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In [12]: import pandas as pd
import tensorflow as tf
import numpy as np
import scipy as sp
from matplotlib import pylab as plt
import sklearn
from scipy import misc
import matplotlib.cm as cm
import imageio
from sklearn.datasets import load_iris
from sklearn.linear_model import LogisticRegression

%%matplotlib inline

labels_train, features_train = [], []
for line in open('./faces/train.txt'):

    # Splits each line in train by "whitespace" (i.e.: the first space), then takes element ZERO (image pixels).
    im = imageio.imread(line.split()[0])

    # Reshapes im objects from 50 x 50 sizes to 2500 flattened vectors (Part b)
    features_train.append(im.reshape(2500,))

    # Splits each line in train by "whitespace" (i.e.: the first space), then takes element ONE (image Labels).
    labels_train.append(line.split()[1])

# Creates numpy arrays from Lists
features_train, labels_train = np.array(features_train, dtype=float), np.array(labels_train, dtype=int)

# PART (b) Prints the shape of each numpy array.
print (features_train.shape)
plt.imshow(features_train[10, :].reshape(50,50), cmap = cm.Greys_r)
plt.show()

labels_test, features_test = [], []
for line in open('./faces/test.txt'):
    im = imageio.imread(line.split()[0])

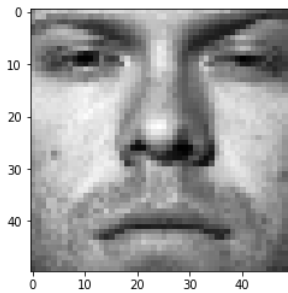
    features_test.append(im.reshape(2500,))
    labels_test.append(line.split()[1])

# Creates numpy arrays from Lists
features_test, labels_test = np.array(features_test, dtype=float), np.array(labels_test, dtype=int)

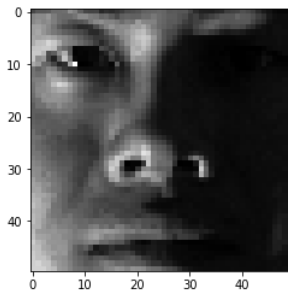
print (features_test.shape)
plt.imshow(features_test[10, :].reshape(50,50), cmap = cm.Greys_r)
plt.show()

```

(540, 2500)



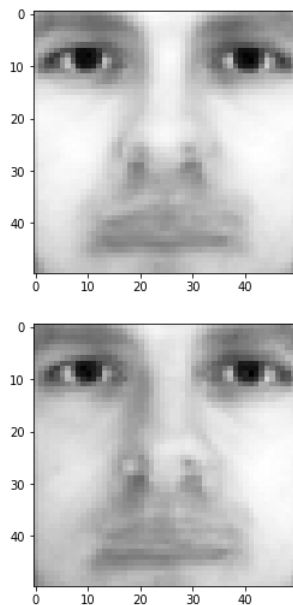
(100, 2500)



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In [13]: average_face_train = np.empty(2500)

average_face_train = (np.sum(features_train, axis = 0)/len(labels_train))
plt.imshow(average_face_train.reshape(50,50), cmap = cm.Greys_r)
plt.show()

average_face_test = np.empty(2500)
average_face_test = (np.sum(features_test, axis = 0)/len(labels_test))
plt.imshow(average_face_test.reshape(50,50), cmap = cm.Greys_r)
plt.show()
```

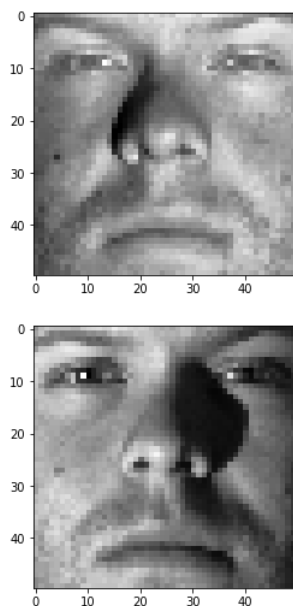


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In [14]: features_train_minus_av = np.empty_like(features_train)
features_test_minus_av = np.empty_like(features_test)

for i,j in enumerate(features_train_minus_av):
    features_train_minus_av[i]= features_train[i]-average_face_train

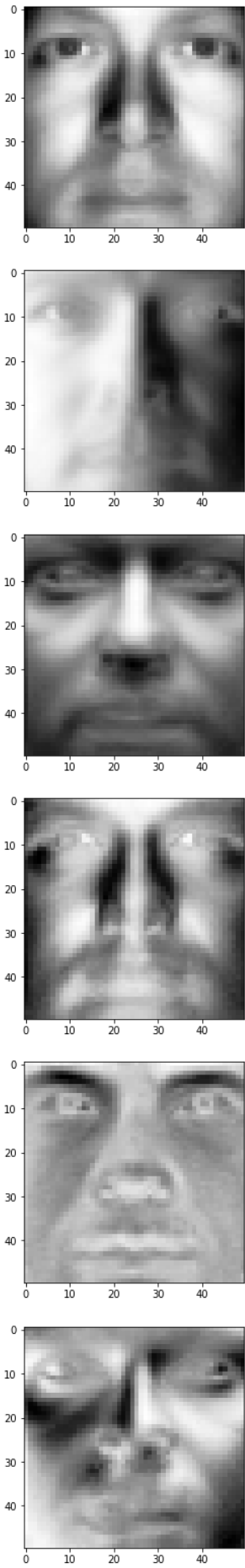
for i,j in enumerate(features_test_minus_av):
    features_test_minus_av[i]= features_test[i]-average_face_test

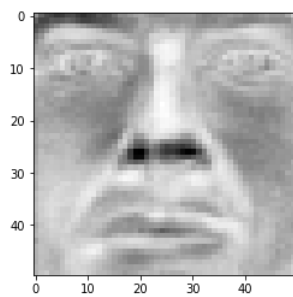
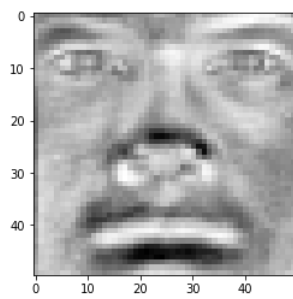
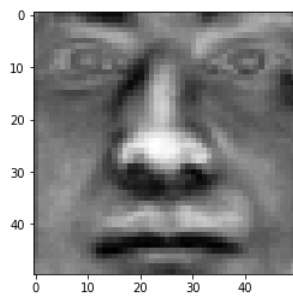
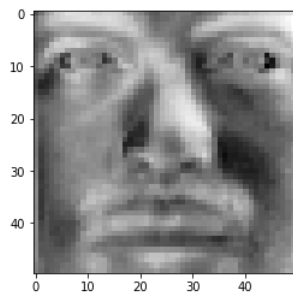
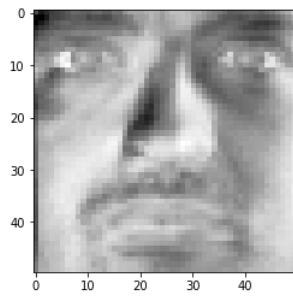
plt.imshow(features_train_minus_av[1].reshape(50,50), cmap = cm.Greys_r)
plt.show()
plt.imshow(features_test[1].reshape(50,50), cmap = cm.Greys_r)
plt.show()
```



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In [15]: # Part 1(e)
u_train, s_train, vh_train = np.linalg.svd(features_train_minus_av) #, compute_uv=True)

for i in range(11):
    plt.imshow(vh_train[i].reshape(50,50), cmap = cm.Greys_r)
    plt.show()
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In [16]: s_train_diag= np.diag(s_train)
# print (s_train_diag)
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In [17]: r = 200
X_pred_r = np.empty([r,540,2500])
F_dist = np.empty(r)

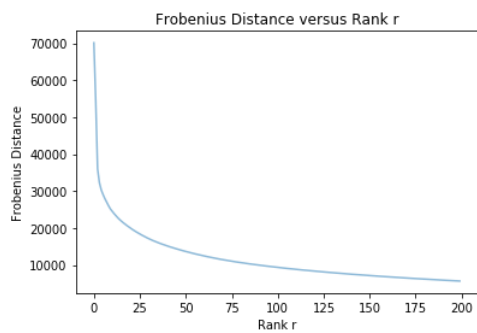
for i in range(0,r):
    X_pred_r[i] = np.linalg.multi_dot ([ u_train[:,i], s_train_diag[:,i] , vh_train[:,i] ])
    F_dist[i] = np.linalg.norm(features_train_minus_av-X_pred_r[i])

# plt.imshow(X_pred_r[i].reshape(540,50,50)[0], cmap = cm.Greys_r)
# plt.show()

# print(F_dist)

plt.plot(np.arange(r),F_dist, alpha=0.5)
plt.title('Frobenius Distance versus Rank r')
plt.xlabel('Rank r')
plt.ylabel('Frobenius Distance')
plt.show()

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In [18]: print(vh_train.shape)

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(2500, 2500)

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In [19]: r = 10
F_train = np.dot(features_train_minus_av , np.transpose(vh_train[:,r,:]))
print(F_train.shape)

F_test = np.dot(features_test_minus_av , np.transpose(vh_train[:,r,:]))
print(F_test.shape)

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(540, 10)
(100, 10)

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In [20]: print((vh_train[:,1,:]).shape)

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(1, 2500)

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In [37]: accu_r = []
for r in range(1,200):

    # This is obtained by multiplying the training feature array by the transpose of the first r rows of vh_train
    F_train = np.dot(features_train_minus_av , np.transpose(vh_train[:r,:]))
    F_test = np.dot(features_test_minus_av , np.transpose(vh_train [:r,:]))

    #solver='liblinear',

    # solver : str, {'newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'}, optional (default='liblinear').
    clf = LogisticRegression(solver='lbfgs', multi_class='ovr', max_iter=10000).fit(F_train, labels_train) #labels_train_ovr_face)

    print("For rank equal to",r, "accuracy is",round(clf.score(F_test, labels_test)*100),"%.")
    accu_r.append(clf.score(F_test, labels_test)*100)

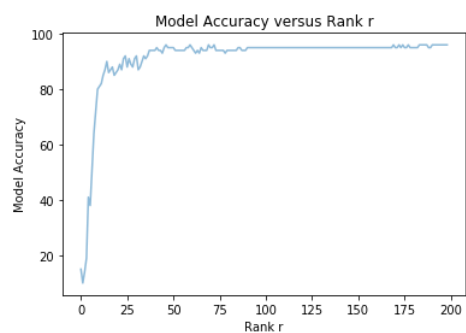
accu_r = np.array(accu_r)
plt.plot(np.arange(len(accu_r)),accu_r, alpha=0.5)
plt.title('Model Accuracy versus Rank r')
plt.xlabel('Rank r')
plt.ylabel('Model Accuracy')
plt.show()
```

For rank equal to 1 accuracy is 15.0 %.  
For rank equal to 2 accuracy is 10.0 %.  
For rank equal to 3 accuracy is 14.0 %.  
For rank equal to 4 accuracy is 19.0 %.  
For rank equal to 5 accuracy is 41.0 %.  
For rank equal to 6 accuracy is 38.0 %.  
For rank equal to 7 accuracy is 51.0 %.  
For rank equal to 8 accuracy is 64.0 %.  
For rank equal to 9 accuracy is 72.0 %.  
For rank equal to 10 accuracy is 80.0 %.  
For rank equal to 11 accuracy is 81.0 %.  
For rank equal to 12 accuracy is 82.0 %.  
For rank equal to 13 accuracy is 85.0 %.  
For rank equal to 14 accuracy is 87.0 %.  
For rank equal to 15 accuracy is 90.0 %.  
For rank equal to 16 accuracy is 86.0 %.  
For rank equal to 17 accuracy is 87.0 %.  
For rank equal to 18 accuracy is 88.0 %.  
For rank equal to 19 accuracy is 85.0 %.  
For rank equal to 20 accuracy is 86.0 %.  
For rank equal to 21 accuracy is 87.0 %.  
For rank equal to 22 accuracy is 89.0 %.  
For rank equal to 23 accuracy is 87.0 %.  
For rank equal to 24 accuracy is 91.0 %.  
For rank equal to 25 accuracy is 92.0 %.  
For rank equal to 26 accuracy is 88.0 %.  
For rank equal to 27 accuracy is 91.0 %.  
For rank equal to 28 accuracy is 89.0 %.  
For rank equal to 29 accuracy is 88.0 %.  
For rank equal to 30 accuracy is 91.0 %.  
For rank equal to 31 accuracy is 92.0 %.  
For rank equal to 32 accuracy is 87.0 %.  
For rank equal to 33 accuracy is 88.0 %.  
For rank equal to 34 accuracy is 90.0 %.  
For rank equal to 35 accuracy is 92.0 %.  
For rank equal to 36 accuracy is 91.0 %.  
For rank equal to 37 accuracy is 92.0 %.  
For rank equal to 38 accuracy is 94.0 %.  
For rank equal to 39 accuracy is 94.0 %.  
For rank equal to 40 accuracy is 94.0 %.  
For rank equal to 41 accuracy is 94.0 %.  
For rank equal to 42 accuracy is 95.0 %.  
For rank equal to 43 accuracy is 94.0 %.  
For rank equal to 44 accuracy is 94.0 %.  
For rank equal to 45 accuracy is 93.0 %.  
For rank equal to 46 accuracy is 95.0 %.  
For rank equal to 47 accuracy is 96.0 %.  
For rank equal to 48 accuracy is 95.0 %.  
For rank equal to 49 accuracy is 95.0 %.  
For rank equal to 50 accuracy is 95.0 %.  
For rank equal to 51 accuracy is 95.0 %.  
For rank equal to 52 accuracy is 94.0 %.  
For rank equal to 53 accuracy is 94.0 %.  
For rank equal to 54 accuracy is 94.0 %.  
For rank equal to 55 accuracy is 94.0 %.  
For rank equal to 56 accuracy is 94.0 %.  
For rank equal to 57 accuracy is 94.0 %.  
For rank equal to 58 accuracy is 95.0 %.  
For rank equal to 59 accuracy is 95.0 %.  
For rank equal to 60 accuracy is 96.0 %.  
For rank equal to 61 accuracy is 95.0 %.  
For rank equal to 62 accuracy is 94.0 %.  
For rank equal to 63 accuracy is 93.0 %.  
For rank equal to 64 accuracy is 94.0 %.  
For rank equal to 65 accuracy is 93.0 %.  
For rank equal to 66 accuracy is 95.0 %.  
For rank equal to 67 accuracy is 94.0 %.  
For rank equal to 68 accuracy is 94.0 %.  
For rank equal to 69 accuracy is 94.0 %.  
For rank equal to 70 accuracy is 96.0 %.  
For rank equal to 71 accuracy is 95.0 %.  
For rank equal to 72 accuracy is 95.0 %.  
For rank equal to 73 accuracy is 96.0 %.  
For rank equal to 74 accuracy is 94.0 %.  
For rank equal to 75 accuracy is 94.0 %.  
For rank equal to 76 accuracy is 94.0 %.  
For rank equal to 77 accuracy is 94.0 %.  
For rank equal to 78 accuracy is 94.0 %.  
For rank equal to 79 accuracy is 93.0 %.  
For rank equal to 80 accuracy is 94.0 %.  
For rank equal to 81 accuracy is 94.0 %.  
For rank equal to 82 accuracy is 94.0 %.  
For rank equal to 83 accuracy is 94.0 %.  
For rank equal to 84 accuracy is 94.0 %.  
For rank equal to 85 accuracy is 94.0 %.  
For rank equal to 86 accuracy is 95.0 %.  
For rank equal to 87 accuracy is 95.0 %.  
For rank equal to 88 accuracy is 94.0 %.  
For rank equal to 89 accuracy is 94.0 %.  
For rank equal to 90 accuracy is 94.0 %.  
For rank equal to 91 accuracy is 95.0 %.  
For rank equal to 92 accuracy is 95.0 %.  
For rank equal to 93 accuracy is 95.0 %.  
For rank equal to 94 accuracy is 95.0 %.  
For rank equal to 95 accuracy is 95.0 %.



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For rank equal to 192 accuracy is 96.0 %.  
For rank equal to 193 accuracy is 96.0 %.  
For rank equal to 194 accuracy is 96.0 %.  
For rank equal to 195 accuracy is 96.0 %.  
For rank equal to 196 accuracy is 96.0 %.  
For rank equal to 197 accuracy is 96.0 %.  
For rank equal to 198 accuracy is 96.0 %.  
For rank equal to 199 accuracy is 96.0 %.
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In [ ]: