.iloc[:,:-1],axis=0)
      print("\nStd-dev of Rainfall for locations\n")
      print(location_std)
     Mean Rainfall for locations
             2.879478
     0
     1
             2.798381
     2
             4.678337
     3
             3.253128
             2.866147
            18.762887
     352
     353
            19.357414
     354
            19.317927
     355
            18.627022
     356
            19.065612
     Length: 357, dtype: float64
     Std-dev of Rainfall for locations
     0
             2.035299
             2.003111
     1
     2
             2.328049
     3
             1.931908
     4
             1.703730
     352
             7.968767
     353
             8.606350
     354
             9.835775
     355
             9.662201
     356
            10.064099
     Length: 357, dtype: float64
[23]: # Question 5
      labels = np.empty((df.shape[0],df.shape[1]-1))
      for i in range(labels.shape[0]):
          for j in range(labels.shape[1]):
              if(df.iloc[i,j] > location_means[j]+location_std[j]):
                  labels[i,j]=1
              elif(df.iloc[i,j] < location_means[j]-location_std[j]):</pre>
                  labels[i,j]=-1
```

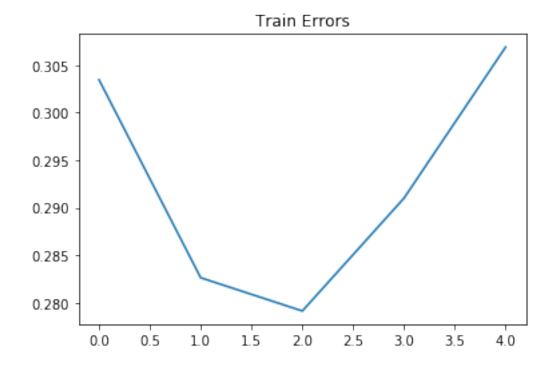
```
else:
                  labels[i,j]=0
[24]: labels.shape
[24]: (118, 357)
[25]: # Creating the new dataset
      new X = []
      new Y = []
      for i in range(labels.shape[0]):
          for j in range(labels.shape[1]):
              X_{row} = []
              for k in range(labels.shape[1]):
                  if(k!=j):
                      X_row.append(df.iloc[i,k])
              new_X.append(X_row)
              new_Y.append(labels[i,j])
[26]: new_X = []
      new_Y = []
      for i in range(labels.shape[0]):
          for j in range(labels.shape[1]):
              X row = []
              for k in range(labels.shape[1]):
                  if(k!=j):
                      X_row.append(df.iloc[i,k])
              new_X.append(X_row)
              new_Y.append(labels[i,j])
[27]: new_X = np.array(new_X)
      new_Y = np.array(new_Y)
[28]: new_X.shape
[28]: (42126, 356)
[29]: new_Y.shape
[29]: (42126,)
[30]: # preparing the train and test splits from new dataset
      # train set contains data rows derived from the first 100 years only
      new_X_train = new_X[:-6426,:]
      new_X_{test} = new_X[-6426:,:]
      new_Y_train = new_Y[:-6426]
```

 $new_Y_test = new_Y[-6426:]$

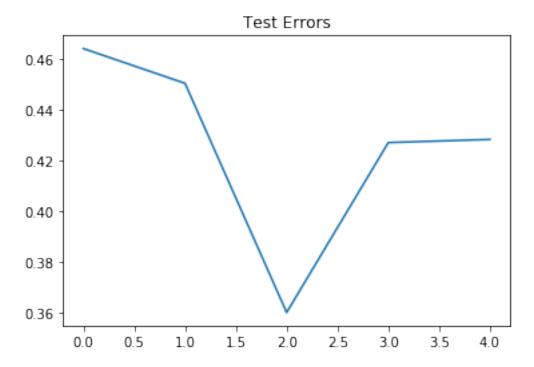
```
[32]: feat_importance = clf.tree_.compute_feature_importances() top_idx = np.argsort(feat_importance)[:-10:-1]
```

```
[33]: train_error = []
  test_error = []
  for i in range(5):
        train_outputs = scores["estimator"][i].predict(new_X_train)
        preds = scores["estimator"][i].predict(new_X_test)
        train_error.append(1-accuracy_score(y_true = new_Y_train,y_pred =_\undersetup train_outputs))
        test_error.append(1-accuracy_score(y_true = new_Y_test,y_pred = preds))
```

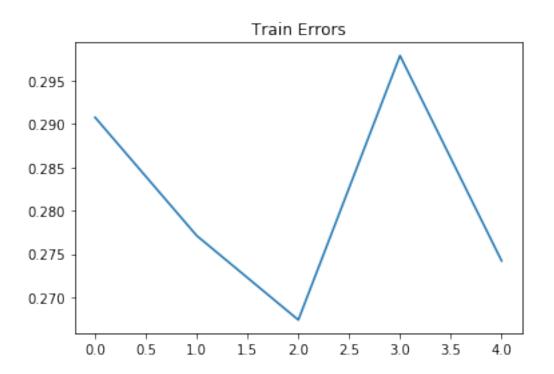
```
[34]: plt.plot(train_error)
  plt.title("Train Errors")
  plt.show()
```

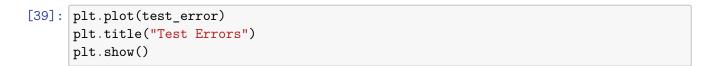


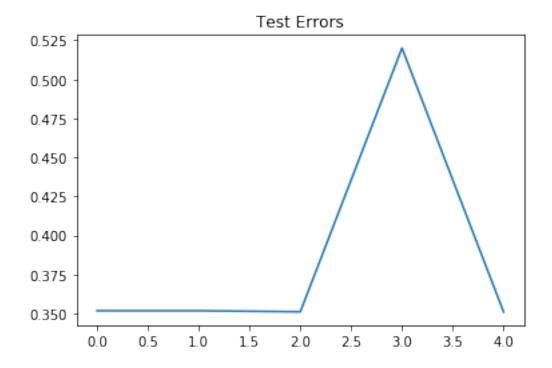
```
[35]: plt.plot(test_error)
  plt.title("Test Errors")
  plt.show()
```



```
[38]: plt.plot(train_error)
  plt.title("Train Errors")
  plt.show()
```







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[]:	
[]:	