

Homework 3 - Dimensionality Reduction

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1 Theory Questions

(a)

Data:

$$\begin{bmatrix} -2 & 1 \\ -5 & -4 \\ -3 & 1 \\ 0 & 3 \\ -8 & 11 \\ -2 & 5 \\ 1 & 0 \\ 5 & -1 \\ -1 & -3 \\ 6 & 1 \end{bmatrix}$$

Calculate mean:

1st column mean:

$$\frac{(-2 + -5 + -3 + 0 + -8 + -2 + 1 + 5 + -1 + 6)}{10} = -0.9$$

2nd column mean:

$$\frac{(1 + -4 + 1 + 3 + 11 + 5 + 0 + -1 + -3 + 1)}{10} = 1.4$$

Calculate Standard Deviation:

1st column std:

$$(-2 + 0.9)^2 + (-5 + 0.9)^2 + (-3 + 0.9)^2 + (0 + 0.9)^2 + (-8 + 0.9)^2 + (-2 + 0.9)^2 + (1 + 0.9)^2 + (5 + 0.9)^2 + (-1 + 0.9)^2 + (6 + 0.9)^2 = 160.90$$

$$std = \sqrt{\frac{160.90}{10 - 1}} = 4.22$$

2nd column std:

$$(1 + 1.4)^2 + (-4 + 1.4)^2 + (1 + 1.4)^2 + (3 + 1.4)^2 + (11 + 1.4)^2 + (5 + 1.4)^2 + (0 + 1.4)^2 + (-1 + 1.4)^2 + (-3 + 1.4)^2 + (1 + 1.4)^2 = 164.40$$

$$std = \sqrt{\frac{164.40}{10 - 1}} = 4.27$$

Standardized matrix = data-mean/std:

$$\begin{bmatrix} -0.2602 & -0.0936 \\ -0.9697 & -1.2635 \\ -0.4967 & -0.0936 \\ 0.2129 & 0.3744 \\ -1.6792 & 2.2462 \\ -0.2602 & 0.8423 \\ 0.4494 & -0.3276 \\ 1.3954 & -0.5615 \\ -0.0237 & -1.0295 \\ 1.6319 & -0.0936 \end{bmatrix}$$

Calculate Covariance Matrix:

$$cov = \frac{w^T w}{N - 1}$$

$$\begin{bmatrix} -0.2602 & -0.9697 & -0.4967 & 0.2129 & -1.6792 & -0.2602 & 0.4494 & 1.3954 & -0.0237 & 1.6319 \\ -0.0936 & -1.2635 & -0.0936 & 0.3744 & 2.2462 & 0.8423 & -0.3276 & -0.5615 & -1.0295 & -0.0936 \end{bmatrix} * \begin{bmatrix} -0.2602 & -0.0936 \\ -0.9697 & -1.2635 \\ -0.4967 & -0.0936 \\ 0.2129 & 0.3744 \\ -1.6792 & 2.2462 \\ -0.2602 & 0.8423 \\ 0.4494 & -0.3276 \\ 1.3954 & -0.5615 \\ -0.0237 & -1.0295 \\ 1.6319 & -0.0936 \end{bmatrix} * \frac{1}{9} =$$

$$\begin{bmatrix} 1 & -0.408 \\ -0.408 & 1 \end{bmatrix}$$

Find Eigenvalues:

$$|A - \lambda I| = 0$$

$$|A - \lambda I| = \begin{vmatrix} a_{11} - \lambda & a_{12} \\ a_{21} & a_{22} - \lambda \end{vmatrix} = (a_{11} - \lambda)(a_{22} - \lambda) - a_{12}a_{21} = \lambda^2 - \lambda(a_{11} + a_{22}) + (a_{11}a_{22} - a_{12}a_{21}) = 0$$

$$\lambda^2 - \lambda(1 + -0.408) + ((1)(-0.408) - (1)(-0.408)) = 0$$

$$\lambda = 0.592, 1.408$$

Find Eigevectors: For each value of λ , solve

$$(A - \lambda I)x = 0$$

$$\begin{aligned} \begin{bmatrix} 1 & -0.408 \\ -0.408 & 1 \end{bmatrix} - \begin{bmatrix} 0.592 & 0 \\ 0 & 0.592 \end{bmatrix} * \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} &= \begin{bmatrix} 0 \\ 0 \end{bmatrix} \\ &= \begin{bmatrix} 1 \\ 1 \end{bmatrix} \\ \begin{bmatrix} 1 & -0.408 \\ -0.408 & 1 \end{bmatrix} - \begin{bmatrix} 1.408 & 0 \\ 0 & 1.408 \end{bmatrix} * \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} &= \begin{bmatrix} 0 \\ 0 \end{bmatrix} \\ &= \begin{bmatrix} -1 \\ 1 \end{bmatrix} \end{aligned}$$

(b)

Largest Eigenvalue = 1.408

$$\begin{bmatrix} -0.2602 & -0.0936 \\ -0.9697 & -1.2635 \\ -0.4967 & -0.0936 \\ 0.2129 & 0.3744 \\ -1.6792 & 2.2462 \\ -0.2602 & 0.8423 \\ 0.4494 & -0.3276 \\ 1.3954 & -0.5615 \\ -0.0237 & -1.0295 \\ 1.6319 & -0.0936 \end{bmatrix} * \begin{bmatrix} -1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.1667 \\ -0.2938 \\ 0.4031 \\ 0.1615 \\ 3.9254 \\ 1.1025 \\ -0.7769 \\ -1.9569 \\ -1.0058 \\ -1.7255 \end{bmatrix}$$

2 Dimensionality Reduction via PCA

```
In [258...
from sklearn.datasets import fetch_lfw_people
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import numpy as np
from math import *
```

```
In [259...
people = fetch_lfw_people(min_faces_per_person=20, resize=0.7)
image_shape = people.images[0].shape
fig,axes = plt.subplots(2, 5, figsize=(15, 8),
                        subplot_kw={'xticks': () , 'yticks': ()})
for target, image, ax in zip(people.target, people.images, axes.ravel()):
    ax.imshow(image, cmap=cm.gray)
    ax.set_title(people.target_names[target])

print(people.images.shape)
print(len(people.target_names))
```



```
In [260...
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
counts = np.bincount(people.target)
for i, (count, name) in enumerate(zip(counts, people.target_names)):
    print('{0:25} {1:3}'.format(name, count), end = ' ')
    if (i+1) % 3 == 0:
        print()
mask = np.zeros(people.target.shape, dtype=bool)
for target in np.unique(people.target):
    mask[np.where(people.target==target)[0][:50]] = 1

X_people = people.data[mask]
y_people = people.target[mask]
X_people = X_people/255
X_train, X_test, y_train, y_test = train_test_split(X_people, y_people,
                                                    stratify=y_people, random_state=0)

knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(X_train,y_train)
```

```
print()
print('Test set score of 1-nn: {:.2f}'.format(knn.score(X_test,y_test)))
```

Alejandro Toledo	39	Alvaro Uribe	35	Amelie Mauresmo	21
Andre Agassi	36	Angelina Jolie	20	Ariel Sharon	77
Arnold Schwarzenegger	42	Atal Bihari Vajpayee	24	Bill Clinton	29
Carlos Menem	21	Colin Powell	236	David Beckham	31
Donald Rumsfeld	121	George Robertson	22	George W Bush	530
Gerhard Schroeder	109	Gloria Macapagal Arroyo	44	Gray Davis	26
Guillermo Coria	30	Hamid Karzai	22	Hans Blix	39
Hugo Chavez	71	Igor Ivanov	20	Jack Straw	28
Jacques Chirac	52	Jean Chretien	55	Jennifer Aniston	21
Jennifer Capriati	42	Jennifer Lopez	21	Jeremy Greenstock	24
Jiang Zemin	20	John Ashcroft	53	John Negroponte	31
Jose Maria Aznar	23	Juan Carlos Ferrero	28	Junichiro Koizumi	60
Kofi Annan	32	Laura Bush	41	Lindsay Davenport	22
Lleyton Hewitt	41	Luiz Inacio Lula da Silva	48	Mahmoud Abbas	29
Megawati Sukarnoputri	33	Michael Bloomberg	20	Naomi Watts	22
Nestor Kirchner	37	Paul Bremer	20	Pete Sampras	22
Recep Tayyip Erdogan	30	Ricardo Lagos	27	Roh Moo-hyun	32
Rudolph Giuliani	26	Saddam Hussein	23	Serena Williams	52
Silvio Berlusconi	33	Tiger Woods	23	Tom Daschle	25
Tom Ridge	33	Tony Blair	144	Vicente Fox	32
Vladimir Putin	49	Winona Ryder	24		
Test set score of 1-nn: 0.23					

In [286...

```
k = 1
i = 0
predictions = []
distances = []

for test in X_test:
    i = 0
    distances = []
    for train in X_train:
        dis = np.sqrt(np.sum((train-test)**2))
        distances.append((dis,y_train[i]))
        i +=1
    l = [x[1] for x in sorted(distances)[:1]]
    labels = {}
    if l[0] not in labels:
        labels[l[0]] = 1
    else:
        labels[l[0]] += 1
    predictions.append(max(labels, key=labels.get))

score = np.sum(predictions == y_test)/len(y_test)
print('1-nn score using personal KNN algo:', score)
```

1-nn score using personal KNN algo: 0.23255813953488372

In [262...

```
m = np.mean(X_train, axis=0)
s = np.std(X_train, axis=0, ddof=1)
sX_train = (X_train-m)/s

sX_test = (X_test-m)/s

cov = (sX_train.T@sX_train)/(len(sX_train)-1)

W,V = np.linalg.eig(cov)
```

In [264...

```
pairs=[(np.abs(W[i]),V[:,i]) for i in range(len(W))]
pairs.sort()
pairs.reverse()
data_pca_100D = np.array([])

data_pca_100D = []

for i in range(0,100):
    data_pca_100D.append(pairs[i][1].reshape(len(pairs[0][1])))
data_pca_100D = np.asarray(data_pca_100D)

data_pca_100D = data_pca_100D.T

new_data = sX_train.dot(data_pca_100D)

Ztest = sX_test.dot(data_pca_100D)
```

In [271...

```
knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(new_data, y_train)
print('Test set 1-nn score using built in KNeighborsClassifier: {:.2f}'.format(knn.score(Ztest,y_test)))

predictions = []
distances = []
dis = 0
l = []

for test in Ztest:
    i = 0
    distances = []
    for train in new_data:
        dis = np.sqrt(np.sum((train-test)**2))
        distances.append((dis,y_train[i]))
        i +=1
    l = [x[1] for x in sorted(distances)[:1]]
    labels = {}
    if l[0] not in labels:
        labels[l[0]] = 1
    else:
        labels[l[0]] += 1
    predictions.append(max(labels, key=labels.get))
```

Test set 1-nn score using built in KNeighborsClassifier: 0.25

In [272...

```
score2 = np.sum(predictions == y_test)/len(y_test)
```

```
print("100D PCA data 1-nn score using personal KNN algo:", score2)

100D PCA data 1-nn score using personal KNN algo: 0.25387596899224807

In [273...
U, s, Vt = np.linalg.svd(sX_train)

In [274...
data_pca_100D = np.asarray(data_pca_100D)

gon = np.diag(1. / np.sqrt(W[:100]))
white = np.dot(np.dot(data_pca_100D, gon), data_pca_100D.T)
x_white = np.dot(sX_train, white)

In [276...
knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(x_white, y_train)
print('Test set score of 1-nn with whitened 100D data using built in KNeighborsClassifier: {:.2f}'.format(knn.score(sX_test,y_test)))
print()

predictions = []
distances2 = []
dis = 0
l = []

for test1 in sX_test:
    distances2 = []
    i = 0
    for train in x_white:
        dis = np.sqrt(np.sum((train-test1)**2))
        distances2.append((dis,y_train[i]))
        i+=1
    l = [x[1] for x in sorted(distances2)[:1]]
    labels = {}
    if l[0] not in labels:
        labels[l[0]] = 1
    else:
        labels[l[0]] += 1
    predictions.append(max(labels, key=labels.get))

score = np.sum(predictions == y_test)/len(y_test)
print("100D PCA whitened data 1-nn score using personal KNN algo:", score)

Test set score of 1-nn with whitened 100D data using built in KNeighborsClassifier: 0.32

100D PCA whitened data 1-nn score using personal KNN algo: 0.32170542635658916

In [277...
pairs=[(np.abs(W[i]),V[:,i]) for i in range(len(W))]
pairs.sort()
pairs.reverse()

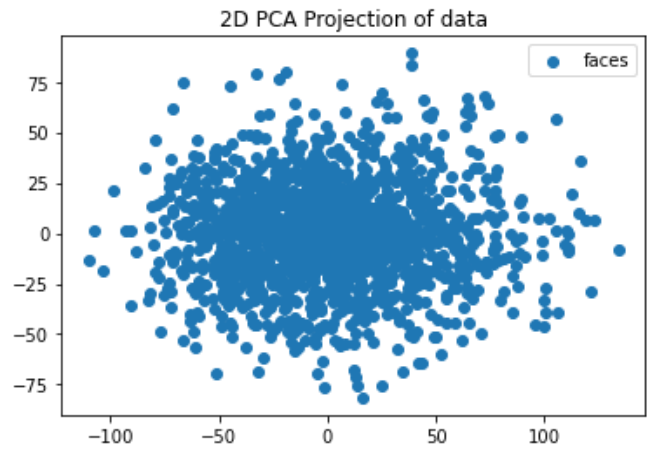
data_pca = np.hstack((pairs[0][1].reshape(len(pairs[0][1]),1), pairs[1][1].reshape(len(pairs[0][1]),1)))

transformed_data = data_pca.T @ sX_train.T
xy_PCA_2D = np.vstack((transformed_data, y_train)).T
```

Part 2: The visualization of the PCA result, KNN accuracies

```
In [279...
plt.scatter(xy_PCA_2D[:,0], xy_PCA_2D[:,1], label="faces")
plt.title("2D PCA Projection of data")
plt.legend()

plt.show()
```



3 Eigenfaces

```
In [281...
indexes = np.argsort(W)[::-1]
vals = W[indexes]
vecs = V[:,indexes]

ppc = vecs[:,0:1]
ppc2 = vecs[:,1:2]

x_hat = sX_train @ ppc[:,0].T
x_hat2 = sX_train @ ppc2[:,0].T

max_pc1 = np.argmax(x_hat)
min_pc1 = np.argmin(x_hat)

max_pc2 = np.argmax(x_hat2)
min_pc2 = np.argmin(x_hat2)

org_people = X_people*225

fullMaxPC1 = org_people[max_pc1]
fullMinPC1 = org_people[min_pc1]
```

```
fullMaxPC2 = org_people[max_pc2]
fullMinPC2 = org_people[min_pc2]

new_img1 = np.reshape(fullMaxPC1, (87,65))
new_img2 = np.reshape(fullMinPC1, (87,65))

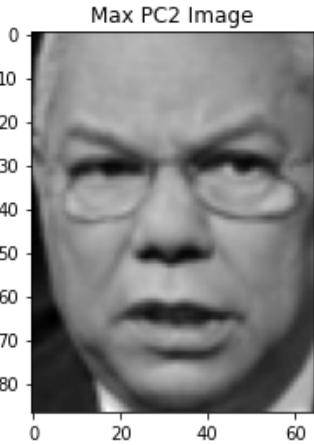
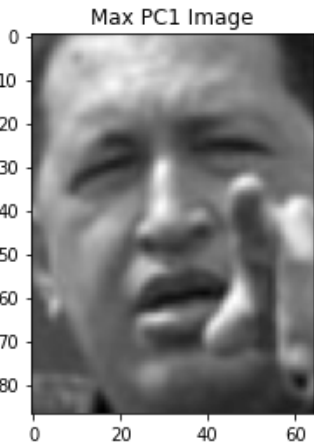
new_img3 = np.reshape(fullMaxPC2, (87,65))
new_img4 = np.reshape(fullMinPC2, (87,65))

plt.imshow(new_img1, cmap=cm.gray)
plt.title('Max PC1 Image')
plt.show()

plt.imshow(new_img2, cmap=cm.gray)
plt.title('Min PC1 Image')
plt.show()

plt.imshow(new_img3, cmap=cm.gray)
plt.title('Max PC2 Image')
plt.show()

plt.imshow(new_img4, cmap=cm.gray)
plt.title('Min PC2 Image')
plt.show()
```



In [282...

```
visual = np.reshape(ppc, (87,65))

zVal = X_train @ ppc

x_hat_reconstruct = zVal @ ppc.T

iml = x_hat_reconstruct[0,:]

alpha = 0.95
n = np.diag(V)
tot = np.sum(abs(n))
check_k = 0

for i in range (0,len(n)):
    check_k = check_k + n[int(indexes[i])]
    if (check_k / tot) >= alpha:
        break
```

```
k = i

components = vecs[:,0:k]

k_z = X_train @ components

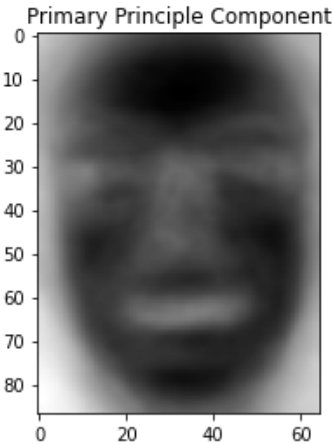
k_x_hat_reconstruct = k_z @ components.T

iml2 = k_x_hat_reconstruct[0,:]
```

i. Visualization of primary principle component

In [283...

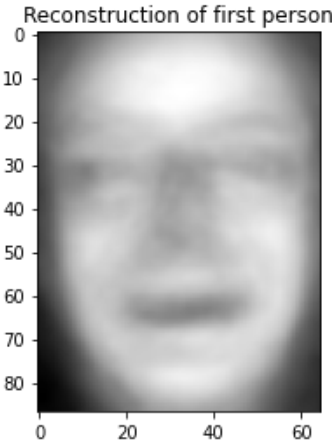
```
plt.imshow(visual, cmap=cm.gray)
plt.title('Primary Principle Component')
plt.show()
```



ii. Number of principle components needed to represent 95% of information, k.

In [284...

```
new_img = np.reshape(iml,(87,65))
plt.imshow(new_img, cmap=cm.gray)
plt.title("Reconstruction of first person")
plt.show()
```



iii. Visualization of the reconstruction of the first person using

In [285...

```
new_img2 = np.reshape(iml2,(87,65))
plt.imshow(new_img2, cmap=cm.gray)
plt.title("95% Reconstruction of first person")
plt.show()
```

