Silas_hw1_submission

February 5, 2023

1 Homework Assignment 1

[1]:
```
# import necessary packages
import numpy as np
from numpy import set_printoptions
import pandas as pd
from pandas import read_csv
import matplotlib.pyplot as plt
from matplotlib import colors
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
from sklearn.decomposition import PCA
from sklearn.ensemble import ExtraTreesClassifier

# reading csv data file
df = read_csv("myClassDataSet.csv")

# data prep
array = df.values
data = array[:,0:8]
target = array[:,8]
```

1.1 Problem 1

1.1.1 (a)

[2]:
```
# shows first 10 rows
df.head(10)
```

[2]:

	f1	f2	f3	f4	f5	f6	f7	\
0	3.125845	4.213543	2.786926	0.832175	-1.178735	3.581140	-2.352872	
1	2.092247	3.383249	0.434993	2.003855	-2.525389	2.231663	-1.043635	
2	1.028549	3.944043	0.059291	0.011443	-1.309637	1.272289	-1.005366	
3	1.331028	4.920674	2.063895	1.424668	-1.073122	1.088142	-1.211250	

```
4   0.699447  5.427693  1.881804  0.387634 -0.134386  3.955468 -1.229464
5   0.694695  3.714401  2.500049  1.920056 -2.025116  2.486468 -1.527237
6  10.504756 -2.354584  5.086298  0.726694  1.799039  8.895587 -7.030143
7   8.694552 -3.626823  6.653397  1.042575  2.567122  8.436418 -8.355885
8   0.351243  3.913395  2.167825  0.242119 -1.459387  3.695486 -1.283999
9   9.101069 -1.121785  5.898558 -0.485882  1.281704  7.984437 -8.119064

         f8  class
0  7.804524      0
1  7.149358      0
2  7.434625      0
3  8.603362      0
4  7.241683      0
5  8.365294      0
6 -8.983998      1
7 -8.235446      1
8  8.171476      0
9 -8.656581      1
```

[3]:
```
# shows shape in (rows,columns) or (data points, features) format
df.shape
```

[3]:
```
(1000, 9)
```

1.1.2 (b)

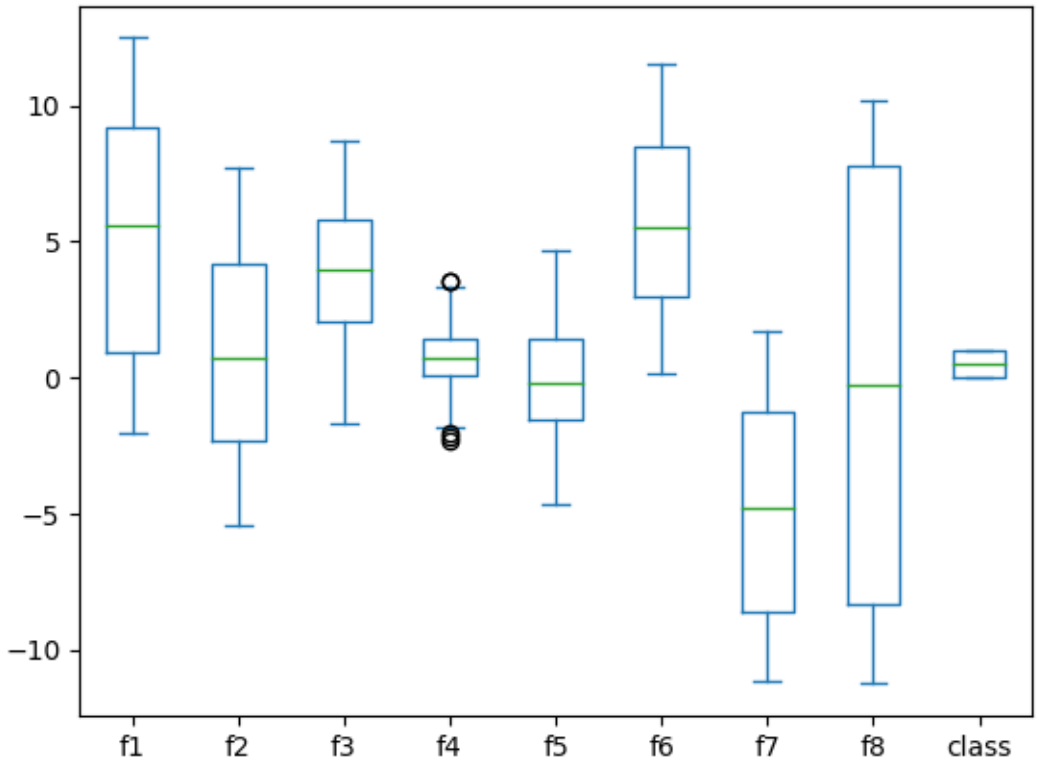
[4]:
```
# display summary of data
pd.set_option("display.precision",4)
pd.set_option("display.width",200)
df.describe()
```

[4]:
```
                f1          f2          f3          f4          f5          f6
f7          f8       class
count   1000.0000   1000.0000   1000.0000   1000.0000   1000.0000   1000.0000
1000.0000   1000.0000   1000.0000
mean       5.1092      0.9219      3.9443      0.7502     -0.0855      5.7543
-4.9722     -0.2408      0.5000
std        4.2549      3.4461      2.1666      0.9963      1.7942      2.9325
3.7644      8.1029      0.5003
min       -2.0302     -5.4004     -1.6848     -2.3146     -4.6438      0.1782
-11.1596    -11.2649      0.0000
25%        0.9464     -2.3457      2.0561      0.0705     -1.5427      2.9813
-8.5976     -8.3088      0.0000
50%        5.5619      0.7030      3.9986      0.7154     -0.1841      5.5234
-4.7716     -0.2441      0.5000
75%        9.2131      4.1889      5.8355      1.4289      1.4234      8.5120
-1.2924      7.7789      1.0000
```

```
max       12.4851     7.7313     8.6763     3.5604     4.6536     11.5151
1.6808    10.1751     1.0000
```

1.1.3 (c)

[5]:
```
# creates boxplot of features
df.plot(kind='box')
plt.show()
```



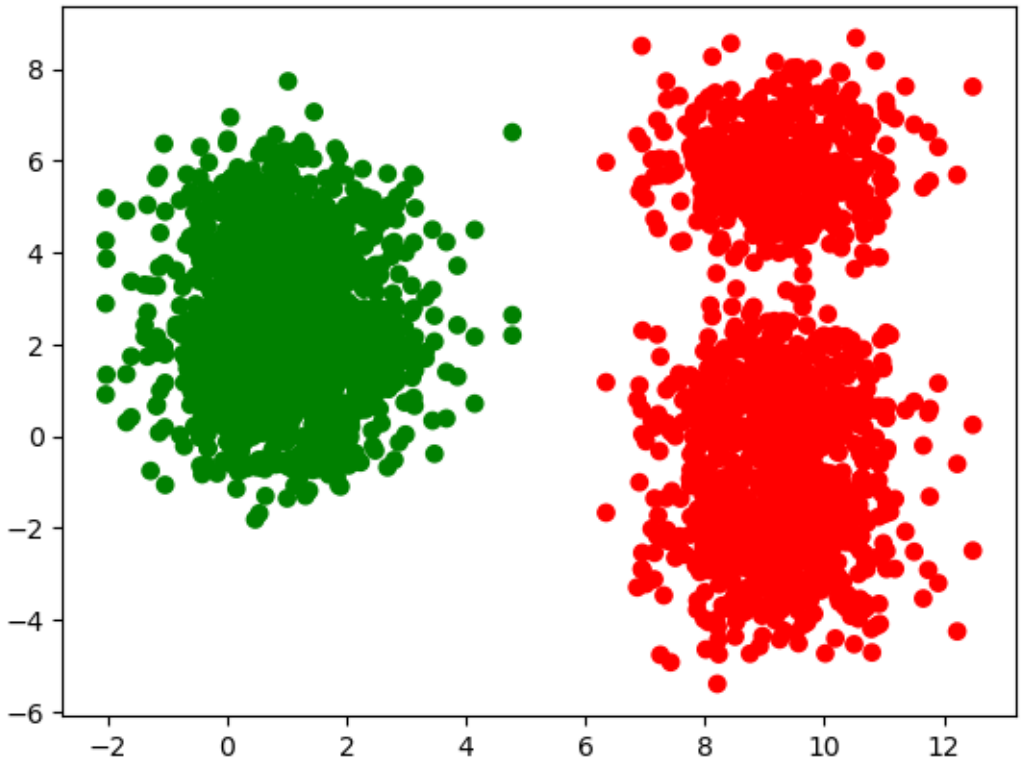
The boxplots above show fairly symmetric distribution in all of the features except for feature 4. Feature 4 clearly shows the presence of outliers on both the upper and lower ends. Far more outliers are present on the lower end and could represent a skew as well.

1.1.4 (d)

[6]:
```
# set up colors for color map
cmap = colors.ListedColormap(['green', 'red'])

# plotting the three feature pairs and output
plt.scatter(df.f1,df.f2,c=target,cmap=cmap)
plt.scatter(df.f1,df.f3,c=target,cmap=cmap)
plt.scatter(df.f1,df.f4,c=target,cmap=cmap)
```

```
plt.show()
```

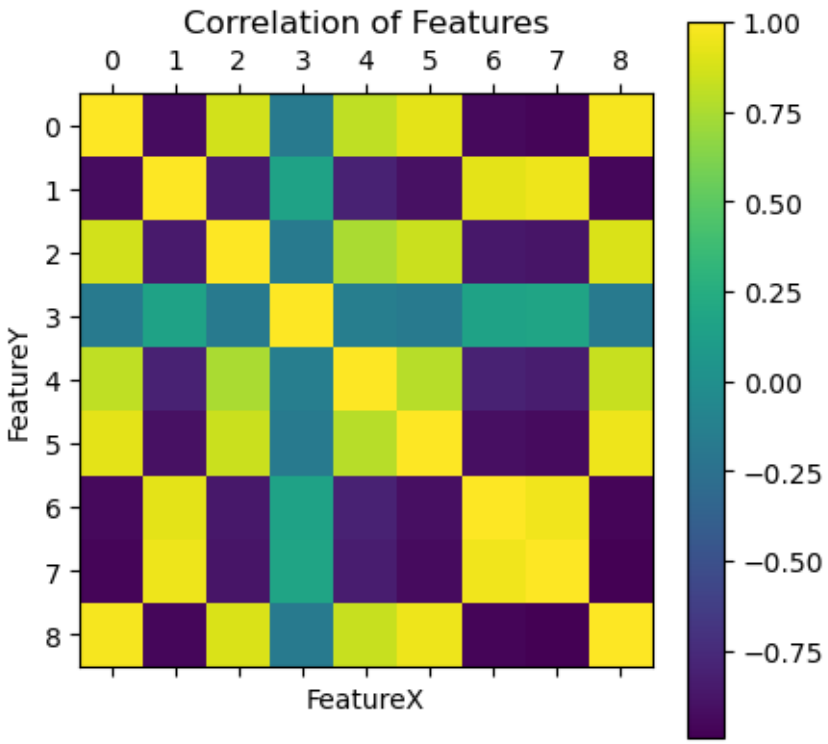


In the figure above, green represents a class value of 0 and red represents a class value of 1.

1.1.5 (e)

[7]:
```
# correlation matrix and plotting
plt.matshow(df.corr())
plt.title("Correlation of Features")
plt.xlabel("FeatureX")
plt.ylabel("FeatureY")
plt.colorbar()

plt.show()
```



1.2 Problem 2

1.2.1 (a)

[8]:
```
# set and use Standard Scaler to transform our data
scaler = StandardScaler()
preparedData = scaler.fit_transform(data)

# print data output
np.set_printoptions(precision = 3)
print(preparedData[:7])
```

```
[[-0.466  0.956 -0.534  0.082 -0.61  -0.741  0.696  0.993]
 [-0.709  0.715 -1.621  1.259 -1.361 -1.202  1.044  0.912]
 [-0.96   0.877 -1.794 -0.742 -0.683 -1.529  1.054  0.948]
 [-0.888  1.161 -0.868  0.677 -0.551 -1.592  1.     1.092]
 [-1.037  1.308 -0.952 -0.364 -0.027 -0.614  0.995  0.924]
 [-1.038  0.811 -0.667  1.175 -1.082 -1.115  0.916  1.063]
 [ 1.269 -0.951  0.527 -0.024  1.051  1.072 -0.547 -1.08 ]]
```

1.2.2 (b)

[9]:
```
# split our data into training and test sets
X_train, X_test, Y_train, Y_test = train_test_split(preparedData, target,␣
 ↪test_size = 0.2)

# shows the first rows of our training set
np.set_printoptions(precision = 3)
print(X_train[0:3])
```

```
[[ 1.077 -0.646  0.492  0.085  0.411  0.889 -1.124 -1.007]
 [-0.988  1.479 -1.216 -0.682 -0.859 -1.194  1.289  0.864]
 [-0.876  1.331 -0.804 -0.833 -0.313 -0.751  1.134  1.086]]
```

[10]:
```
# SelectKBest
kBestData = SelectKBest(score_func=f_classif,k=6).fit_transform(X_train,␣
 ↪Y_train)

# shows the chosen top 6 features
np.set_printoptions(precision = 3)
print(kBestData[0:6])
```

```
[[ 1.077 -0.646  0.492  0.889 -1.124 -1.007]
 [-0.988  1.479 -1.216 -1.194  1.289  0.864]
 [-0.876  1.331 -0.804 -0.751  1.134  1.086]
 [ 1.232 -1.351  1.108  1.41  -0.598 -0.913]
 [ 0.939 -0.593  0.902  0.761 -0.836 -1.039]
 [ 0.955 -1.101  0.283  1.151 -0.922 -0.927]]
```

From comparing the arrays, we can tell that features 1,2,3,6,7, & 8 are the top 6 features.

1.2.3 (c)

[11]:
```
# split our data into training and test sets
X_train, X_test, Y_train, Y_test = train_test_split(preparedData, target,␣
 ↪test_size = 0.2)

# RFE w/ Regression
regressionData = RFE(estimator=LogisticRegression(), n_features_to_select=6)
regressionData = regressionData.fit(X_train, Y_train)

# print n_features_,support_, and ranking_
print(regressionData.n_features_)
print(regressionData.support_)
print(regressionData.ranking_)
```

```
6
[ True  True  True False False  True  True  True]
[1 1 1 3 2 1 1 1]
```

In this case, features 1,2,3,6,7,& 8 were chosen as the top 6 features with 5 being considered higher than 4 after that.

1.2.4 (d)

[12]:
```
# PCA
pca = PCA(n_components=2)
pcaData = pca.fit_transform(preparedData)

# print explained_variance_ratio_
print(pca.explained_variance_ratio_)
```

```
[0.788 0.121]
```

78.8% of the variance is explained by feature 1 and 12.1% is explained by feature 2

1.2.5 (e)

[13]:
```
# ExtraTreesClassifier
extraTrees = ExtraTreesClassifier(n_estimators=8)
extraTrees.fit(X_train,Y_train)

# print feature_importances_
print(extraTrees.feature_importances_)
```

```
[0.312 0.22  0.061 0.    0.005 0.01  0.14  0.252]
```