CAP 5610 - Machine Learning Homework 1

Suma Marri

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Problem 1: Python & Data Exploration

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

filename_loaded = "Dataset/myClassDataSet.csv"
data_df = pd.read_csv(filename_loaded)
```

In [2]:
```
#testing if data was read and loaded correctly
data_df.head()
```

Out[2]:

	f1	f2	f3	f4	f5	f6	f7	f8	class
0	3.125845	4.213543	2.786926	0.832175	-1.178735	3.581140	-2.352872	7.804524	0
1	2.092247	3.383249	0.434993	2.003855	-2.525389	2.231663	-1.043635	7.149358	0
2	1.028549	3.944043	0.059291	0.011443	-1.309637	1.272289	-1.005366	7.434625	0
3	1.331028	4.920674	2.063895	1.424668	-1.073122	1.088142	-1.211250	8.603362	0
4	0.699447	5.427693	1.881804	0.387634	-0.134386	3.955468	-1.229464	7.241683	0

In [3]:
```
# (a)
# Use count() function to find the number of data points
print('Count Function: ')
data_count_df = data_df.count()
data_count_df
```

Out[3]:
```
Count Function:
f1       1000
f2       1000
f3       1000
f4       1000
f5       1000
f6       1000
f7       1000
f8       1000
class    1000
dtype: int64
```

In [4]:
```
# (a)
#  Use shape attribute to get the number of features for each data point.
# print('Shape Function: (rows, columns)')
```

```
m, n = data_df.shape
data_df.shape
print('Number of features:'); print(n)
print('Number of data points:'); print(m)
```

```
Number of features:
9
Number of data points:
1000
```

In [5]:

```
Y = data_df.values[:,-1]
#Y = data_df[data_df.columns[-1]] # class
X = data_df.values[:,0:-1]
#X = data_df[data_df.columns[data_df.columns.isin(['f1', 'f2', 'f3', 'f4', 'f5', 'f6',
```

In [6]:

```
# (b)
# Use the info() function to create a short summary of your data
data_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 9 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   f1      1000 non-null   float64
 1   f2      1000 non-null   float64
 2   f3      1000 non-null   float64
 3   f4      1000 non-null   float64
 4   f5      1000 non-null   float64
 5   f6      1000 non-null   float64
 6   f7      1000 non-null   float64
 7   f8      1000 non-null   float64
 8   class   1000 non-null   int64  
dtypes: float64(8), int64(1)
memory usage: 70.4 KB
```

In [7]:

```
# (b)
# Use set_option() to make the data more readable
pd.set_option('display.precision', 3, 'display.width', 100)
```

In [8]:

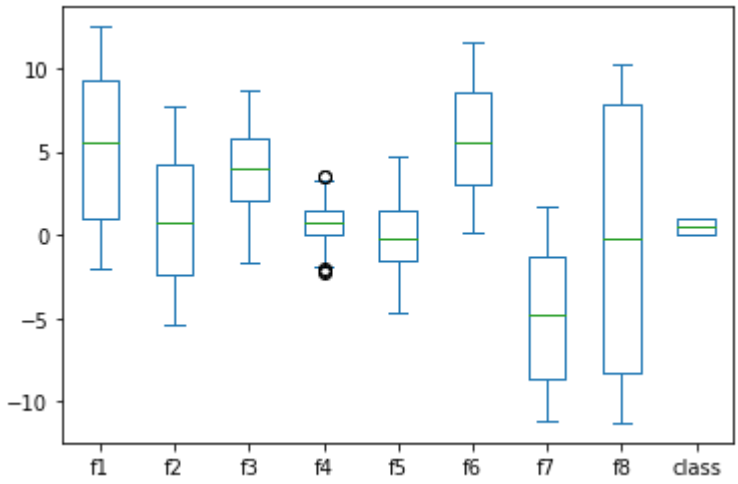
```
# Testing if set_option worked.
data_df.head()
```

Out[8]:

	f1	f2	f3	f4	f5	f6	f7	f8	class
0	3.126	4.214	2.787	0.832	-1.179	3.581	-2.353	7.805	0
1	2.092	3.383	0.435	2.004	-2.525	2.232	-1.044	7.149	0
2	1.029	3.944	0.059	0.011	-1.310	1.272	-1.005	7.435	0
3	1.331	4.921	2.064	1.425	-1.073	1.088	-1.211	8.603	0
4	0.699	5.428	1.882	0.388	-0.134	3.955	-1.229	7.242	0

In [9]:

```
# (c)
# Use Box and Whisker Plots to review the distribution of each attribute
data_df.plot(kind='box')
plt.show()
```

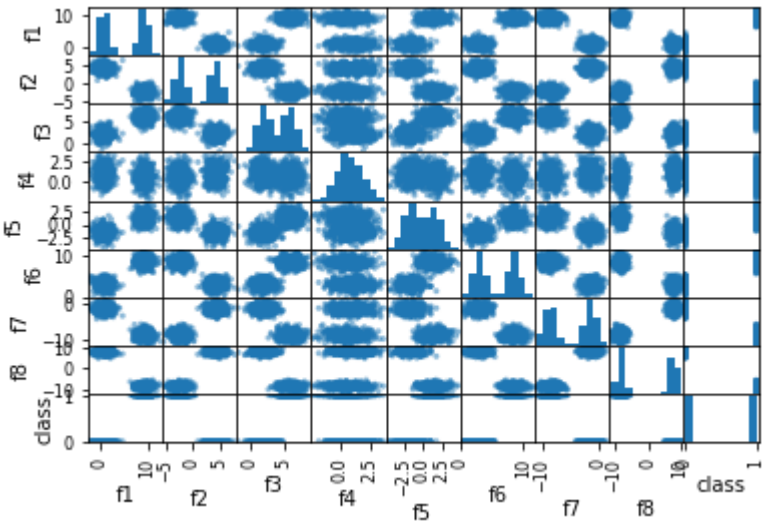


In [10]:
```
# (c)
# The boxplots helps see analyze the the minimum, maximum, median, and quartiles of eac
# This is helpful to compare the median and range of each feature.
```

In [11]:
```
import seaborn as sns
%matplotlib inline
```

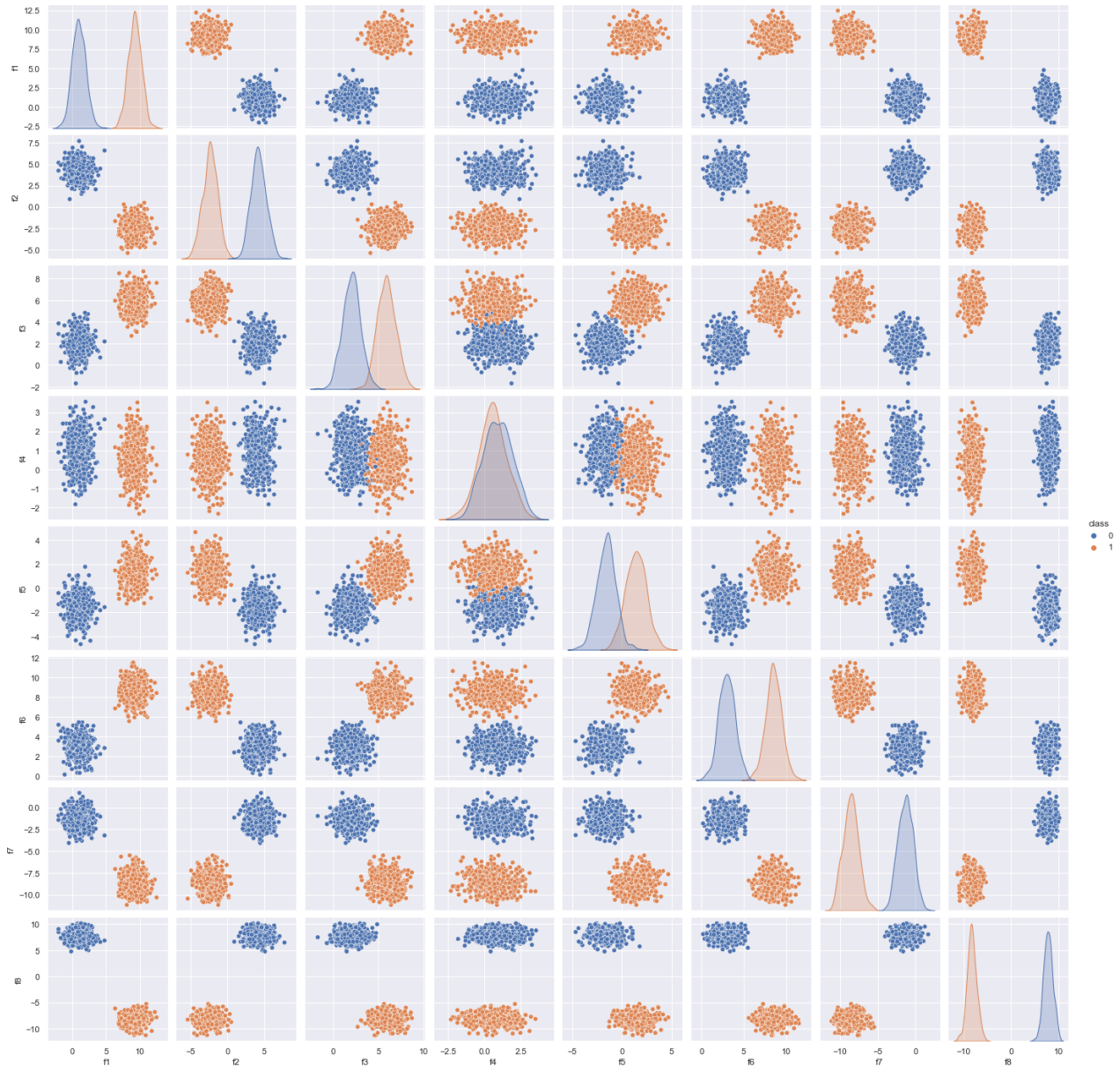
#testing colors = ['g','b','r'] #print(np.unique(Y)) for i in np.unique(Y): plt.plot(X[Y==i, 0], X[Y==i, 1], 'o', color=colors[int(i)]) #X[Y==1], color=colors[int(i)] #plt.plot(X, Y, color=colors[int(i)]) plt.show()

In [12]:
```
# (d)
# Plotting a scatterplot for each pair of feature
pd.plotting.scatter_matrix(data_df)
plt.show()
```



In [13]:
```
# (d)
# Plotting a scatterplot for each pair of feature and colored according to their target
```

```
sns.set()
sns.pairplot(data_df, hue='class');
```



In [14]:

```
# (e)
# Create a Covariance matrix
data_df.cov()
```

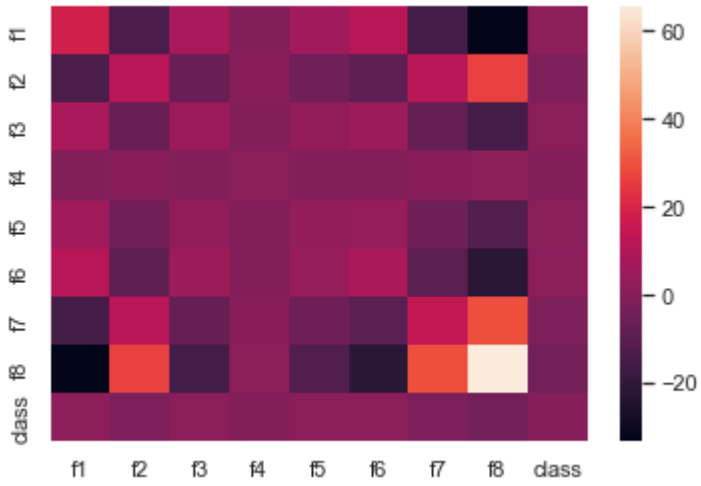
Out[14]:

	f1	f2	f3	f4	f5	f6	f7	f8	class
f1	18.104	-13.627	7.996	-0.727	6.187	11.449	-15.044	-33.268	2.070
f2	-13.627	11.876	-6.343	0.546	-4.951	-9.119	11.891	26.508	-1.647
f3	7.996	-6.343	4.694	-0.373	2.905	5.341	-7.058	-15.476	0.965
f4	-0.727	0.546	-0.373	0.993	-0.257	-0.520	0.593	1.375	-0.088
f5	6.187	-4.951	2.905	-0.257	3.219	4.143	-5.400	-12.087	0.748
f6	11.449	-9.119	5.341	-0.520	4.143	8.600	-10.068	-22.265	1.388

	f1	f2	f3	f4	f5	f6	f7	f8	class
f7	-15.044	11.891	-7.058	0.593	-5.400	-10.068	14.171	29.199	-1.816
f8	-33.268	26.508	-15.476	1.375	-12.087	-22.265	29.199	65.657	-4.024
class	2.070	-1.647	0.965	-0.088	0.748	1.388	-1.816	-4.024	0.250

In [15]:
```
# Plot and show the Covariance matrix.
cov = np.cov(data_df, bias=True)
```

In [16]:
```
sns.heatmap(data_df.cov())
plt.show()
```



Problem 2: Data Preparation and Feature Selection for Machine Learning

In [17]:
```
# import necessary packages to the Jupyter notebook
from pandas import read_csv
from numpy import set_printoptions
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

# read and load the csv data file
filename = "Dataset/myClassDataSet.csv"
dataframe = read_csv(filename)
array = dataframe.values

# separate array into input and output components
X = array [:,0:8]
Y = array [:,8]
```

In [18]:

```
# (a)
# Standardize data
scaler = StandardScaler()
scaler.fit_transform(array)

# transformed data with a precision of 2
np.set_printoptions(precision=2)
scaler.transform(array)
```

Out[18]:
```
array([[-0.47,  0.96, -0.53, ...,  0.7 ,  0.99, -1.  ],
       [-0.71,  0.71, -1.62, ...,  1.04,  0.91, -1.  ],
       [-0.96,  0.88, -1.79, ...,  1.05,  0.95, -1.  ],
       ...,
       [ 0.86, -0.4 ,  0.81, ..., -0.86, -1.05,  1.  ],
       [ 1.03, -1.26,  0.46, ..., -1.36, -0.88,  1.  ],
       [ 0.85, -0.96,  0.87, ..., -1.29, -0.78,  1.  ]])
```

In [19]:
```
# (a)
# Print the first 5 rows
features = scaler.transform(array)
scaled_features = pd.DataFrame(features)
scaled_features.head(5)
```

Out[19]:

	0	1	2	3	4	5	6	7	8
0	-0.466	0.956	-0.534	0.082	-0.610	-0.741	0.696	0.993	-1.0
1	-0.709	0.715	-1.621	1.259	-1.361	-1.202	1.044	0.912	-1.0
2	-0.960	0.877	-1.794	-0.742	-0.683	-1.529	1.054	0.948	-1.0
3	-0.888	1.161	-0.868	0.677	-0.551	-1.592	1.000	1.092	-1.0
4	-1.037	1.308	-0.952	-0.364	-0.027	-0.614	0.995	0.924	-1.0

In [20]:
```
# (b)
# Select the 5 best features in your data.
X_new = SelectKBest(f_classif, k=8)

# Print the scores with a precision of 2
np.set_printoptions(precision=2)
X_new.fit_transform(X, Y)
```

Out[20]:
```
array([[  3.13,   4.21,   2.79, ...,   3.58,  -2.35,   7.8 ],
       [  2.09,   3.38,   0.43, ...,   2.23,  -1.04,   7.15],
       [  1.03,   3.94,   0.06, ...,   1.27,  -1.01,   7.43],
       ...,
       [  8.75,  -0.45,   5.7 , ...,   8.56,  -8.2 ,  -8.73],
       [  9.49,  -3.42,   4.95, ...,   7.69, -10.1 ,  -7.34],
       [  8.71,  -2.38,   5.83, ...,   8.31,  -9.81,  -6.57]])
```

In [21]:
```
# (b)
# Print the first 5 rows of selected features
k_best = X_new.fit_transform(X, Y)
best_selected = pd.DataFrame(k_best)
best_selected.head(5)
```

Out[21]:

	0	1	2	3	4	5	6	7
0	3.126	4.214	2.787	0.832	-1.179	3.581	-2.353	7.805
1	2.092	3.383	0.435	2.004	-2.525	2.232	-1.044	7.149
2	1.029	3.944	0.059	0.011	-1.310	1.272	-1.005	7.435
3	1.331	4.921	2.064	1.425	-1.073	1.088	-1.211	8.603
4	0.699	5.428	1.882	0.388	-0.134	3.955	-1.229	7.242

In [22]:
```
# (c)
# Select the top 5 features of your data
lm = LogisticRegression(random_state=0)
lm.fit(X, Y)
rfe = RFE(lm, n_features_to_select=8)
rfe.fit(X, Y)
```

Out[22]:
```
RFE(estimator=LogisticRegression(random_state=0), n_features_to_select=8)
```

In [23]:
```
# (c)
# Print number of features
print(rfe.n_features_)
```

```
8
```

In [24]:
```
# (c)
# Print selected features
pd.DataFrame(list(rfe.support_)).T
```

Out[24]:

	0	1	2	3	4	5	6	7
0	True	True	True	True	True	True	True	True

In [25]:
```
# (c)
# Print  feature ranking
pd.DataFrame(list(rfe.ranking_)).T
```

Out[25]:

	0	1	2	3	4	5	6	7
0	1	1	1	1	1	1	1	1

In [26]:
```
# (d)
# Reduce the dimension of your data to 2
pca = PCA(n_components=2)
pca.fit(X)
#new_df = pca.transform(data_df)
#print(pca.explained_variance_ratio_)

# % of variance explained of each selected component
print(pca.explained_variance_ratio_)
```

```
[0.95 0.01]
```

In [27]:

```
# (e)
# estimate the importance score
tree = ExtraTreesClassifier(n_estimators=100, random_state=0)
tree.fit(X, Y)

tree.feature_importances_
```

Out[27]:

```
array([0.17, 0.16, 0.08, 0.  , 0.05, 0.12, 0.18, 0.25])
```

In [ ]: