

This homework is done by Tianwei Mo.

1.

a) $[1.5 \ 2.5 \ 3.5]$

b) $\begin{bmatrix} 1.25 & 0.25 & -1.25 \\ 0.25 & 0.75 & 0.75 \\ -1.25 & 0.75 & 2.75 \end{bmatrix}$

c) Eigenvalue = $[3.56166464 \ 1.1733803 \ 0.01495506]$

Eigenvectors =

$$\begin{bmatrix} -0.45056922 & -0.6667717184 & -0.59363515 \\ 0.19247228 & -0.72187235 & 0.66472154 \\ 0.87174641 & -0.18524476 & -0.45358856 \end{bmatrix}$$

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d) PCA coefficients = $\begin{bmatrix} -2.95145599 & -0.17610969 & -0.0888421 \\ 1.37104342 & -1.69406159 & 0.0198819 \\ -0.30682473 & 0.78694448 & 0.19125108 \\ 1.8872373 & 1.0832268 & -0.12229089 \end{bmatrix}$

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e) $\hat{X} = \begin{bmatrix} 3.0000000e+00 & 2.0000000e+00 & 1.0000000e+00 \\ 2.0000000e+00 & 4.0000000e+00 & 5.0000000e+00 \\ 1.0000000e+00 & 2.0000000e+00 & 3.0000000e+00 \\ 4.4408921e-16 & 2.0000000e+00 & 5.0000000e+00 \end{bmatrix}$

$$\begin{bmatrix} 2.0000000e+00 & 4.0000000e+00 & 5.0000000e+00 \\ 1.0000000e+00 & 2.0000000e+00 & 3.0000000e+00 \\ 4.4408921e-16 & 2.0000000e+00 & 5.0000000e+00 \end{bmatrix}$$

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$$\begin{bmatrix} 4.4408921e-16 & 2.0000000e+00 & 5.0000000e+00 \end{bmatrix}$$

f) $\hat{X} = \begin{bmatrix} 2.05905526 & 0.95970224 \\ 3.98678407 & 5.0090182 \\ 1.87287129 & 3.0867493 \\ 2.08128939 & 4.94453025 \end{bmatrix}$

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g) $e = 0.014955061432806003$

python code:

```

5  x = np.array([
6      [3, 2, 1],
7      [2, 4, 5],
8      [1, 2, 3],
9      [0, 2, 5],
10 ])
11 mean = np.mean(x, axis=0)
12 cov = np.zeros((3, 3))
13 for i in range(3):
14     for j in range(3):
15         for n in range(4):
16             cov[i, j] += (x[n, i] - mean[i]) * (x[n, j] - mean[j])
17 cov = cov / 4
18 eigvalue, eigvector = np.linalg.eig(cov)
19
20 Z = (x - mean).dot(eigvector)
21
22 xhat = Z.dot(eigvector.T) + mean
23
24 Z_2 = Z[:, :2].dot(eigvector[:, :2].T) + mean
25
26 e1 = np.mean(np.sum((Z_2 - x) ** 2, axis=1))
27 # print(mean)
28 print(cov)
29 print(eigvalue, eigvector)
30 print(Z)
31 print(xhat)
32 print(Z_2)
33 print(e1, eigvalue[-1])
34

```

2.

- a) $x-u = [1, 3, 2]$
 $a_1 = v_1^T * (x-u) = 4/\sqrt{2}$
 $a_2 = v_2^T * (x-u) = -2/\sqrt{2}$
- b) Approximation = $u + a_1 v_1 + a_2 v_2 = [1, 0, 2] + [2, 2, 0] + [-1, 1, 0] = [2, 3, 2]$
- c) $\|x - \hat{x}\|^2 = 4$

3. The python code:

```

1  import numpy as np
2  from sklearn.decomposition import PCA
3  from sklearn.preprocessing import StandardScaler
4  from sklearn.linear_model import LogisticRegression
5  from sklearn.model_selection import KFold
6  X = np.zeros(3, 5)
7  y = np.zeros(3)
8
9  nfold = 4
10
11 # Create a K-fold object
12 kf = KFold(n_splits=nfold)
13 kf.get_n_splits(X)
14
15 # Number of PCs to try
16 ncomp_test = np.arange(2,12)
17 num_nc = len(ncomp_test)
18
19 # Accuracy: acc[icomp,ifold] is test accuracy when using `ncomp = ncomp_test[icomp]` in fold `ifold`.
20 acc = np.zeros((num_nc,nfold))
21
22 # Loop over number of components to test
23 for icomp, ncomp in enumerate(ncomp_test):
24
25     # Look over the folds
26     for ifold, I in enumerate(kf.split(X)):
27         Itr, Its = I
28
29         # Split data into training
30         Xtr, Xts, ytr, yts = X[Itr], X[Its], y[Itr], y[Its]
31
32         # Create a scaling object and fit the scaling on the training data
33         scaling = StandardScaler()
34         scaling.fit(Xtr, ytr)
35
36         # Fit the PCA on the scaled training data
37         Xtrs = scaling.transform(Xtr)
38         pca = PCA(n_components=ncomp, svd_solver='randomized', whiten=True)
39         pca.fit(Xtrs, ytr)
40         Ztr = pca.transform(Xtrs)
41
42         # Train a classifier on the transformed training data
43         # Use a Logistic regression classifier
44         logreg = LogisticRegression(multi_class='auto', solver='lbfgs')
45
46         # Transform the test data through data scaler and PCA
47         Xtss = scaling.transform(Xts)
48         pca.fit(Xtss, yts)
49         Zts = pca.transform(Xtss)
50
51         # Predict the Labels the test data
52         logreg.fit(Ztr, ytr)
53         yhat = logreg.predict(Zts)
54
55         # Measure the accuracy
56         acc[icomp, ifold] = np.mean(yhat == yts)
57
58 acc_mean = np.mean(acc, axis=1)
59 optimal_index = np.argmax(acc_mean)
60 optimal_order = ncomp_test[optimal_index]
61
62 # Measure the accuracy
63 acc[icomp, ifold] = np.mean(yhat == yts)
64
65 acc_mean = np.mean(acc, axis=1)
66 optimal_index = np.argmax(acc_mean)
67 optimal_order = ncomp_test[optimal_index]
68 print('optimal normal order is {}'.format(optimal_order, acc_mean[optimal_order]))

```

```

1  import numpy as np
2  from sklearn.decomposition import PCA
3  import matplotlib.pyplot as plt
4
5  def plt_face(x):
6      h = 50
7      w = 37
8      plt.imshow(x.reshape((h, w)), cmap=plt.cm.gray)
9      plt.xticks([])
10     plt.yticks([])
11
12     X = np.arange(1000 * 28 * 28).reshape(1000, 28, 28)
13     Y = np.reshape(X, (1000, 28*28))
14
15     Y = Y[:500, :]
16     nc = 100
17
18     pca = PCA(n_components=nc)
19     pca.fit(Y)
20     Z = pca.transform(Y)
21     Yhat = pca.inverse_transform(Z)
22     plt_face(Yhat)
23
24

```

5. The python function:

```

6  scaling = StandardScaler()
7  scaling.fit(X)
8  Z = scaling.transform(X)
9
10 U, S, Vtr = svd(Z, full_matrices = False)
11
12 # i)
13 PCs = Vtr
14 mean = np.mean(X, axis=0)
15
16 # ii)
17 PoV_len = S.shape[0]
18 lam = S**2
19 PoV = np.cumsum(lam)/np.sum(lam)
20 min_PoV = np.min(np.where(PoV >= 0.9)) + 1
21
22 # iii)
23 Z = U[:, :min_PoV]*S[None, :min_PoV]
24 W = PCs[:min_PoV, :]
25 print(Z.shape)
26 Xhat = mean + Z.dot(W)

```