In [1]: import numpy as np import pandas as pd import matplotlib.pyplot as plt from PIL import Image from scipy.spatial.distance import cdist as cd from mpl toolkits.mplot3d import Axes3D from scipy.stats import multivariate\_normal K-Means to calculate centroids In [2]: def distance(a,centroids): index2 = np.shape(centroids)[1] temp = np.zeros((1,index2)) #print(np.shape(a)) for i in range(0, np.shape(a)[1]): temp = cd([a[0:a.shape[0]-1,i].transpose()],centroids[0:a.shape[0]-1,:].transpose(),metric = 'euclidean') closest centroid = np.argmin(temp) temp2 = centroids[a.shape[0]-1,closest centroid] a[a.shape[0]-1,i] = temp2return a def new centroids(a,k): new centroids = np.zeros((np.shape(a)[0],k)) for i in range (0, k):  $new_centroids[:,i] = np.mean(a[:,a[a.shape[0]-1,:]==i],axis = 1)$ #print(np.shape(new centroids)) return new centroids def init centroids(a,k): centroids = np.zeros((np.shape(a)[0],k)) for i in range (0, k): num = np.random.randint(0,np.shape(a)[1]) centroids[:,i] = a[:,num] centroids[a.shape[0]-1,i] = ia[a.shape[0]-1,num] = ireturn centroids def Kmeans(X, k): labels = np.zeros((1, X.shape[1])) X = np.append(X, labels, axis = 0)num centroids = kX temp = np.zeros((X.shape[0]+1,X.shape[1]))centroids = init\_centroids(X, num\_centroids) X temp = distance(X, centroids) for i in range (0, 15): centroids\_new = new\_centroids(X\_temp,num\_centroids) centroids = centroids\_new X temp = distance(X temp, centroids) return (X\_temp,centroids) Calculate centroids and cluster means using kmeans In [3]: data\_0 = pd.read\_csv('data1', sep=" ", header=None) data 1 = pd.read csv('data2', sep=" ", header=None) data 2 = pd.read csv('data3', sep=" ", header=None) data 0 = np.array(data 0)data\_1 = np.array(data\_1) data\_2 = np.array(data\_2) no of gaussians = 3data\_0\_clustered, centroids\_0 = Kmeans(data\_0.transpose(), no\_of\_gaussians) data 1 clustered, centroids 1 = Kmeans (data 1.transpose(), no of gaussians) data 2 clustered, centroids 2 = Kmeans(data 2.transpose(), no of gaussians) /Library/Frameworks/Python.framework/Versions/3.4/lib/python3.4/site-packages/ipykernel launche r.py:1: ParserWarning: Falling back to the 'python' engine because the 'c' engine does not suppo rt regex separators (separators > 1 char and different from '\s+' are interpreted as regex); you can avoid this warning by specifying engine='python'. """Entry point for launching an IPython kernel. /Library/Frameworks/Python.framework/Versions/3.4/lib/python3.4/site-packages/ipykernel\_launche r.py:2: ParserWarning: Falling back to the 'python' engine because the 'c' engine does not suppo rt regex separators (separators > 1 char and different from '\s+' are interpreted as regex); you can avoid this warning by specifying engine='python'. /Library/Frameworks/Python.framework/Versions/3.4/lib/python3.4/site-packages/ipykernel\_launche r.py:3: ParserWarning: Falling back to the 'python' engine because the 'c' engine does not suppo rt regex separators (separators > 1 char and different from '\s+' are interpreted as regex); you can avoid this warning by specifying engine='python'. This is separate from the ipykernel package so we can avoid doing imports until K-means Vizualization for data sets In [4]: plt.scatter(data\_0\_clustered[0,data\_0\_clustered[2,:]==0],data\_0\_clustered[1,data\_0\_clustered[2,:]==0 ],c='c') plt.scatter(data\_0\_clustered[0,data\_0\_clustered[2,:]==1],data\_0\_clustered[1,data\_0\_clustered[2,:]==1 plt.scatter(data\_0\_clustered[0,data\_0\_clustered[2,:]==2],data\_0\_clustered[1,data\_0\_clustered[2,:]==2 plt.scatter(centroids 0[0,0],centroids 0[1,0],c='r') plt.scatter(centroids 0[0,1],centroids 0[1,1],c='b') plt.scatter(centroids\_0[0,2],centroids\_0[1,2],c='g') plt.show() plt.scatter(data\_1\_clustered[0,data\_1\_clustered[2,:]==0],data\_1\_clustered[1,data\_1\_clustered[2,:]==0 plt.scatter(data\_1\_clustered[0,data\_1\_clustered[2,:]==1],data\_1\_clustered[1,data\_1\_clustered[2,:]==1 ],c='m') plt.scatter(data\_1\_clustered[0, data\_1\_clustered[2,:]==2], data\_1\_clustered[1, data\_1\_clustered[2,:]==2 plt.scatter(centroids 1[0,0],centroids 1[1,0],c='r') plt.scatter(centroids 1[0,1],centroids 1[1,1],c='b') plt.scatter(centroids\_1[0,2],centroids\_1[1,2],c='g') plt.show() plt.scatter(data\_2\_clustered[0,data\_2\_clustered[2,:]==0],data\_2\_clustered[1,data\_2\_clustered[2,:]==0 plt.scatter(data\_2\_clustered[0,data\_2\_clustered[2,:]==1],data\_2\_clustered[1,data\_2\_clustered[2,:]==1 ],c='m') plt.scatter(data\_2\_clustered[0,data\_2\_clustered[2,:]==2],data\_2\_clustered[1,data\_2\_clustered[2,:]==2 plt.scatter(centroids\_2[0,0],centroids\_2[1,0],c='r') plt.scatter(centroids 2[0,1],centroids 2[1,1],c='b') plt.scatter(centroids 2[0,2],centroids 2[1,2],c='g') plt.show() -2 1.0 0.5 0.0 -0.5-1.0-1.52 0 -1-2 Regularize\_cov In [5]: def regularize\_cov(covariance\_fun\_1, epsilon): for i in range(0,covariance\_fun\_1.shape[0]): u,s,vh = (np.linalg.svd(covariance\_fun\_1[i,:,:])) s = np.diag(s)s += epsilon \* np.eye(covariance\_fun\_1.shape[1]) s = np.diag(s) $temp_svd = np.matmul(u,s)$ covariance\_matrix\_regularized = np.matmul(temp\_svd,vh) return covariance fun 1 **Mstep function** In [6]: def Mstep(gamma fun 2, X fun 2): centroid fun 2 = np.zeros((X fun 2.shape[0],gamma fun 2.shape[0])) temp\_fun\_2 = np.zeros((X\_fun\_2.shape[0], X\_fun\_2.shape[1])) for i in range(0,gamma\_fun\_2.shape[0]): for k in range (0, X fun 2.shape[0]-1): centroid\_fun\_2[k,i] = np.sum(np.multiply(gamma\_fun\_2[i,:], X\_fun\_2[k,:])) centroid\_fun\_2[k,i] /= np.sum(gamma\_fun\_2[i,:]) covar\_fun\_2 = np.zeros((centroid\_fun\_2.shape[1], X\_fun\_2.shape[0]-1, X\_fun\_2.shape[0]-1)) for i in range(0,gamma\_fun\_2.shape[0]): temp\_fun\_2 = X\_fun\_2[0:X\_fun\_2.shape[0]-1,:].transpose() - centroid\_fun\_2[0:centroid\_fun\_2.s hape[0]-1,i].transpose() temp\_fun\_2 = temp\_fun\_2.transpose() for k in range(0, X\_fun\_2.shape[0]-1): temp fun 2[k,:] = np.multiply(gamma\_fun\_2[i,:],temp\_fun\_2[k,:]) covar\_fun\_2[i,:,:] = np.matmul(temp\_fun\_2,temp\_fun\_2.transpose()) covar\_fun\_2[i,:,:] /= np.sum(gamma\_fun\_2[i,:]) covar\_fun\_2 = regularize\_cov(covar\_fun\_2, 0.0001) priori fun 2 = np.zeros(gamma fun 2.shape[0]) for i in range(0,gamma\_fun\_2.shape[0]): priori\_fun\_2[i] = np.sum(gamma\_fun\_2[i,:])/X\_fun\_2.shape[1] return (centroid\_fun\_2,covar\_fun\_2,priori\_fun\_2) **Estep function** In [7]: def Estep(means\_fun\_3, covariance\_fun\_3, weights\_fun\_3, X\_fun\_3): temp\_fun\_3 = np.zeros((means\_fun\_3.shape[1], X\_fun\_3.shape[1])) y\_fun\_3 = np.zeros((means\_fun\_3.shape[1], X\_fun\_3.shape[1])) for i in range(0, means\_fun\_3.shape[1]): for j in range(0, X\_fun\_3.shape[1]): temp fun 3[i,j] = weights fun 3[i] \*multivariate normal.pdf(X fun 3[0:X fun 3.shape[0]-1, j], means\_fun\_3[0:X\_fun\_3.shape[0]-1,i], covariance\_fun\_3[i,:,:], allow\_singular=True) for i in range(0, means fun 3.shape[1]): y fun 3[i,:] = temp fun <math>3[i,:]/temp fun 3.sum(axis=0)return y\_fun\_3 estGaussianMixEM function In [8]: def estGaussMixEM(data fun 3,K fun 3,num iter fun 3,epsilon fun 3): data new fun 3, initial centroids new fun 3 = Kmeans(data fun 3.transpose(), K fun 3) #data should be in row vector form cov\_new\_fun\_3 = np.zeros((K\_fun\_3, data\_fun\_3.transpose().shape[0], data\_fun\_3.transpose().shape[0] priori new fun 3 = np.zeros(K fun 3) for i in range(0,K fun 3):  $\verb|cov_new_fun_3[i,:,:]| = (np.cov(data_new_fun_3[0:data_new_fun_3.shape[0]-1,data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[0:data_new_fun_3.shape[0]-1,data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[0:data_new_fun_3.shape[0]-1,data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[0:data_new_fun_3.shape[0]-1,data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[0:data_new_fun_3.shape[0]-1,data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[data_new_fun_3.shape[0]-1,data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[data_new_fun_3[data_new_fun_3[data_new_fun_3[data_new_fun_3])| + (np.cov(data_new_fun_3[data_new_fun_3$ a new fun 3.shape[0]-1,:]==i]))priori new fun 3[i] = (data new fun 3[0:data new fun 3.shape[0]-1,data new fun 3[data new fu n 3.shape[0]-1,:]==i]).shape[1]/data new fun 3.shape[1] gamma\_fun\_3 = Estep(initial\_centroids\_new\_fun\_3, cov\_new\_fun\_3, priori\_new\_fun\_3,data\_new\_fun\_3) for i in range(0, num iter fun 3): initial\_centroids\_new\_fun\_3, cov\_new\_fun\_3, priori\_new\_fun\_3 = Mstep(gamma\_fun\_3,data\_new\_fu n\_3) gamma\_fun\_3 = Estep(initial\_centroids\_new\_fun\_3, cov\_new\_fun\_3, priori\_new\_fun\_3,data\_new\_fu n\_3) return (initial\_centroids\_new\_fun\_3, cov\_new\_fun\_3, priori\_new\_fun\_3, data\_new\_fun\_3) Visualizing fitted gaussians for data set 3 In [9]: centroi , covari , prior ,data = estGaussMixEM(data 2,3,50,0.001) g = np.linspace(-10, 10, 500)h = np.linspace(-10, 10, 500)G,H = np.meshgrid(g,h)pos = np.array([G.flatten(),H.flatten()]).T rv\_1 = multivariate\_normal(centroi\_[0:2,0], covari\_[0,:,:]) rv\_2 = multivariate\_normal(centroi\_[0:2,1], covari\_[1,:,:]) rv\_3 = multivariate\_normal(centroi\_[0:2,2], covari\_[2,:,:]) fig = plt.figure(figsize=(10,10)) ax0 = fig.add subplot(111)ax0.contour(rv\_1.pdf(pos\_).reshape(500,500)) ax0.contour(rv\_2.pdf(pos\_).reshape(500,500)) ax0.contour(rv\_3.pdf(pos\_).reshape(500,500)) ax0.scatter(data [0,data [2,:]==0],data [1,data [2,:]==0],c='c') ax0.scatter(data [0,data [2,:]==1],data [1,data [2,:]==1],c='m') ax0.scatter(data\_[0,data\_[2,:]==2],data\_[1,data\_[2,:]==2],c='y') plt.show() 400 300 200 100 100 400 **Skin model Training** In [10]: skin = pd.read\_csv('skin.dat', sep=" ", header=None) skin = np.array(skin) fig = plt.figure(figsize=(10,10)) ax = fig.add\_subplot(111, projection='3d') ax.scatter(skin[:,0],skin[:,1],skin[:,2]) plt.show() centroi\_skin, covari\_skin, prior\_skin, data\_skin = estGaussMixEM(skin,1,50,0.001) 0.7 0.6 0.5 0.4 0.3 0.2 0.1 0.0 0.7 0.6 0.5 0.4 0.2 0.4 0.2 0.1 0.0 Mixture model of single gaussian In [11]: g = np.linspace(-1,1,1000)h = np.linspace(-1, 1, 1000)G,H = np.meshgrid(g,h)pos = np.array([G.flatten(),H.flatten()]).T rv\_1 = multivariate\_normal(centroi\_skin[0:2,0], covari\_skin[0,0:2,0:2]) fig = plt.figure(figsize=(10,10)) ax0 = fig.add subplot(111)ax0.contour(rv 1.pdf(pos ).reshape(1000,1000)) plt.show() 800 600 400 200 800 Non skin model training In [12]: non skin = pd.read csv('non-skin.txt', sep=" ", header=None, error bad lines=False) non skin = np.array(non skin) fig = plt.figure(figsize=(10,10)) ax1 = fig.add subplot(111)ax1.scatter(non\_skin[:,0],non\_skin[:,1],non\_skin[:,2]) plt.show() centroi\_non\_skin, covari\_non\_skin, prior\_non\_skin, data\_non\_skin = estGaussMixEM(non\_skin,6,50,0.001 b'Skipping line 3035: expected 3 fields, saw 19\nSkipping line 3111: expected 3 fields, saw 19\n Skipping line 3124: expected 3 fields, saw 19\nSkipping line 3137: expected 3 fields, saw 19\nSk ipping line 3539: expected 3 fields, saw 19\nSkipping line 3627: expected 3 fields, saw 19\nSkip ping line 3642: expected 3 fields, saw 19\nSkipping line 3846: expected 3 fields, saw 19\nSkippi ng line 3921: expected 3 fields, saw 19\nSkipping line 3935: expected 3 fields, saw 19\nSkipping line 4006: expected 3 fields, saw 19\nSkipping line 4195: expected 3 fields, saw 19\nSkipping li ne 4210: expected 3 fields, saw 19\nSkipping line 4693: expected 3 fields, saw 19\nSkipping line 4727: expected 3 fields, saw 19\nSkipping line 4773: expected 3 fields, saw 19\nSkipping line 47 97: expected 3 fields, saw 19\nSkipping line 4834: expected 3 fields, saw 19\nSkipping line 487 2: expected 3 fields, saw 19\nSkipping line 5015: expected 3 fields, saw 19\nSkipping line 5042: expected 3 fields, saw 19\nSkipping line 5043: expected 3 fields, saw 19\nSkipping line 5044: ex pected 3 fields, saw 19\nSkipping line 5053: expected 3 fields, saw 19\nSkipping line 5058: expe cted 3 fields, saw 19\nSkipping line 5096: expected 3 fields, saw 19\nSkipping line 5104: expect ed 3 fields, saw 19\nSkipping line 5125: expected 3 fields, saw 51\nSkipping line 5175: expected 3 fields, saw 19\nSkipping line 5197: expected 3 fields, saw 19\nSkipping line 5199: expected 3 fields, saw 19\nSkipping line 5269: expected 3 fields, saw 19\nSkipping line 5334: expected 3 fi elds, saw 19\nSkipping line 5335: expected 3 fields, saw 19\nSkipping line 5362: expected 3 fiel ds, saw 19\nSkipping line 5366: expected 3 fields, saw 19\nSkipping line 5431: expected 3 field s, saw 19\nSkipping line 5456: expected 3 fields, saw 19\nSkipping line 5501: expected 3 fields, saw 19\nSkipping line 5502: expected 3 fields, saw 19\nSkipping line 7221: expected 3 fields, sa w 19\nSkipping line 7693: expected 3 fields, saw 19\nSkipping line 7707: expected 3 fields, saw 19\nSkipping line 7900: expected 3 fields, saw 19\nSkipping line 8000: expected 3 fields, saw 19 \nSkipping line 8015: expected 3 fields, saw 19\nSkipping line 8016: expected 3 fields, saw 19\n Skipping line 8030: expected 3 fields, saw 19\nSkipping line 8044: expected 3 fields, saw 19\nSk ipping line 8074: expected 3 fields, saw 19\n' 1.0 0.8 0.6 0.4 0.2 0.2 0.4 1.0 0.0 0.8 Mixture model of 6 gaussians In [13]: q = np.linspace(-1, 1, 1000)h = np.linspace(-1, 1, 1000)G,H = np.meshgrid(g,h)pos\_ = np.array([G.flatten(),H.flatten()]).T rv 1 = multivariate normal(centroi non skin[0:2,0], covari non skin[0,0:2,0:2]) rv\_2 = multivariate\_normal(centroi\_non\_skin[0:2,1], covari\_non\_skin[1,0:2,0:2]) rv 3 = multivariate\_normal(centroi\_non\_skin[0:2,2], covari\_non\_skin[2,0:2,0:2]) rv\_4 = multivariate\_normal(centroi\_non\_skin[0:2,3], covari\_non\_skin[3,0:2,0:2]) rv\_5 = multivariate\_normal(centroi\_non\_skin[0:2,4], covari\_non\_skin[4,0:2,0:2]) rv\_6 = multivariate\_normal(centroi\_non\_skin[0:2,5], covari\_non\_skin[5,0:2,0:2]) fig = plt.figure(figsize=(10,10)) ax0 = fig.add subplot(111)ax0.contour(rv 1.pdf(pos ).reshape(1000,1000)) ax0.contour(rv 2.pdf(pos ).reshape(1000,1000)) ax0.contour(rv 3.pdf(pos ).reshape(1000,1000)) ax0.contour(rv\_4.pdf(pos\_).reshape(1000,1000)) ax0.contour(rv 5.pdf(pos ).reshape(1000,1000)) ax0.contour(rv\_6.pdf(pos\_).reshape(1000,1000)) plt.show() 800 600 400 200 200 400 600 800 Classify skin for given image In [22]: **def** classify(dat,centroid a,covari a,centroid b,covari b,confidence): if((multivariate normal.pdf(dat,centroid a,covari a))/(multivariate normal.pdf(dat,centroid b,co vari b)) > confidence): return 1 else: return 0 The parameter theta is just the confidence level that a pixel belongs to gaussian of skin instead of nonskin. Lets say that if theta is said to be 5 then, those pixel would be highlighted which are 5 times as close to skin gaussia as compared to non skin gaussians. In [45]: def findskin(X\_image\_1,theta): new image = np.zeros((X image 1.shape[0], X image 1.shape[1])) lenght image = X image 1.shape[0] height\_image = X\_image\_1.shape[1] for i in range(0,lenght\_image): for j in range(0, height image): if(classify(X\_image\_1[i,j,0:3],centroi\_skin[0:3,0],covari\_skin[0,:,:],centroi\_non\_skin[0 :3,0],covari non skin[0,:,:],theta)): if(classify(X image 1[i,j,0:3],centroi skin[0:3,0],covari skin[0,:,:],centroi non sk in[0:3,1], covari non skin[1,:,:], theta)): if(classify(X\_image\_1[i,j,0:3],centroi\_skin[0:3,0],covari\_skin[0,:,:],centroi\_no n\_skin[0:3,2],covari\_non\_skin[2,:,:],theta)):  $if(classify(X_image_1[i,j,0:3],centroi_skin[0:3,0],covari_skin[0,:,:],centroi_skin[0:3,0])$ i non skin[0:3,3],covari non skin[3,:,:],theta)): if(classify(X\_image\_1[i,j,0:3],centroi\_skin[0:3,0],covari\_skin[0,:,:],ce ntroi non skin[0:3,4],covari non skin[4,:,:],theta)): if(classify(X\_image\_1[i,j,0:3],centroi\_skin[0:3,0],covari\_skin[0 ,:,:],centroi\_non\_skin[0:3,5],covari\_non\_skin[5,:,:],theta)): new image[i,j] = 255 $new_image[i,j] = 0$ plt.imshow(new image, cmap="gray") In [50]: from PIL import Image image = Image.open('faces.png') X image = np.array(image) imgplot = plt.imshow(X image) plt.show()  $X_{image} = X_{image}/255$ findskin(X\_image,5) image2 = Image.open('test.jpg') X\_image\_2 = np.array(image2) imgplot\_2 = plt.imshow(X\_image\_2) plt.show() X image 2 = X image 2/255findskin(X\_image\_2,50) 50 100 150 200 250 250 350 150 200 300 /Library/Frameworks/Python.framework/Versions/3.4/lib/python3.4/site-packages/ipykernel\_launche r.py:2: RuntimeWarning: divide by zero encountered in double scalars /Library/Frameworks/Python.framework/Versions/3.4/lib/python3.4/site-packages/ipykernel launche r.py:2: RuntimeWarning: overflow encountered in double scalars 50 100 150 200 250 Ó 50 100 150 200 250 300 350 400

100

200

300

400

500

600

700

100

200

300

400

500

600

700

200

In [17]: from multiprocessing import Pool
 X image temp = X image 1

p.close()

p.close()
p.close()
p.terminate

p = Pool(4)

lenght\_image = X\_image\_1.shape[0]
height\_image = X\_image\_1.shape[1]
print(lenght\_image, height\_image)

chunks = [X\_image\_temp[i::2] for i in range(2)]

#new\_image\_total = np.array(new\_image\_total)

new\_image\_total = p.map(function2,np.array(chunks))

#new\_image\_total = np.reshape(new\_image\_total(720, 1080))

400

600

800

X\_image\_temp = np.reshape(X\_image\_temp,(lenght\_image\*height\_image,3))

This wont work with noisy images as evident with above image taken with webcam

1000

Multiprocessing attempt (failed)