

▼ Import Libraries

First, we need to import matplotlib libraries as well as numpy library.

```
from matplotlib import pyplot as plt
from matplotlib.image import imread
import numpy as np
import os
```

▼ Data loading

```
TRAIN_IMG_FOLDER = (r"/content/sample_data/Training images")
TEST_IMG_FOLDER = (r"/content/sample_data/TEST")
```

```
train_set_files = os.listdir(TRAIN_IMG_FOLDER)
test_set_files = os.listdir(TEST_IMG_FOLDER)
```

```
width  = 128
height = 128
```

Check: All data from 'train' is included in 'test'?

```
train_id_file = set([f.split('_')[0] for f in train_set_files])
test_id_file = set([f.split('_')[0] for f in test_set_files])
print(train_id_file <= test_id_file)
```

```
True
```

```
print('Train Images:')
```

```
train_image_names = os.listdir(TRAIN_IMG_FOLDER)
training_tensor    = np.ndarray(shape=(len(train_image_names), height*width), dtype=np.floating)
```

```
for i in range(len(train_image_names)):
    img = plt.imread(os.path.join(TRAIN_IMG_FOLDER, train_image_names[i]))
    training_tensor[i,:] = np.array(img, dtype='float64').flatten()
    plt.subplot(5,5,1+i)
    plt.imshow(img, cmap='gray')
    plt.tick_params(labelleft='off', labelbottom='off', bottom='off', top='off', right='off')
plt.show()
```

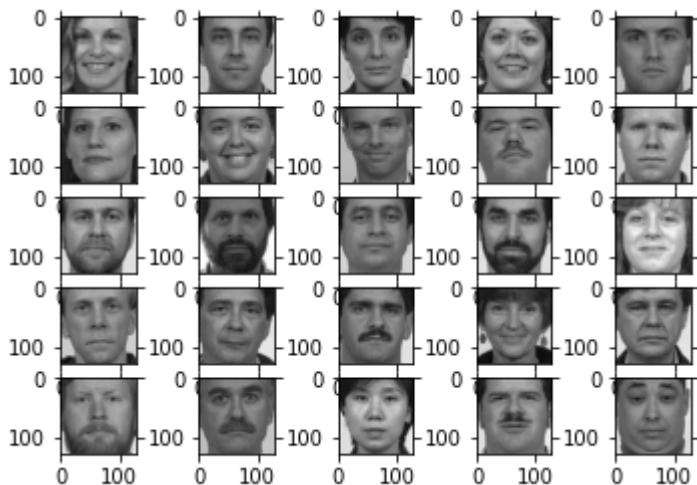
```

print('Test Images:')
test_image_names = os.listdir(TEST_IMG_FOLDER)#[i for i in dataset_dir if i not in train_i
testing_tensor = np.ndarray(shape=(len(test_image_names), height*width), dtype=np.float64)

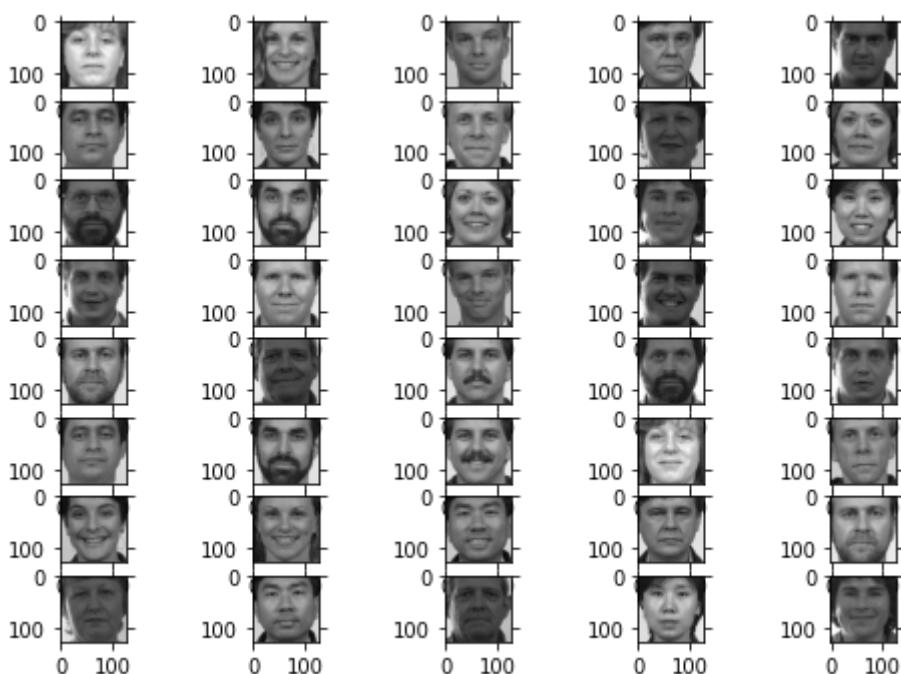
for i in range(len(test_image_names)):
    img = imread(os.path.join(TEST_IMG_FOLDER, test_image_names[i]))
    testing_tensor[i,:] = np.array(img, dtype='float64').flatten()
    plt.subplot(8,5,1+i)
    plt.imshow(img, cmap='gray')
    plt.subplots_adjust(right=1.2, top=1.2)
    plt.tick_params(labelleft='off', labelbottom='off', bottom='off', top='off', right='off')
plt.show()

```

Train Images:



Test Images:



▼ Calculate the mean face

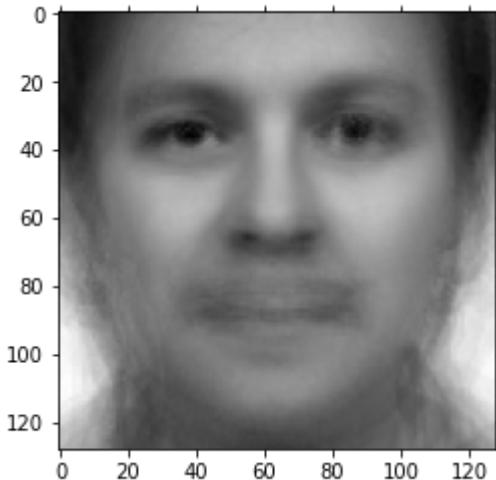
The mean is just the sum of all of the pictures divided by the number of pictures. As a result, we

```
mean_face = np.zeros((1,height*width))

for i in training_tensor:
    mean_face = np.add(mean_face,i)

mean_face = np.divide(mean_face,float(len(train_image_names))).flatten()

plt.imshow(mean_face.reshape(height, width), cmap='gray')
plt.tick_params(labelleft='off', labelbottom='off', bottom='off', top='off', right='off', left='off')
plt.show()
```



Calculation of difference between training vector and mean vector

To normalize the training set, we just simply need to subtract for each picture in the training set the mean that was calculated in the previous step.

The reason why this is necessary is because we want to create a system that is able to represent any face. Therefore, we calculated the elements that all faces have in common (the mean). If we extract this average from the pictures, the features that distinguish each picture from the rest of the set are visible.

```
normalised_training_tensor = np.ndarray(shape=(len(train_image_names), height*width))

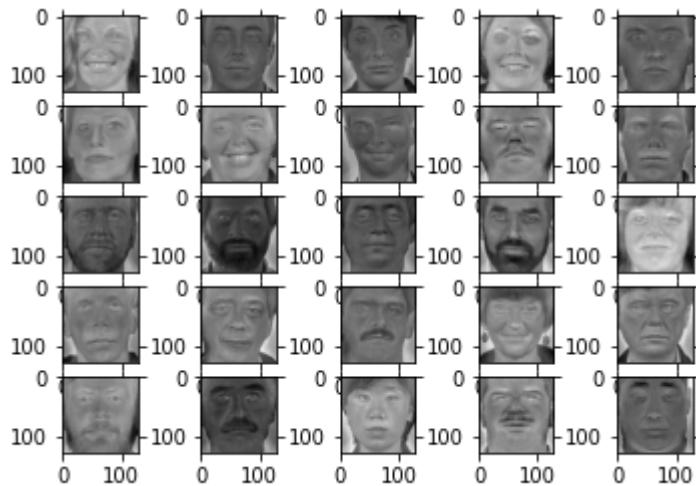
for i in range(len(train_image_names)):
    normalised_training_tensor[i] = np.subtract(training_tensor[i],mean_face)
```

Display normalised faces

```

for i in range(len(train_image_names)):
    img = normalised_training_tensor[i].reshape(height, width)
    plt.subplot(5, 5, 1+i)
    plt.imshow(img, cmap='gray')
    plt.tick_params(labelleft='off', labelbottom='off', bottom='off', top='off', right='off')
plt.show()

```



▼ Convenience Matrix

The covariance represents how two variables change together. After the previous step, we have a set of images that have different features, so now we want to see how these features for each individual picture change in relation to the rest of the pictures.

```

cov_matrix=np.cov(normalised_training_tensor)
cov_matrix = np.divide(cov_matrix, 25.0)
print('Covariance Matrix Shape:', cov_matrix.shape)
#print('Covariance matrix of X: \n%s' %cov_matrix)

Covariance Matrix Shape: (25, 25)

```

▼ Eigenvector of covariance

From the covariance we can extract the eigenvectors. Fortunately, there is a function that helps us in this step. There is plenty of information in the internet about eigenvectors but the general idea is that eigenvectors are the vectors of the covariance that describe the direction of the data.

```

#eigenvalues and eigenvectors
eigenvalues, eigenvectors, = np.linalg.eig(cov_matrix)
print('eigenvalues.shape: {} eigenvectors.shape: {}'.format(eigenvalues.shape, eigenvector

eigenvalues.shape: (25,) eigenvectors.shape: (25, 25)

```

```
eig_pairs = [(eigenvalues[index], eigenvectors[:,index]) for index in range(len(eigenvalues))]

# Sort the eigen pairs in descending order:
eig_pairs.sort(reverse=True)
eigenvalues_sort = [eig_pairs[index][0] for index in range(len(eigenvalues))]
eigenvectors_sort = [eig_pairs[index][1] for index in range(len(eigenvalues))]

sorted_ind = sorted(range(eigenvalues.shape[0]), key=lambda k: eigenvalues[k], reverse=True)

eigenvalues_sort = eigenvalues[sorted_ind]
eigenvectors_sort = eigenvectors[sorted_ind]
train_set_files_sort = np.array(train_set_files)[sorted_ind]
```

▼ Find cumulative variance of each principle component

```
var_comp_sum = np.cumsum(eigenvalues_sort)/sum(eigenvalues_sort)

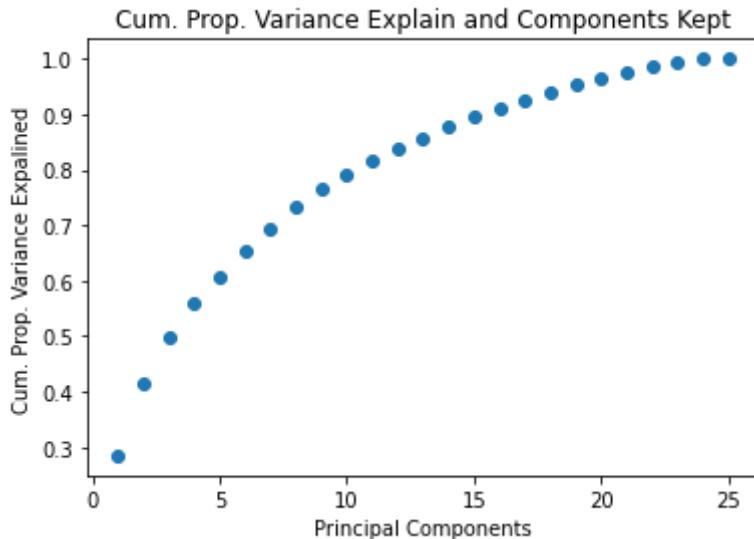
# Show cumulative proportion of variance with respect to components
print("Cumulative proportion of variance explained vector: \n%s" %var_comp_sum)

# x-axis for number of principal components kept
num_comp = range(1,len(eigenvalues_sort)+1)
plt.title('Cum. Prop. Variance Explain and Components Kept')
plt.xlabel('Principal Components')
plt.ylabel('Cum. Prop. Variance Explained')

plt.scatter(num_comp, var_comp_sum)
plt.show()
```

→ Cumulative proportion of variance explained vector:

```
[0.28481989 0.41576165 0.49714907 0.55777059 0.60785024 0.65427472
 0.69489721 0.73168527 0.7641529 0.7916646 0.81546473 0.83669985
 0.85752859 0.87642433 0.89418977 0.91069532 0.92659352 0.94017913
 0.95309028 0.96500642 0.97612862 0.98491526 0.99275274 1.
 1. ]
```



▼ Choose the necessary of principal components:

```
reduced_data = np.array(eigvectors_sort[:25]).transpose()  
reduced_data.shape
```

```
(25, 25)
```

```
print(training_tensor.transpose().shape, reduced_data.shape)
```

```
(16384, 25) (25, 25)
```

▼ Calculate eigenfaces

Each eigenvector is multiplied by the whole normalized training set matrix and as a result, we will have the same amount of eigenfaces as images in our training set.

```
proj_data = np.dot(training_tensor.transpose(), reduced_data)  
proj_data = proj_data.transpose()  
proj_data.shape
```

```
(25, 16384)
```

▼ Plot eigen faces

```
for i in range(proj_data.shape[0]):  
    img = proj_data[i].reshape(height, width)  
    plt.subplot(5,5,1+i)  
    plt.imshow(img, cmap='gray')  
    plt.tick_params(labelleft='off', labelbottom='off', bottom='off', top='off', right='off')  
plt.show()
```

▼ Finding weights for each training image

Each normalized face in the training set multiplies each eigenface. Consequently, there will be N set of weights with M elements (N = amount of pictures in the training set, M = number of eigenfaces).

```
w = np.array([np.dot(proj_data,i) for i in normalised_training_tensor])
print(w.shape)
```

```
(25, 25)
```

▼ Recognizing all test images

```
def recogniser(test_image_names, train_image_names, proj_data, w, t0=2e8, prn=False):

    count      = 0
    num_images = 0
    correct_pred = 0

    result = []
    wts = []

    #False match rate (FMR)
    FMR_count = 0

    #False non-match rate (FNMR)
    FNMR_count = 0

    test_image_names2 = sorted(test_image_names)

    for img in test_image_names2:
        #img = imread(os.path.join(TEST_IMG_FOLDER, test_image_names[i]))
        unknown_face = plt.imread(os.path.join(TEST_IMG_FOLDER, img))
        num_images += 1

        unknown_face_vector = np.array(unknown_face, dtype='float64').flatten()
        normalised_uface_vector = np.subtract(unknown_face_vector, mean_face)

        w_unknown = np.dot(proj_data, normalised_uface_vector)
        diff = w - w_unknown
        norms = np.linalg.norm(diff, axis=1)
        index = np.argmin(norms)

        wts.append([count, norms[index]])
```

```

if prn: print('Input:'+'.'.join(img.split('.')[2]), end='\t')
count+=1

match = img.split('_')[0] == train_image_names[index].split('_')[0]
if norms[index] < t0: # It's a face
    if match:
        if prn: print('Matched: ' + train_image_names[index], end = '\t')
        correct_pred += 1
        result.append(1)
    else:
        if prn: print('F/Matched:' +train_image_names[index], end = '\t')
        result.append(0)
        FMR_count += 1
else:
    if match:
        if prn: print('Unknown face!' +train_image_names[index], end = '\t')
        FNMR_count +=1

    else:
        pass
        correct_pred += 1

if prn: print(norms[index], end=' ')
if prn: print()

FMR = FMR_count/num_images
FNMR = FNMR_count/num_images

print('Correct predictions: {} / {} = {} \t\t'.format(correct_pred, num_images, correct_))
print('FMR: {} \t'.format(FMR), end=' ')
print('FNMR: {} \t'.format(FNMR))

return wts, result, correct_pred, num_images, FMR, FNMR

```

wts, result, correct_pred, num_images, FMR, FNMR =recogniser(test_image_names, train_image_

Input:00770_960530_fa.jpg	Matched:00770_960530_fa.jpg	0.0
Input:00770_960530_fa_a.jpg	F/Matched:00744_941201_fa.jpg	40443667.46730239
Input:00771_941205_fa.jpg	Matched:00771_941205_fa.jpg	0.0
Input:00771_941205_fb.jpg	Matched:00771_941205_fa.jpg	12411902.370116899
Input:00772_941201_fa.jpg	Matched:00772_941201_fa.jpg	0.0
Input:00772_941201_fb.jpg	F/Matched:00763_941201_fa.jpg	21167349.76704071
Input:00773_941201_fa.jpg	Matched:00773_941201_fa.jpg	0.0
Input:00773_941201_fb.jpg	Matched:00773_941201_fa.jpg	21385298.89308537
Input:00775_941205_fa.jpg	Matched:00775_941205_fa.jpg	0.0
Input:00775_941205_fb.jpg	Matched:00775_941205_fa.jpg	9590985.449027391
Input:00779_941205_fa.jpg	Matched:00779_941205_fa.jpg	0.0
Input:00779_941205_fb.jpg	Matched:00779_941205_fa.jpg	38922068.40712187

Input:00781_941205_fa.jpg	Matched:00781_941205_fa.jpg	0.0
Input:00781_941205_fb.jpg	F/Matched:00804_941205_fa.jpg	14277462.667984817
Input:00787_941205_fa.jpg	Matched:00787_941205_fa.jpg	0.0
Input:00787_941205_fb.jpg	F/Matched:00744_941201_fa.jpg	32827038.492167294
Input:00794_941205_fa.jpg	Matched:00794_941205_fa.jpg	0.0
Input:00794_941205_fb.jpg	F/Matched:00775_941205_fa.jpg	13696831.306772253
Input:00797_941205_fa.jpg	Matched:00797_941205_fa.jpg	0.0
Input:00797_941205_fb.jpg	Matched:00797_941205_fa.jpg	22738402.814766455
Input:00804_941205_fa.jpg	Matched:00804_941205_fa.jpg	0.0
Input:00804_941205_fb.jpg	Matched:00804_941205_fa.jpg	23695586.06549764
Input:00806_941205_fa.jpg	Matched:00806_941205_fa.jpg	0.0
Input:00806_941205_fb.jpg	Matched:00806_941205_fa.jpg	22783423.946304098
Input:00807_941205_fa.jpg	Matched:00807_941205_fa.jpg	0.0
Input:00807_941205_fb.jpg	Matched:00807_941205_fa.jpg	19176199.709934838
Input:00809_941205_fa.jpg	F/Matched:00761_941201_fa.jpg	13086008.769753514
Input:00809_941205_fb.jpg	F/Matched:00761_941201_fa.jpg	22463983.150025796
Input:00816_941205_fa.jpg	F/Matched:00766_941201_fa.jpg	16977907.094737023
Input:00816_941205_fb.jpg	F/Matched:00794_941205_fa.jpg	10808932.965668758
Input:00876_960530_fa.jpg	F/Matched:00744_941201_fa.jpg	55433907.515526965
Input:00876_960530_fb.jpg	F/Matched:00744_941201_fa.jpg	44354768.593997344
Input:00879_960530_fa.jpg	F/Matched:00797_941205_fa.jpg	44897093.13547314
Input:00879_960530_fb.jpg	F/Matched:00797_941205_fa.jpg	42228054.2415042
Input:00894_960530_fa.jpg	F/Matched:00781_941205_fa.jpg	40255117.3914715
Input:00894_960530_fb.jpg	F/Matched:00781_941205_fa.jpg	37625178.90044493
Input:00900_960530_fa.jpg	F/Matched:00745_941201_fa.jpg	55566607.455226995
Input:00900_960530_fb.jpg	F/Matched:00745_941201_fa.jpg	50361147.60444705
Input:00903_960530_fa.jpg	F/Matched:00745_941201_fa.jpg	91323857.85102595
Input:00903_960530_fb.jpg	F/Matched:00745_941201_fa.jpg	54705102.14316333
Correct predictions: 21/40 = 0.525	FMR: 0.475	FNMR: 0.0

▼ Visualisation result of prediction

with high error threshold: t0 = 2e8

```

def rg(r):
    if r: return 'g'
    else: return 'r'
cl = [rg(r) for r in result]

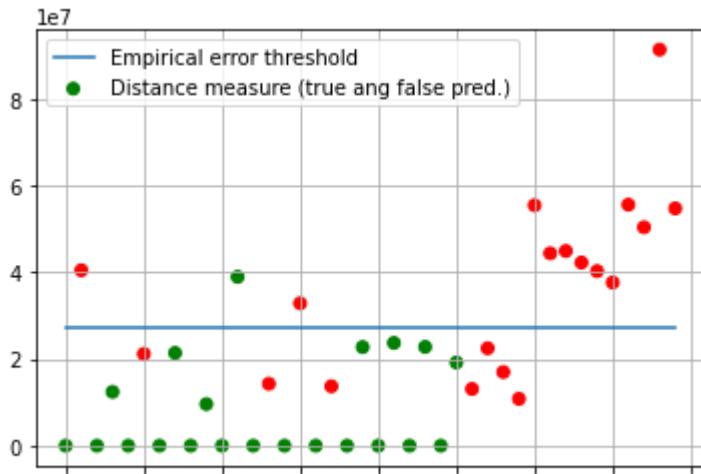
x=[x[0] for x in wts]
y=[y[1] for y in wts]
plt.scatter(x,y, color=cl, label = 'Distance measure (true ang false pred.)')

x2=[x[0] for x in wts]
y2=[2.7e7 for y in wts]

plt.plot(x2,y2, label = 'Empirical error threshold')
plt.legend()
plt.grid()

plt.show()

```



```
CPR_list, t0_list, FMR_list, FNMR_list = [], [] , [] , []
for t0 in np.linspace(start=0, stop=1e8, num=20):
    print('{:e}'.format(t0), end=' ')
    wts, result, correct_pred, num_images, FMR, FNMR = recogniser(test_image_names, train_
    
    CPR_list.append(correct_pred/num_images)
    t0_list.append(t0)
    FMR_list.append(FMR)
    FNMR_list.append(FNMR)

0.000000e+00 Correct predictions: 19/40 = 0.475
5.263158e+06 Correct predictions: 32/40 = 0.8
1.052632e+07 Correct predictions: 33/40 = 0.825
1.578947e+07 Correct predictions: 30/40 = 0.75
2.105263e+07 Correct predictions: 30/40 = 0.75
2.631579e+07 Correct predictions: 32/40 = 0.8
3.157895e+07 Correct predictions: 32/40 = 0.8
3.684211e+07 Correct predictions: 31/40 = 0.775
4.210526e+07 Correct predictions: 29/40 = 0.725
4.736842e+07 Correct predictions: 26/40 = 0.65
5.263158e+07 Correct predictions: 25/40 = 0.625
5.789474e+07 Correct predictions: 22/40 = 0.55
6.315789e+07 Correct predictions: 22/40 = 0.55
6.842105e+07 Correct predictions: 22/40 = 0.55
7.368421e+07 Correct predictions: 22/40 = 0.55
7.894737e+07 Correct predictions: 22/40 = 0.55
8.421053e+07 Correct predictions: 22/40 = 0.55
8.947368e+07 Correct predictions: 22/40 = 0.55
9.473684e+07 Correct predictions: 21/40 = 0.525
1.000000e+08 Correct predictions: 21/40 = 0.525
FMR: 0.0          FNMI
FMR: 0.0          FNMR: 0.2
FMR: 0.0          FNMI
FMR: 0.1          FNMR: 0.15
FMR: 0.125        FNMR: 0.125
FMR: 0.175        FNMR: 0.025
FMR: 0.175        FNMR: 0.025
FMR: 0.2          FNMI
FMR: 0.275        FNMI
FMR: 0.35         FNMR: 0.0
FMR: 0.375        FNMI
FMR: 0.45         FNMR: 0.0
FMR: 0.475        FNMI
FMR: 0.475        FNMI
```

```
x1=t0_list
y1=FMR_list
```

```
x2=t0_list
y2=FNMR_list
```

```
x3=t0_list
y3=CPR_list
```

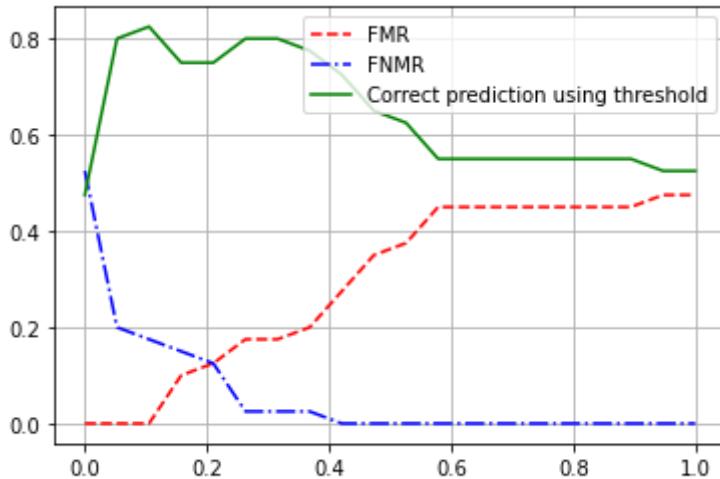
```

plt.plot(x1,y1, ls='--', color='r', label='FMR')
plt.plot(x2,y2, ls='-.', color='b', label='FNMR')
plt.plot(x3,y3, color='g', label='Correct prediction using threshold')

plt.grid()
plt.legend()

```

<matplotlib.legend.Legend at 0x7f2ba40e5c10>



▼ Visualization of prediction result on all test images

```

count      = 0
num_images = 0
correct_pred = 0
def Visualization(img, train_image_names,proj_data,w, t0):
    global count,highest_min,num_images,correct_pred
    unknown_face      = plt.imread(os.path.join(TEST_IMG_FOLDER, img))
    num_images        += 1
    unknown_face_vector = np.array(unknown_face, dtype='float64').flatten()
    normalised_uface_vector = np.subtract(unknown_face_vector,mean_face)

    plt.subplot(40,2,1+count)
    plt.imshow(unknown_face, cmap='gray')
    plt.title('Input:'+'.'.join(img.split('.')[1:]))
    plt.tick_params(labelleft='off', labelbottom='off', bottom='off', top='off', right='off')
    count+=1

    w_unknown = np.dot(proj_data, normalised_uface_vector)
    diff   = w - w_unknown
    norms = np.linalg.norm(diff, axis=1)
    index = np.argmin(norms)

    plt.subplot(40,2,1+count)
    if norms[index] < t0: # It's a face

```

```
match = img.split('_')[0] == train_image_names[index].split('_')[0]
#if img.split('.')[0] == train_image_names[index].split('.')[0]:
if match:
    #plt.title('Matched:'+'.'.join(train_image_names[index].split('.')[2:])), color
    plt.title('Matched:', color='g')
    plt.imshow(imread(os.path.join(TRAIN_IMG_FOLDER, train_image_names[index])), c
               #img = plt.imread(os.path.join(TRAIN_IMG_FOLDER, train_image_names[i])))
    correct_pred += 1
else:
    #plt.title('Matched:'+'.'.join(train_image_names[index].split('.')[2:])), color
    plt.title('False matched:', color='r')
    plt.imshow(imread(os.path.join(TRAIN_IMG_FOLDER, train_image_names[index])), c
               #img = plt.imread(os.path.join(TRAIN_IMG_FOLDER, train_image_names[i])))
else:
    #if img.split('.')[0] not in [i.split('.')[0] for i in train_image_names] and img.
    if img.split('_')[0] not in [i.split('_')[0] for i in train_image_names]:
        plt.title('Unknown face', color='g')
        correct_pred += 1
    else:
        plt.title('Unknown face', color='r')

plt.tick_params(labelleft='off', labelbottom='off', bottom='off', top='off', right='off'
plt.subplots_adjust(right=1.2, top=2.5)

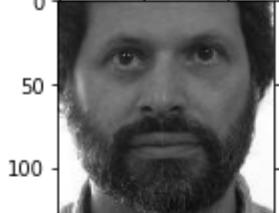
count+=1

fig = plt.figure(figsize=(5, 30))

test_image_names2 = sorted(test_image_names)
for i in range(len(test_image_names2)):
    Visualization(test_image_names2[i], train_image_names, proj_data, w, t0=2.7e7)

plt.show()
```

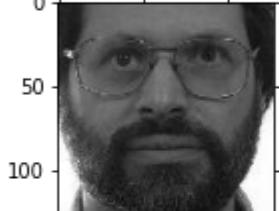
Input:00770_960530_fa.jpg



Matched:

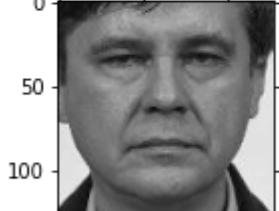


Input:00770_960530_fa_a.jpg



Unknown face

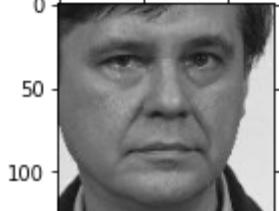
Input:00770_941205_fa.jpg



Matched



Input:00770_941205_fb.jpg



Matched



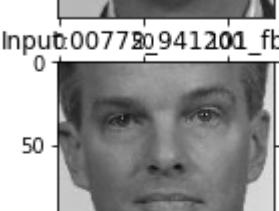
Input:00770_941201_fa.jpg



Matched



Input:00770_941201_fb.jpg



False matched



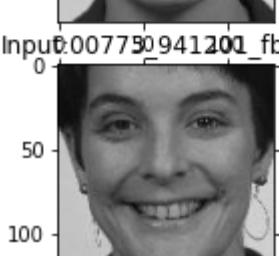
Input:00770_941201_fa.jpg



Matched



Input:00770_941201_fb.jpg



Matched



