UCS2612 Machine Learning Laboratory

A9. Applications of dimensionality reduction techniques

ANANDH K

3122 21 5001 009

CSE-A

Description

The two datasets are related to red and white variants of the Portuguese "Vinho Verde" wine. For more details, consult: http://www.vinhoverde.pt/en/ or the reference [Cortez et al., 2009]. Due to privacy and logistic issues, only physicochemical (inputs) and sensory (the output) variables are available (e.g. there is no data about grape types, wine brand, wine selling price, etc.). These datasets can be viewed as classification or regression tasks. The classes are ordered and not balanced (e.g. there are many more normal wines than excellent or poor ones). Outlier detection algorithms could be used to detect the few excellent or poor wines. Also, we are not sure if all input variables are relevant. So it could be interesting to test feature selection methods. The data can be used to test (ordinal) regression or classification (in effect, this is a multi-class task, where the clases are ordered) methods. Other research issues are feature selection and outlier detection. The data includes two datasets:

- winequality-red.csv - red wine preference samples;
- winequality-white.csv - white wine preference samples;

Aim

Develop a python program to perform dimensionality reduction using PCA and LDA. Visualize the features from the dataset and interpret the results obtained by the model using Matplotlib library.

Dataset:- http://www3.dsi.uminho.pt/pcortez/wine/winequality.zip

Import libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.model_selection import train_test_split
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
import numpy as np
import matplotlib.pyplot as plt
```

Load dataset

```
# importing or loading the dataset
data1 = pd.read_csv('C:/Users/ashwi/Downloads/ML
Lab/A9/winequality/winequality-white.csv', sep=";")

data1.head()
```

```
   fixed acidity volatile acidity citric acid residual sugar
chlorides \
0            7.0              0.27         0.36            20.7
0.045
1            6.3              0.30         0.34             1.6
0.049
2            8.1              0.28         0.40             6.9
0.050
3            7.2              0.23         0.32             8.5
0.058
4            7.2              0.23         0.32             8.5
0.058

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates
\
0                 45.0                 170.0   1.0010  3.00       0.45

1                 14.0                 132.0   0.9940  3.30       0.49
```

```
2                 30.0                    97.0   0.9951  3.26       0.44

3                 47.0                   186.0   0.9956  3.19       0.40

4                 47.0                   186.0   0.9956  3.19       0.40
```

```
   alcohol  quality
0      8.8        6
1      9.5        6
2     10.1        6
3      9.9        6
4      9.9        6
```

```
data1.describe()
```

```
      fixed acidity  volatile acidity  citric acid  residual sugar \
count   4898.000000       4898.000000  4898.000000     4898.000000
mean       6.854788          0.278241     0.334192        6.391415
std        0.843868          0.100795     0.121020        5.072058
min        3.800000          0.080000     0.000000        0.600000
25%        6.300000          0.210000     0.270000        1.700000
50%        6.800000          0.260000     0.320000        5.200000
75%        7.300000          0.320000     0.390000        9.900000
max       14.200000          1.100000     1.660000       65.800000

        chlorides  free sulfur dioxide  total sulfur dioxide
density  \
count  4898.000000          4898.000000           4898.000000
4898.000000
mean      0.045772            35.308085            138.360657
0.994027
std       0.021848            17.007137             42.498065
0.002991
min       0.009000             2.000000              9.000000
0.987110
25%       0.036000            23.000000            108.000000
0.991723
50%       0.043000            34.000000            134.000000
0.993740
75%       0.050000            46.000000            167.000000
0.996100
max       0.346000           289.000000            440.000000
1.038980

                pH    sulphates      alcohol      quality
count  4898.000000  4898.000000  4898.000000  4898.000000
mean      3.188267     0.489847    10.514267     5.877909
std       0.151001     0.114126     1.230621     0.885639
```

min	2.720000	0.220000	8.000000	3.000000
25%	3.090000	0.410000	9.500000	5.000000
50%	3.180000	0.470000	10.400000	6.000000
75%	3.280000	0.550000	11.400000	6.000000
max	3.820000	1.080000	14.200000	9.000000

Data pre-processing

```
data1.corr()
```

	fixed acidity	volatile acidity	citric acid \
fixed acidity	1.000000	-0.022697	0.289181
volatile acidity	-0.022697	1.000000	-0.149472
citric acid	0.289181	-0.149472	1.000000
residual sugar	0.089021	0.064286	0.094212
chlorides	0.023086	0.070512	0.114364
free sulfur dioxide	-0.049396	-0.097012	0.094077
total sulfur dioxide	0.091070	0.089261	0.121131
density	0.265331	0.027114	0.149503
pH	-0.425858	-0.031915	-0.163748
sulphates	-0.017143	-0.035728	0.062331
alcohol	-0.120881	0.067718	-0.075729
quality	-0.113663	-0.194723	-0.009209

	residual sugar	chlorides	free sulfur dioxide \
fixed acidity	0.089021	0.023086	-0.049396
volatile acidity	0.064286	0.070512	-0.097012
citric acid	0.094212	0.114364	0.094077
residual sugar	1.000000	0.088685	0.299098
chlorides	0.088685	1.000000	0.101392
free sulfur dioxide	0.299098	0.101392	1.000000
total sulfur dioxide	0.401439	0.198910	0.615501
density	0.838966	0.257211	0.294210
pH	-0.194133	-0.090439	-0.000618
sulphates	-0.026664	0.016763	0.059217
alcohol	-0.450631	-0.360189	-0.250104
quality	-0.097577	-0.209934	0.008158

```
                              total sulfur dioxide   density        pH  
sulphates  \
fixed acidity                             0.091070  0.265331 -0.425858  -
0.017143
volatile acidity                          0.089261  0.027114 -0.031915  -
0.035728
citric acid                               0.121131  0.149503 -0.163748  
0.062331
residual sugar                            0.401439  0.838966 -0.194133  -
0.026664
chlorides                                 0.198910  0.257211 -0.090439  
0.016763
free sulfur dioxide                       0.615501  0.294210 -0.000618  
0.059217
total sulfur dioxide                      1.000000  0.529881  0.002321  
0.134562
density                                   0.529881  1.000000 -0.093591  
0.074493
pH                                        0.002321 -0.093591  1.000000  
0.155951
sulphates                                 0.134562  0.074493  0.155951  
1.000000
alcohol                                  -0.448892 -0.780138  0.121432  -
0.017433
quality                                  -0.174737 -0.307123  0.099427  
0.053678

                       alcohol   quality
fixed acidity        -0.120881 -0.113663
volatile acidity      0.067718 -0.194723
citric acid          -0.075729 -0.009209
residual sugar       -0.450631 -0.097577
chlorides            -0.360189 -0.209934
free sulfur dioxide  -0.250104  0.008158
total sulfur dioxide -0.448892 -0.174737
density              -0.780138 -0.307123
pH                    0.121432  0.099427
sulphates            -0.017433  0.053678
alcohol               1.000000  0.435575
quality               0.435575  1.000000
```

```
data1.dropna(inplace=True)

scaler_standard = StandardScaler()
data1_standardized = scaler_standard.fit_transform(data1)

scaler_normal = MinMaxScaler()
data1_normalized = scaler_normal.fit_transform(data1)
```

```
data1_standardized = pd.DataFrame(data1_standardized,
columns=data1.columns)
data1_normalized = pd.DataFrame(data1_normalized,columns=data1.columns)

data1_standardized.head()

   fixed acidity  volatile acidity  citric acid  residual sugar
chlorides  \
0       0.172097         -0.081770     0.213280        2.821349  -
0.035355
1      -0.657501          0.215896     0.048001       -0.944765
0.147747
2       1.475751          0.017452     0.543838        0.100282
0.193523
3       0.409125         -0.478657    -0.117278        0.415768
0.559727
4       0.409125         -0.478657    -0.117278        0.415768
0.559727

   free sulfur dioxide  total sulfur dioxide    density        pH
sulphates \
0             0.569932              0.744565  2.331512 -1.246921  -
0.349184
1            -1.253019             -0.149685 -0.009154  0.740029
0.001342
2            -0.312141             -0.973336  0.358665  0.475102  -
0.436816
3             0.687541              1.121091  0.525855  0.011480  -
0.787342
4             0.687541              1.121091  0.525855  0.011480  -
0.787342

    alcohol  quality
0 -1.393152  0.13787
1 -0.824276  0.13787
2 -0.336667  0.13787
3 -0.499203  0.13787
4 -0.499203  0.13787

data1_normalized.head()

   fixed acidity volatile acidity citric acid residual sugar
chlorides \
0       0.307692          0.186275     0.216867        0.308282
0.106825
1       0.240385          0.215686     0.204819        0.015337
0.118694
2       0.413462          0.196078     0.240964        0.096626
0.121662
```

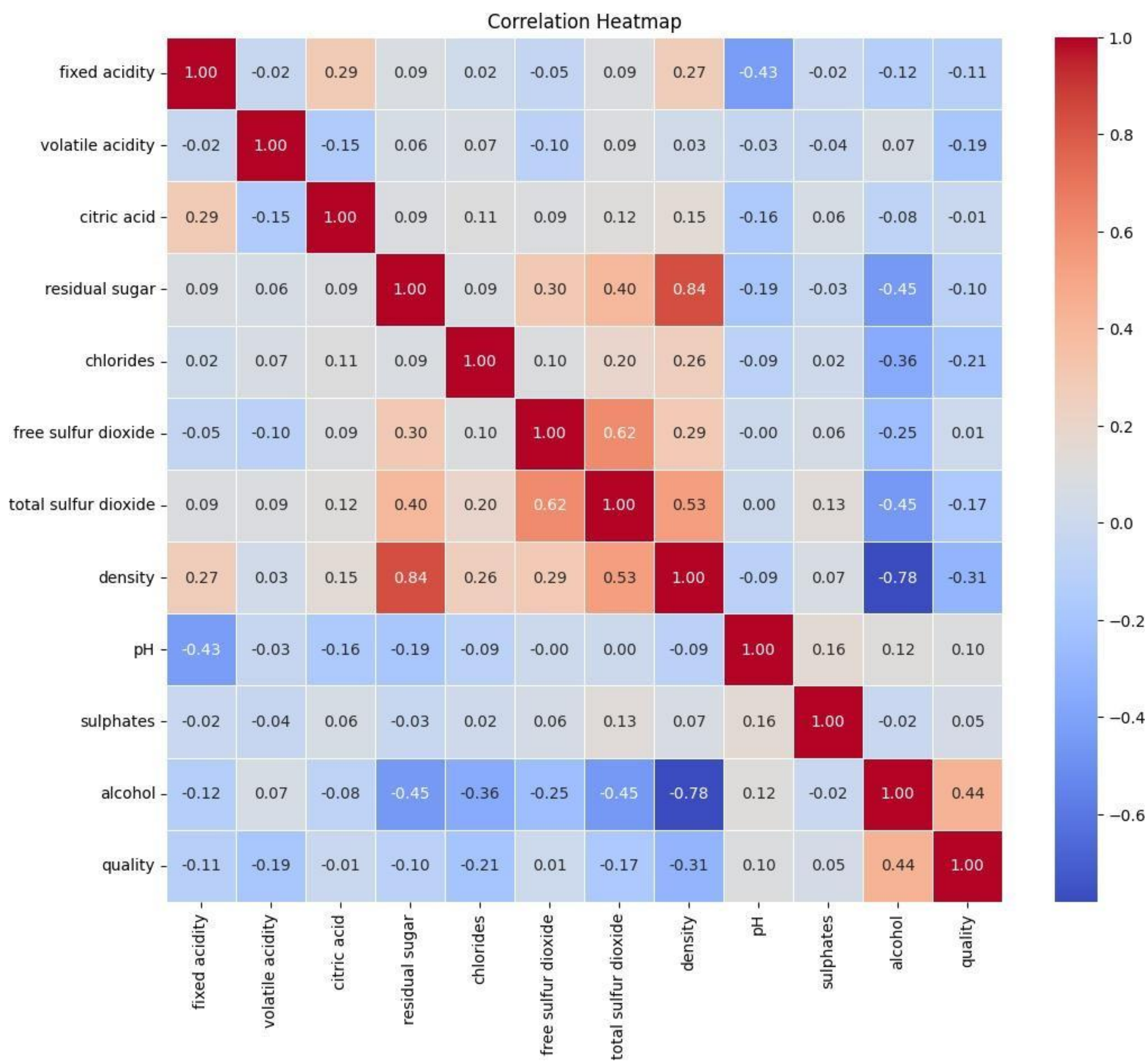
```
3        0.326923           0.147059      0.192771         0.121166
0.145401
4        0.326923           0.147059      0.192771         0.121166
0.145401

   free sulfur dioxide  total sulfur dioxide   density         pH
sulphates \
0              0.149826              0.373550  0.267785  0.254545
0.267442
1              0.041812              0.285383  0.132832  0.527273
0.313953
2              0.097561              0.204176  0.154039  0.490909
0.255814
3              0.156794              0.410673  0.163678  0.427273
0.209302
4              0.156794              0.410673  0.163678  0.427273
0.209302

    alcohol  quality
0  0.129032      0.5
1  0.241935      0.5
2  0.338710      0.5
3  0.306452      0.5
4  0.306452      0.5
```

EDA

```
plt.figure(figsize=(12, 10))
sns.heatmap(data1.corr(), annot=True, cmap='coolwarm', fmt='.2f',
linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```



Splitting the data into Testing and training

```
X_white = data1.iloc[:, 0:11].values
y_white = data1.iloc[:, 11].values

X_train_white, X_test_white, y_train_white, y_test_white =
train_test_split(X_white,y_white, test_size=0.2, random_state=0)
```

Feature selection and preprocessing

```
# performing preprocessing part
from sklearn.preprocessing import StandardScaler
```

```
sc = StandardScaler()

X_train_white = sc.fit_transform(X_train_white)
X_test_white = sc.transform(X_test_white)
```

Model building(PCA)

```
from sklearn.decomposition import PCA

PCa = PCA (n_components = 2)

X_train_white = PCa.fit_transform(X_train_white)
X_test_white = PCa.transform(X_test_white)

explained_variance = PCa.explained_variance_ratio_

from sklearn.linear_model import LogisticRegression
classifier_1 = LogisticRegression(random_state = 0)
classifier_1.fit(X_train_white, y_train_white)
```

```
LogisticRegression(random_state=0)
```

```
y_pred_white = classifier_1.predict(X_test_white)

from sklearn.metrics import confusion_matrix as CM
c_m_white = CM(y_test_white, y_pred_white)
print(c_m_white)
accuracy_score(y_test_white,y_pred_white)
```

```
[[  0   0   2   7   0   0]
 [  0   0  10  38   3   0]
 [  0   0  77 216   2   0]
 [  0   0  67 338   4   0]
 [  0   0  16 161   6   0]
 [  0   0   1  32   0   0]]
```

```
0.42959183673469387
```

```
print("Accuracy score of PCA model is " ,
accuracy_score(y_test_white,y_pred_white))
```

```
Accuracy score of PCA model is  0.42959183673469387
```

Result of PCA

```
# result through scatter plot
from matplotlib.colors import ListedColormap
```

```
X_set, y_set = X_train_white, y_train_white
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 1,
                     stop = X_set[:, 0].max() + 1, step = 0.01),
                     np.arange(start = X_set[:, 1].min() - 1,
                     stop = X_set[:, 1].max() + 1, step = 0.01))

plt.contourf(X1, X2, classifier_1.predict(np.array([X1.ravel(),
             X2.ravel()]).T).reshape(X1.shape), alpha = 0.75,
             cmap = ListedColormap(('yellow', 'white', 'aquamarine')))

plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())

for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
                c = ListedColormap(('red', 'green', 'blue'))(i), label
= j)

plt.title('Logistic Regression (Training set)')
plt.xlabel('PC1') # for Xlabel
plt.ylabel('PC2') # for Ylabel
plt.legend() # to show legend

# show scatter plot
plt.show()

# Visualising the Test set results through scatter plot
from matplotlib.colors import ListedColormap

X_set, y_set = X_test_white, y_test_white

X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 1,
                     stop = X_set[:, 0].max() + 1, step = 0.01),
                     np.arange(start = X_set[:, 1].min() - 1,
                     stop = X_set[:, 1].max() + 1, step = 0.01))

plt.contourf(X1, X2, classifier_1.predict(np.array([X1.ravel(),
             X2.ravel()]).T).reshape(X1.shape), alpha = 0.75,
             cmap = ListedColormap(('yellow', 'white', 'aquamarine')))


plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())

for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
                c = ListedColormap(('red', 'green', 'blue'))(i), label
= j)

# title for scatter plot
```

```
plt.title('Logistic Regression (Test set)')
plt.xlabel('PC1') # for Xlabel
plt.ylabel('PC2') # for Ylabel
plt.legend()

# show scatter plot
plt.show()
```

Model building(LDA)

```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
as LDA
lda = LDA(n_components = 2)
X_train_red = lda.fit_transform(X_train_white, y_train_white)
X_test_red = lda.transform(X_test_white)

from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train_white, y_train_white)

y_pred_white = classifier_1.predict(X_test_white)
print(y_pred_white)

accuracy = accuracy_score(y_test_white, y_pred_white)
print("Accuracy of LDA model:", accuracy)

Accuracy of LDA model: 0.42959183673469387
```

Result of LDA

```
from matplotlib.colors import ListedColormap
X_set, y_set = X_test_white, y_test_white

X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 1, stop =
X_set[:, 0].max() + 1, step = 0.01), np.arange(start = X_set[:,
1].min() - 1, stop = X_set[:, 1].max() + 1, step = 0.01))

plt.contourf(X1,X2,classifier.predict(np.array([X1.ravel(),X2.ravel()]
).T).reshape(X1.shape), alpha = 0.75, cmap = ListedColormap(('red',
'green', 'blue')))

plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())

for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
                c = ListedColormap(('red', 'green', 'blue'))(i), label
```

```
= j)

plt.title('Logistic Regression (Test set)')plt.xlabel('LD1')
plt.ylabel('LD2')
plt.legend()
plt.show()

from matplotlib.colors import ListedColormap
X_set, y_set = X_train_white, y_train_white

X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 1, stop =
X_set[:, 0].max() + 1, step = 0.01), np.arange(start = X_set[:,
1].min() - 1, stop = X_set[:, 1].max() + 1, step = 0.01))

plt.contourf(X1,X2,classifier.predict(np.array([X1.ravel(),X2.ravel()]
).T).reshape(X1.shape), alpha = 0.75, cmap = ListedColormap(('red',
'green', 'blue')))

plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())

for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
                c = ListedColormap(('red', 'green', 'blue'))(i), label
= j)

plt.title('Logistic Regression (Training set)')
plt.xlabel('LD1')
plt.ylabel('LD2')
plt.legend()
plt.show()
```

Inferences

1. After applying PCA, you can analyze the principal components to understand which original features contribute the most to the variance in the data. You can also visualize the data in reduced dimensions to explore patterns or clusters.

2. After applying LDA, you can interpret the learned linear discriminants to understand how the classes are separated in the reduced-dimensional space. LDA provides insight into which features are most discriminative for class separation.

Learning Outcomes

1. Implementation of Pre-processing, EDA and feature selection.
2. Implementation of PCA nad LDA models and visualising it.

3. Displaying the confusion matrix.
4. Understanding the techniques of dimentionality reduction.

GITHUB LINK :
https://github.com/Anandh-007/Machine-learning-lab/tree/main/ML_A9