In [36]: **import** numpy **as** np import matplotlib.pyplot as plt from sklearn.discriminant analysis import LinearDiscriminantAnalysis from sklearn.datasets import make blobs #Problem 2a #X^1 mean matrix1 = np.array([2, 2])std matrix1 = np.array([[2, -1], [-1, 1]])mean1 = np.mean(mean matrix1) std1 = np.std(std matrix1) mean matrix2 = np.array([0, 0])std matrix2 = np.array([[1, 0.5], [0.5, 1]])mean2 = np.mean(mean matrix2) std2 = np.std(std matrix2) #Generate 10 random normally distributed samples of N(x, X) for both  $X^1$  and  $X^2$ X1 = np.random.normal(loc = mean1, scale = std1, size = (10, 2)) X2 = np.random.normal(loc = mean2, scale = std2, size = (10, 2))X = [y for x in [X1, X2] for y in X]#Generate labels for X1 and X2 y1 = [1 for i in range(10)]y2 = [2 for i in range(10)]y = [y for x in [y1, y2] for y in x]#Linear discriminant for i in range(10): plt.scatter(X1[i][0], X1[i][1], color = 'b') plt.scatter(X2[i][0], X2[i][1], color = 'r') #Get LDA decision boundary lda = LinearDiscriminantAnalysis() ldafit = lda.fit(X, y)lda intercept = ldafit.intercept\_ lda slope = ldafit.coef lda y = np.dot(lda slope, np.transpose(X)) + lda intercept  $lda_y = np.reshape(lda_y, (20, 1))$ lda\_y = lda\_y.tolist() lda x = []for i in range(20): lda x.append(X[i][0]) lda\_m, lda\_b = np.polyfit(lda\_x, lda\_y, 1) plt.plot(lda x, lda m \* lda x + lda b, color = 'orange', label = 'LDA Decision Boundary') #Get Theoretical Bayes Decision Boundary  $g \times lim = (-1, 8)$  $g y \lim = (-1, 5)$  $g_x$ ,  $g_y = np.meshgrid(np.linspace(<math>g_xlim[0]$ ,  $g_xlim[1]$ , 71), np.linspace(g ylim[0], g ylim[1], 81)) Z = ldafit.predict\_proba(np.c\_[g\_x.ravel(), g\_y.ravel()]) Z = Z[:, 1].reshape(g x.shape) $g_plot = plt.contour(g_x, g_y, Z, [0.5], colors= 'black')$ labels = ['Theoretical Bayes Decision Boundary'] for i in range(len(labels)): g plot.collections[i].set label(labels[i]) #Get Empirical Bayes Decision Boundary #Generating empirical sample mean/std from existing sample X1 mean = sum(X1)/len(X1)X1 std = np.std(X1)X2 mean = sum(X2)/len(X2)X2 std = np.std(X2)X1 new = np.random.normal(loc = X1 mean, scale = X1 std, size = (10, 2)) X2 new = np.random.normal(loc = X2 mean, scale = X2 std, size = (10, 2))X\_new = [y for x in [X1\_new, X2\_new] for y in x] lda new = LinearDiscriminantAnalysis() ldafit new = lda.fit(X new, y)  $g \times lim = (-1, 8)$ g ylim = (-1, 5) $g_x$ ,  $g_y = np.meshgrid(np.linspace(<math>g_xlim[0]$ ,  $g_xlim[1]$ , 71), np.linspace(g\_ylim[0], g\_ylim[1], 81)) Z = ldafit\_new.predict\_proba(np.c\_[g\_x.ravel(), g\_y.ravel()])  $Z = Z[:, 1].reshape(g_x.shape)$ g\_plot = plt.contour(g\_x, g\_y, Z, [0.5], colors= 'green') #Labeling labels = ['Empirical Bayes Decision Boundary'] for i in range(len(labels)): g plot.collections[i].set label(labels[i]) plt.legend() plt.axis([-1, 5, -2, 6])plt.show() 6 LDA Decision Boundary 5 Theoretical Bayes Decision Boundary Empirical Bayes Decision Boundary 4 3 2 1 0 -1# Problem 2b mean matrix1 = np.array([2, 2]) $std_matrix1 = np.array([[2, -1], [-1, 1]])$ mean1 = np.mean(mean matrix1) std1 = np.std(std matrix1) mean matrix2 = np.array([0, 0])std matrix2 = np.array([[1, 0.5], [0.5, 1]]) mean2 = np.mean(mean matrix2) std2 = np.std(std matrix2) #Generate 10 random normally distributed samples of N(x, X) for both X^1 and X^2 X1 = np.random.normal(loc = mean1, scale = std1, size = (1000, 2))X2 = np.random.normal(loc = mean2, scale = std2, size = (1000, 2))X = [y for x in [X1, X2] for y in X]#Generate labels for X1 and X2 y1 = [1 for i in range(1000)]y2 = [2 for i in range(1000)]y = [y for x in [y1, y2] for y in x]#Linear discriminant **for** i **in** range(1000): plt.scatter(X1[i][0], X1[i][1], color = 'b', alpha = 0.5) plt.scatter(X2[i][0], X2[i][1], color = 'r', alpha = 0.5) #Get LDA decision boundary lda = LinearDiscriminantAnalysis() ldafit = lda.fit(X, y)lda intercept = ldafit.intercept lda slope = ldafit.coef lda y = np.dot(lda slope, np.transpose(X)) + lda intercept  $lda_y = np.reshape(lda_y, (2000, 1))$ lda y = lda y.tolist() lda x = []for i in range(2000): lda x.append(X[i][0]) lda\_m, lda\_b = np.polyfit(lda\_x, lda\_y, 1) plt.plot(lda x, lda m \* lda x + lda b, color = 'orange', label = 'LDA Decision Boundary') #Get Theoretical Bayes Decision Boundary  $g \times lim = (-1, 8)$ g ylim = (-1, 5) $g_x$ ,  $g_y = np.meshgrid(np.linspace(<math>g_xlim[0]$ ,  $g_xlim[1]$ , 71), np.linspace(g\_ylim[0], g\_ylim[1], 81))  $Z = ldafit.predict_proba(np.c_[g_x.ravel(), g_y.ravel()])$  $Z = Z[:, 1].reshape(g_x.shape)$ g\_plot = plt.contour(g\_x, g\_y, Z, [0.5], colors= 'black') #Labeling labels = ['Theoretical Bayes Decision Boundary'] for i in range(len(labels)): g plot.collections[i].set label(labels[i]) #Get Empirical Bayes Decision Boundary #Generating empirical sample mean/std from existing sample X1 mean = sum(X1)/len(X1)X1 std = np.std(X1) $X2_{mean} = sum(X2)/len(X2)$ X2 std = np.std(X2)X1 new = np.random.normal(loc = X1 mean, scale = X1 std, size = (1000, 2))  $X2_{new} = np.random.normal(loc = X2_{mean}, scale = X2_{std}, size = (1000, 2))$ X\_new = [y for x in [X1\_new, X2\_new] for y in x] lda new = LinearDiscriminantAnalysis() ldafit new = lda.fit(X new, y)  $g_x = (-1, 8)$  $g_ylim = (-1, 5)$  $g_x$ ,  $g_y = np.meshgrid(np.linspace(<math>g_xlim[0]$ ,  $g_xlim[1]$ , 71), np.linspace(g\_ylim[0], g\_ylim[1], 81)) Z = ldafit\_new.predict\_proba(np.c\_[g\_x.ravel(), g\_y.ravel()])  $Z = Z[:, 1].reshape(g_x.shape)$ g\_plot = plt.contour(g\_x, g\_y, Z, [0.5], colors= 'green') #Labeling labels = ['Empirical Bayes Decision Boundary'] for i in range(len(labels)): g plot.collections[i].set label(labels[i]) plt.legend() plt.axis([-3, 6, -1, 7])plt.show() LDA Decision Boundary 6 Theoretical Bayes Decision Boundary Empirical Bayes Decision Boundary 5 4 3 2 1 0 -1In [9]: from sklearn.discriminant analysis import QuadraticDiscriminantAnalysis #Problem 3a #X^1 mean matrix1 = np.array([2, 2])std matrix1 = np.array([[2, -1], [-1, 1]])mean1 = np.mean(mean matrix1) std1 = np.std(std matrix1) #X^2 mean matrix2 = np.array([0, 0])std matrix2 = np.array([[1, 0.5], [0.5, 1]])mean2 = np.mean(mean matrix2) std2 = np.std(std matrix2) #Generate 10 random normally distributed samples of N(x, X) for both X^1 and X^2 X1 = np.random.normal(loc = mean1, scale = std1, size = (10, 2))X2 = np.random.normal(loc = mean2, scale = std2, size = (10, 2))X = [y for x in [X1, X2] for y in x]#Generate labels for X1 and X2 y1 = [1 for i in range(10)]y2 = [2 for i in range(10)]y = [y for x in [y1, y2] for y in x]#Quadratic discriminant for i in range(10): plt.scatter(X1[i][0], X1[i][1], color = 'b') plt.scatter(X2[i][0], X2[i][1], color = 'r') #Get QDA Decision Boundary qda = QuadraticDiscriminantAnalysis(store covariance = True) qdafit = qda.fit(X, y)qdad = LinearDiscriminantAnalysis() qdadfit = lda.fit(X, y)qdad intercept = ldafit.intercept qdad\_slope = ldafit.coef\_ qda y = np.dot(qdad slope, np.transpose(X)) + qdad intercept  $qda y = np.reshape(qda_y, (20, 1))$ qda\_y = qda\_y.tolist() qda x = []for i in range(20): qda\_x.append(X[i][0]) qda\_m, qda\_b = np.polyfit(qda\_x, qda\_y, 1) plt.plot(qda\_x, qda\_m \* qda\_x + qda\_b, color = 'orange', label = 'QDA Decision Boundary') #Get Theoretical Bayes Decision Boundary  $g \times lim = (-1, 8)$  $g_ylim = (-1, 5)$  $g_x$ ,  $g_y = np.meshgrid(np.linspace(<math>g_xlim[0]$ ,  $g_xlim[1]$ , 71), np.linspace(g\_ylim[0], g\_ylim[1], 81))  $Z = qdafit.predict_proba(np.c_[g_x.ravel(), g_y.ravel()])$  $Z = Z[:, 1].reshape(g_x.shape)$ qda\_plot = plt.contour(g\_x, g\_y, Z, [0.5], colors= 'black') #Labeling labels = ['Theoretical Bayes Decision Boundary'] for i in range(len(labels)): qda\_plot.collections[i].set\_label(labels[i]) #Get Empirical Bayes Decision Boundary #Generating empirical sample mean/std from existing sample X1 mean = sum(X1)/len(X1) $X1_std = np.std(X1)$ X2 mean = sum(X2)/len(X2) $X2_std = np.std(X2)$ X1 new = np.random.normal(loc = X1 mean, scale = X1 std, size = (10, 2)) X2\_new = np.random.normal(loc = X2\_mean, scale = X2\_std, size = (10, 2)) X\_new = [y for x in [X1\_new, X2\_new] for y in x] qda new = QuadraticDiscriminantAnalysis() qdafit\_new = qda\_new.fit(X\_new, y)  $g \times lim = (-1, 8)$ g ylim = (-1, 5)g x, g y = np.meshgrid(np.linspace(g xlim[0], g xlim[1], 71),np.linspace(g ylim[0], g ylim[1], 81)) Z = qdafit\_new.predict\_proba(np.c\_[g\_x.ravel(), g\_y.ravel()])  $Z = Z[:, 1].reshape(g_x.shape)$ g\_plot = plt.contour(g\_x, g\_y, Z, [0.5], colors= 'green') labels = ['Empirical Bayes Decision Boundary'] for i in range(len(labels)): g\_plot.collections[i].set\_label(labels[i]) plt.legend() plt.axis([-1, 5, -2, 6]) plt.show() QDA Decision Boundary 5 Theoretical Bayes Decision Boundary Empirical Bayes Decision Boundary 4 3 2 1 0 -1#Problem 3b mean\_matrix1 = np.array([2, 2])  $std_matrix1 = np.array([[2, -1], [-1, 1]])$ mean1 = np.mean(mean\_matrix1) std1 = np.std(std\_matrix1) #X^2  $mean_matrix2 = np.array([0, 0])$  $std_matrix2 = np.array([[1, 0.5], [0.5, 1]])$ mean2 = np.mean(mean\_matrix2) std2 = np.std(std\_matrix2)  $\# Generate \ 10$  random normally distributed samples of  $N(x,\ X)$  for both  $X^1$  and  $X^2$ X1 = np.random.normal(loc = mean1, scale = std1, size = (1000, 2))X2 = np.random.normal(loc = mean2, scale = std2, size = (1000, 2))X = [y for x in [X1, X2] for y in X]#Generate labels for X1 and X2 y1 = [1 for i in range(1000)]y2 = [2 for i in range(1000)]y = [y for x in [y1, y2] for y in x]#Quadratic discriminant **for** i **in** range (1000): plt.scatter(X1[i][0], X1[i][1], color = 'b') plt.scatter(X2[i][0], X2[i][1], color = 'r') #Get QDA Decision Boundary qda = QuadraticDiscriminantAnalysis(store\_covariance = **True**) qdafit = qda.fit(X, y)qdad = LinearDiscriminantAnalysis() qdadfit = lda.fit(X, y)qdad\_intercept = ldafit.intercept\_ qdad\_slope = ldafit.coef\_ qda\_y = np.dot(qdad\_slope, np.transpose(X)) + qdad\_intercept  $qda_y = np.reshape(qda_y, (2000, 1))$ qda\_y = qda\_y.tolist()  $qda_x = []$ for i in range(2000): qda\_x.append(X[i][0]) qda\_m, qda\_b = np.polyfit(qda\_x, qda\_y, 1) plt.plot(qda\_x, qda\_m \* qda\_x + qda\_b, color = 'orange', label = 'QDA Decision Boundary') #Get Theoretical Bayes Decision Boundary  $g_x = (-1, 8)$  $g_ylim = (-1, 5)$  $g_x$ ,  $g_y = np.meshgrid(np.linspace(<math>g_xlim[0]$ ,  $g_xlim[1]$ , 71), np.linspace(g\_ylim[0], g\_ylim[1], 81)) Z = qdafit.predict\_proba(np.c\_[g\_x.ravel(), g\_y.ravel()])  $Z = Z[:, 1].reshape(g_x.shape)$ qda\_plot = plt.contour(g\_x, g\_y, Z, [0.5], colors= 'black') #Labeling labels = ['Theoretical Bayes Decision Boundary'] for i in range(len(labels)): qda\_plot.collections[i].set\_label(labels[i]) #Get Empirical Bayes Decision Boundary #Generating empirical sample mean/std from existing sample  $X1_{mean} = sum(X1)/len(X1)$  $X1_std = np.std(X1)$  $X2_{mean} = sum(X2)/len(X2)$  $X2\_std = np.std(X2)$ X1\_new = np.random.normal(loc = X1\_mean, scale = X1\_std, size = (1000, 2))  $X2_{new} = np.random.normal(loc = X2_{mean}, scale = X2_{std}, size = (1000, 2))$ X\_new = [y for x in [X1\_new, X2\_new] for y in x] qda\_new = QuadraticDiscriminantAnalysis() qdafit\_new = qda\_new.fit(X\_new, y)  $g_x = (-1, 8)$  $g_ylim = (-1, 5)$  $g_x$ ,  $g_y = np.meshgrid(np.linspace(<math>g_x lim[0]$ ,  $g_x lim[1]$ , 71), np.linspace(g\_ylim[0], g\_ylim[1], 81)) Z = qdafit\_new.predict\_proba(np.c\_[g\_x.ravel(), g\_y.ravel()])  $Z = Z[:, 1].reshape(g_x.shape)$ g\_plot = plt.contour(g\_x, g\_y, Z, [0.5], colors= 'green') #Labeling labels = ['Empirical Bayes Decision Boundary'] for i in range(len(labels)): g\_plot.collections[i].set\_label(labels[i]) plt.legend() plt.axis([-1, 5, -2, 6])plt.show() QDA Decision Boundary 5 Theoretical Bayes Decision Boundary Empirical Bayes Decision Boundary 4 3 2 1 0 -1