# Question 4

#### February 11, 2022

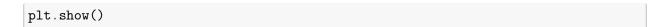
```
[18]: #importing necessary packaages
      import numpy as np
      import PIL
      from PIL import Image
      import os
      import ntpath
      import math
      import matplotlib.pyplot as plt
[19]: #Placing the input images into numpy array
      all_data = []
      happy_data = []
      sad_data = []
      N = 0
      directory = r"C:\Users\ujjaw\Desktop\MLSP Assignments\Ass1\4. Fischer
       →Faces\Data\emotion_classification\train"
      for filename in os.scandir(directory):
          if filename.is_file():
              filename2 = directory + "\\" + ntpath.basename(filename)
              img = Image.open(filename2).resize((100,100))
              np_img = np.array(img)
              flat_array = np.transpose(np.ravel(np_img))
              x = ntpath.basename(filename).split(".")
              if x[1] == "happy":
                  happy_data.append(list(flat_array))
              else:
                  sad_data.append(list(flat_array))
              N += 1
      happy_data = np.transpose(np.array(happy_data))
      sad_data = np.transpose(np.array(sad_data))
      all_data = np.concatenate((happy_data,sad_data),axis = 1)
      # print(all_data.shape)
      # print(happy_data.shape)
      # print(sad_data.shape)
```

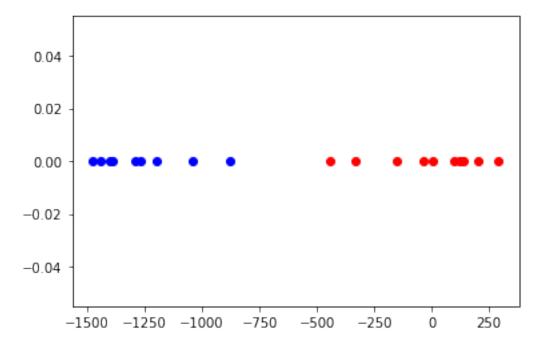
### 1 PCA Train Data

```
[20]: #Finding the mean of train data
      mean_array = all_data.mean(axis=1)
      mean_array = np.reshape(mean_array,(10000,1))
      # print(mean_array.shape)
[21]: # Without High Dimensional PCA
      \# Sx = (np.cov(np.transpose(all data)))
      #With High Dimesional PCA
      X = all_data - mean_array
      Sx = np.matmul(np.transpose(X),X)
      Sx = np.multiply(Sx, 1/N)
      # print(Sx.shape)
[22]: #Finding the eigen values and eigen vector of Sx
      e_val, e_vec = np.linalg.eig(Sx)
      #Sorting Eigen Values and Corresponding Eigen Vectors
      idx = e_val.argsort()[::-1]
      e_val = e_val[idx]
      e_vec = e_vec[:,idx]
      # print(e_vec.shape)
      # print(e val)
[23]: #Converting Vi to Ui for the first k eigen vector
      k = 16
      V = e_vec[:,:k]
                           #Taking first k EVector
      V = np.transpose(V)
      U = []
      for i in range(k):
          temp = np.matmul(all_data, V[i])
          U.append(np.multiply(temp,1/math.sqrt(e_val[i]*20)))
      U = np.transpose(np.array(U))
      # print(U.shape)
[24]: #Reducing the dimensions
      reduced_all_data = np.matmul(np.transpose(U), all_data)
      # print(reduced_all_data.shape)
      reduced_happy_data = np.matmul(np.transpose(U), happy_data)
      # print(reduced_happy_data.shape)
      reduced_sad_data = np.matmul(np.transpose(U), sad_data)
      # print(reduced_sad_data.shape)
```

### 2 LDA on Train Data

```
[25]: #Finding mean of different data classes
      mean_sad = reduced_sad_data.mean(axis=1)
      mean_happy = reduced_happy_data.mean(axis=1)
[26]: #Finding mean_diff and Sb
      mean_diff = mean_sad-mean_happy
      Sb = np.matmul(mean_diff.reshape(k,1),mean_diff.reshape(1,k))
[27]: #Calculating Sw
      mean_happy = np.reshape(mean_happy,(k,1))
      mean_sad = np.reshape(mean_sad,(k,1))
      r1,c1 = reduced happy data.shape
      r2,c2 = reduced_sad_data.shape
      Sw_term1 = np.matmul((reduced_happy_data - mean_happy), np.
       →transpose(reduced_happy_data - mean_happy))
      Sw_term2 = np.matmul((reduced_sad_data - mean_sad), np.
       stranspose(reduced_sad_data - mean_sad))
      Sw = np.multiply(Sw term1, 1/c1) + np.multiply(Sw term2, 1/c2)
[28]: Sw_inverse = np.linalg.inv(Sw)
[29]: | lda_e_val, lda_e_vec = np.linalg.eig(np.matmul(Sw_inverse,Sb))
      # print(lda_e_val)
      #Sorting Eigen Values and Corresponding Eigen Vectors
      idx = lda_e_val.argsort()[::-1]
      lda e val = lda e val[idx]
      lda_e_vec = lda_e_vec[:,idx]
      required_e_vec = lda_e_vec[:,0].real
      required_e_vec = np.reshape(required_e_vec,(k,1))
      final_lda_projection_happy = np.matmul(np.transpose(required_e_vec),_u
       →reduced_happy_data)
      final_lda_projection_sad = np.matmul(np.transpose(required_e_vec),_
       →reduced_sad_data)
      # print(final_lda_projection_happy)
      # print(final_lda_projection_sad)
[30]: plt.scatter(final_lda_projection_happy ,np.zeros((c1,), dtype = int),color =__
      plt.scatter(final_lda_projection_sad ,np.zeros((c2,),dtype = int), color = 'r')
```





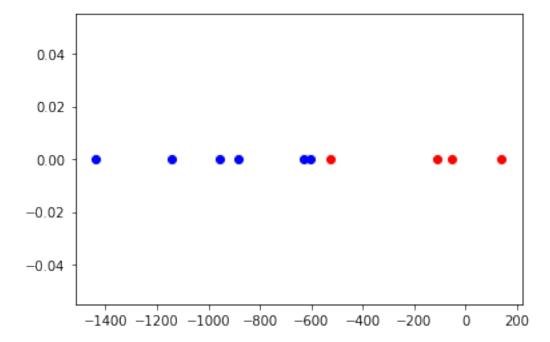
## 3 Applying Dimensionality Reduction and Testing Test Data

```
[31]: happy_data_test = []
      happy_data_test_filename = []
      sad_data_test = []
      sad_data_test_filename = []
      N_{\text{test}} = 0
      directory = r"C:\Users\ujjaw\Desktop\MLSP_Assignments\Ass1\4. Fischer
       \hookrightarrowFaces\Data\emotion_classification\test"
      for filename in os.scandir(directory):
          if filename.is_file():
              filename2 = directory + "\\" + ntpath.basename(filename)
              img = Image.open(filename2).resize((100,100))
              np_img = np.array(img)/1
              flat_array = np.transpose(np.ravel(np_img))
              x = ntpath.basename(filename).split(".")
              if x[1] == "happy":
                  happy_data_test.append(list(flat_array))
                  happy_data_test_filename.append(ntpath.basename(filename))
                  sad_data_test.append(list(flat_array))
                  sad_data_test_filename.append(ntpath.basename(filename))
```

```
N_test += 1
happy_data_test = np.transpose(np.array(happy_data_test))
sad_data_test = np.transpose(np.array(sad_data_test))
```

```
[32]: # print(happy_data_test.shape)
# print(sad_data_test.shape)
r1, c1 = happy_data_test.shape
r2, c2 = sad_data_test.shape
```

```
[33]: reduced_happy_data_test = np.matmul(np.transpose(U), happy_data_test)
# print(reduced_happy_data_test.shape)
reduced_sad_data_test = np.matmul(np.transpose(U), sad_data_test)
# print(reduced_sad_data_test.shape)
```



```
[36]: total = N_test
      correct = 0
      for i in range(c1):
          if (final_lda_projection_happy_test[0][i]<-550):</pre>
              print(happy_data_test_filename[i],"->","happy")
              correct += 1
          else:
              print(happy_data_test_filename[i],"->","sad")
      for i in range(c2):
          if (final lda projection sad test[0][i]<-550):
              print(sad_data_test_filename[i],"->","happy")
          else:
              print(sad_data_test_filename[i],"->","sad")
              correct += 1
      print ("Accuracy =", correct/total * 100,"%")
     subject03.happy.gif -> happy
     subject05.happy.gif -> happy
```

```
subject03.happy.gif -> happy
subject05.happy.gif -> happy
subject08.happy.gif -> happy
subject11.happy.gif -> happy
subject14.happy.gif -> happy
subject15.happy.gif -> happy
subject01.sad.gif -> sad
subject08.sad.gif -> sad
subject14.sad.gif -> sad
subject15.sad.gif -> sad
Accuracy = 100.0 %
```

I have tested the accuracy for different values of k. Accuracy of 100% is observed for k>=16. For  $k \le 15$ , the two classes are not completely separated after projecting in one dimensional LDA.