STATS 3DA3

Homework Assignment 6

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```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score, silhouette_samples
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import numpy as np
import seaborn as sns

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix,
 ↪  classification_report

from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier
from mlxtend.feature_selection import SequentialFeatureSelector as SFS
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
```

(1)

A classification problem is to use a set of 13 features to predict whether a person has heart disease or not.

(2)

```
# Load the dataset
data = pd.read_csv('ass6-dataset.csv')
```

```
# Scale the data (excluding the target variable "num")
features = data.drop(columns=['num'])
scaler = StandardScaler()
scaled_features = scaler.fit_transform(features)
scaled_data = pd.DataFrame(scaled_features, columns=features.columns)
scaled_data['num'] = data['num']
```

(3)

```
# Get the list of variables of the dataset
variables = data.columns.tolist()
print("Variables in the dataset:")
for var in variables:
    print(var)

# Get a summary of the dataset
summary = data.describe()
print("\nSummary of the dataset:")
print(summary)

# Get the number of observations
num_observations = data.shape[0]
print(f"\nNumber of observations: {num_observations}")

# Get the data types of the variables
data_types = data.dtypes
print("\nData types of the variables:")
print(data_types)

# Get the distribution of the variables
print("\nDistribution of the variables:")
```

```
for var in variables:
    print(f"\n{var}:")
    print(data[var].value_counts())
    print(data[var].describe())
    print(data[var].hist())
```

```
Variables in the dataset:
age
sex
cp
trestbps
chol
fbs
restecg
thalach
exang
oldpeak
slope
ca
thal
num

Summary of the dataset:
              age         sex          cp    trestbps        chol         fbs  \
count  303.000000  303.000000  303.000000  303.000000  303.000000  303.000000
mean    54.438944    0.679868    3.158416  131.689769  246.693069    0.148515
std      9.038662    0.467299    0.960126   17.599748   51.776918    0.356198
min     29.000000    0.000000    1.000000   94.000000  126.000000    0.000000
25%     48.000000    0.000000    3.000000  120.000000  211.000000    0.000000
50%     56.000000    1.000000    3.000000  130.000000  241.000000    0.000000
75%     61.000000    1.000000    4.000000  140.000000  275.000000    0.000000
```

```
max     77.000000    1.000000    4.000000  200.000000  564.000000    1.000000

          restecg     thalach       exang     oldpeak       slope          ca  \
count  303.000000  303.000000  303.000000  303.000000  303.000000  299.000000
mean     0.990099  149.607261    0.326733    1.039604    1.600660    0.672241
std      0.994971   22.875003    0.469794    1.161075    0.616226    0.937438
min      0.000000   71.000000    0.000000    0.000000    1.000000    0.000000
25%      0.000000  133.500000    0.000000    0.000000    1.000000    0.000000
50%      1.000000  153.000000    0.000000    0.800000    2.000000    0.000000
75%      2.000000  166.000000    1.000000    1.600000    2.000000    1.000000
max      2.000000  202.000000    1.000000    6.200000    3.000000    3.000000

             thal         num
count  301.000000  303.000000
mean     4.734219    0.937294
std      1.939706    1.228536
min      3.000000    0.000000
25%      3.000000    0.000000
50%      3.000000    0.000000
75%      7.000000    2.000000
max      7.000000    4.000000

Number of observations: 303

Data types of the variables:
age           int64
sex           int64
cp            int64
trestbps      int64
chol          int64
fbs           int64
restecg       int64
```

```
thalach       int64
exang         int64
oldpeak     float64
slope         int64
ca          float64
thal        float64
num           int64
dtype: object

Distribution of the variables:

age:
age
58    19
57    17
54    16
59    14
52    13
60    12
51    12
56    11
62    11
44    11
64    10
41    10
67     9
63     9
42     8
43     8
45     8
53     8
55     8
```

```
61     8
65     8
50     7
66     7
48     7
46     7
47     5
49     5
70     4
68     4
35     4
39     4
69     3
71     3
40     3
34     2
37     2
38     2
29     1
77     1
74     1
76     1
Name: count, dtype: int64
count    303.000000
mean      54.438944
std        9.038662
min       29.000000
25%       48.000000
50%       56.000000
75%       61.000000
max       77.000000
Name: age, dtype: float64
```

```
Axes(0.125,0.11;0.775x0.77)

sex:
sex
1    206
0     97
Name: count, dtype: int64
count    303.000000
mean       0.679868
std        0.467299
min        0.000000
25%        0.000000
50%        1.000000
75%        1.000000
max        1.000000
Name: sex, dtype: float64
Axes(0.125,0.11;0.775x0.77)

cp:
cp
4    144
3     86
2     50
1     23
Name: count, dtype: int64
count    303.000000
mean       3.158416
std        0.960126
min        1.000000
25%        3.000000
50%        3.000000
75%        4.000000
```

```
max        4.000000
Name: cp, dtype: float64
Axes(0.125,0.11;0.775x0.77)

trestbps:
trestbps
120    37
130    36
140    32
110    19
150    17
138    12
128    12
160    11
125    11
112     9
132     8
118     7
124     6
108     6
135     6
152     5
134     5
145     5
100     4
170     4
122     4
126     3
136     3
115     3
180     3
142     3
```

```
105     3
102     2
146     2
144     2
148     2
178     2
94      2
165     1
123     1
114     1
154     1
156     1
106     1
155     1
172     1
200     1
101     1
129     1
192     1
158     1
104     1
174     1
117     1
164     1
Name: count, dtype: int64
count    303.000000
mean     131.689769
std       17.599748
min       94.000000
25%      120.000000
50%      130.000000
75%      140.000000
```

```
max      200.000000
Name: trestbps, dtype: float64
Axes(0.125,0.11;0.775x0.77)

chol:
chol
204    6
197    6
234    6
269    5
212    5
      ..
340    1
160    1
394    1
184    1
131    1
Name: count, Length: 152, dtype: int64
count    303.000000
mean     246.693069
std       51.776918
min      126.000000
25%      211.000000
50%      241.000000
75%      275.000000
max      564.000000
Name: chol, dtype: float64
Axes(0.125,0.11;0.775x0.77)

fbs:
fbs
0    258
```

```
1     45
Name: count, dtype: int64
count    303.000000
mean       0.148515
std        0.356198
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000
Name: fbs, dtype: float64
Axes(0.125,0.11;0.775x0.77)

restecg:
restecg
0    151
2    148
1      4
Name: count, dtype: int64
count    303.000000
mean       0.990099
std        0.994971
min        0.000000
25%        0.000000
50%        1.000000
75%        2.000000
max        2.000000
Name: restecg, dtype: float64
Axes(0.125,0.11;0.775x0.77)

thalach:
thalach
```

```
162    11
160     9
163     9
152     8
150     7
       ..
177     1
127     1
97      1
190     1
90      1
Name: count, Length: 91, dtype: int64
count    303.000000
mean     149.607261
std       22.875003
min       71.000000
25%      133.500000
50%      153.000000
75%      166.000000
max      202.000000
Name: thalach, dtype: float64
Axes(0.125,0.11;0.775x0.77)

exang:
exang
0    204
1     99
Name: count, dtype: int64
count    303.000000
mean       0.326733
std        0.469794
min        0.000000
```

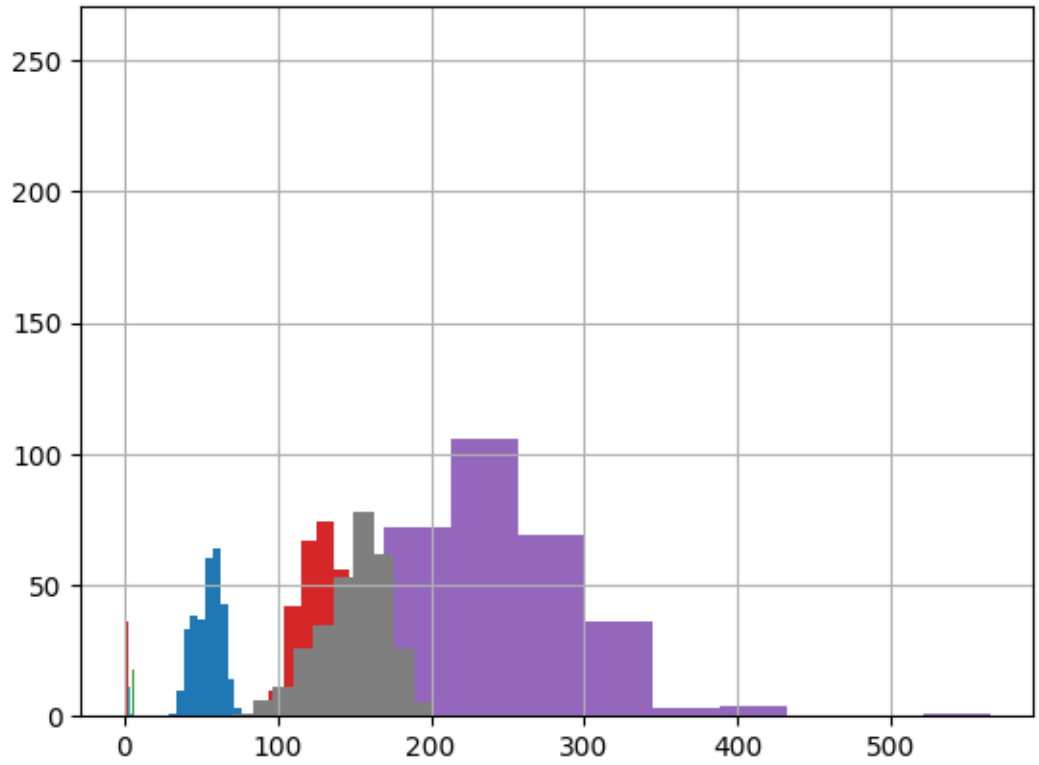
```
25%        0.000000
50%        0.000000
75%        1.000000
max        1.000000
Name: exang, dtype: float64
Axes(0.125,0.11;0.775x0.77)

oldpeak:
oldpeak
0.0    99
1.2    17
0.6    14
1.0    14
1.4    13
0.8    13
0.2    12
1.6    11
1.8    10
2.0     9
0.4     9
0.1     7
2.8     6
2.6     6
1.9     5
0.5     5
3.0     5
1.5     5
3.6     4
2.2     4
3.4     3
0.9     3
2.4     3
```

```
0.3     3
4.0     3
1.1     2
4.2     2
2.3     2
2.5     2
3.2     2
5.6     1
2.9     1
6.2     1
2.1     1
1.3     1
3.1     1
3.8     1
0.7     1
3.5     1
4.4     1
Name: count, dtype: int64
count    303.000000
mean       1.039604
std        1.161075
min        0.000000
25%        0.000000
50%        0.800000
75%        1.600000
max        6.200000
Name: oldpeak, dtype: float64
Axes(0.125,0.11;0.775x0.77)

slope:
slope
1    142
```

```
2    140
3     21
Name: count, dtype: int64
count    303.000000
mean       1.600660
std        0.616226
min        1.000000
25%        1.000000
50%        2.000000
75%        2.000000
max        3.000000
Name: slope, dtype: float64
Axes(0.125,0.11;0.775x0.77)

ca:
ca
0.0    176
1.0     65
2.0     38
3.0     20
Name: count, dtype: int64
count    299.000000
mean       0.672241
std        0.937438
min        0.000000
25%        0.000000
50%        0.000000
75%        1.000000
max        3.000000
Name: ca, dtype: float64
Axes(0.125,0.11;0.775x0.77)
```

```
thal:
thal
3.0    166
7.0    117
6.0     18
Name: count, dtype: int64
count    301.000000
mean       4.734219
std        1.939706
min        3.000000
25%        3.000000
50%        3.000000
75%        7.000000
max        7.000000
Name: thal, dtype: float64
Axes(0.125,0.11;0.775x0.77)

num:
num
0    164
1     55
2     36
3     35
4     13
Name: count, dtype: int64
count    303.000000
mean       0.937294
std        1.228536
min        0.000000
25%        0.000000
50%        0.000000
75%        2.000000
```

```
max         4.000000
Name: num, dtype: float64
Axes(0.125,0.11;0.775x0.77)
```



The dataset contains missing values and have different scales and distributions. For the variables, sex, fbs, exang are binary varialbes, oldpeak is a continuous variable, and the remaining vriables are numeric variables. There are 303 observations in the dataset.

(4)

```
# Convert the num column to a binary variable
scaled_data['num'] = scaled_data['num'].apply(lambda x: 1 if x > 0 else 0)
```

(5)

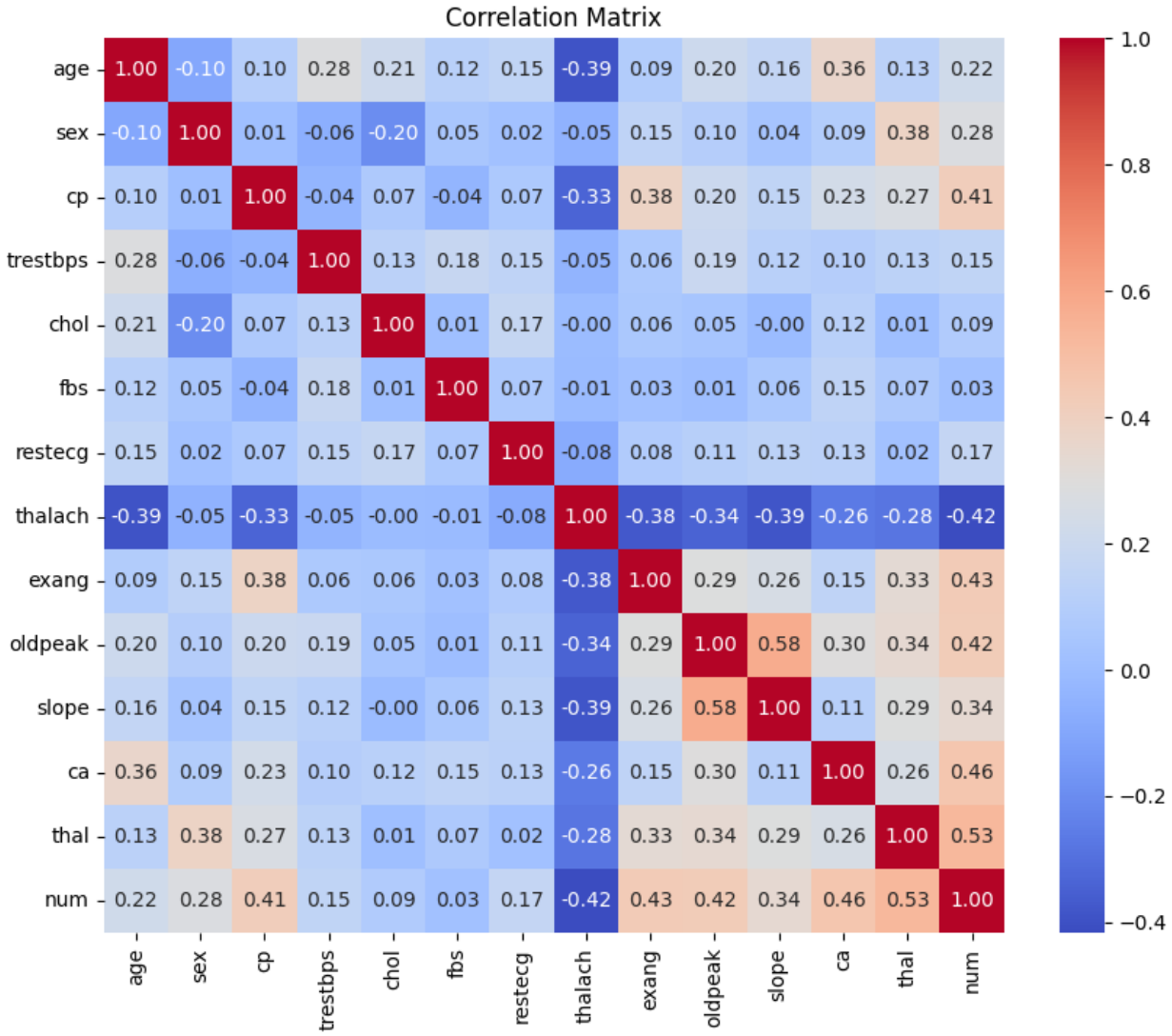
```
# Correlation matrix
correlation_matrix = scaled_data.corr()
```

```
print("\nCorrelation matrix:")
print(correlation_matrix)

# Visualize the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```

```
Correlation matrix:
               age       sex        cp  trestbps      chol       fbs  \
age       1.000000 -0.097542  0.104139  0.284946  0.208950  0.118530
sex      -0.097542  1.000000  0.010084 -0.064456 -0.199915  0.047862
cp        0.104139  0.010084  1.000000 -0.036077  0.072319 -0.039975
trestbps  0.284946 -0.064456 -0.036077  1.000000  0.130120  0.175340
chol      0.208950 -0.199915  0.072319  0.130120  1.000000  0.009841
fbs       0.118530  0.047862 -0.039975  0.175340  0.009841  1.000000
restecg   0.148868  0.021647  0.067505  0.146560  0.171043  0.069564
thalach  -0.393806 -0.048663 -0.334422 -0.045351 -0.003432 -0.007854
exang     0.091661  0.146201  0.384060  0.064762  0.061310  0.025665
oldpeak   0.203805  0.102173  0.202277  0.189171  0.046564  0.005747
slope     0.161770  0.037533  0.152050  0.117382 -0.004062  0.059894
ca        0.362605  0.093185  0.233214  0.098773  0.119000  0.145478
thal      0.127389  0.380936  0.265246  0.133554  0.014214  0.071358
num       0.223120  0.276816  0.414446  0.150825  0.085164  0.025264

           restecg   thalach     exang   oldpeak     slope        ca  \
age       0.148868 -0.393806  0.091661  0.203805  0.161770  0.362605
sex       0.021647 -0.048663  0.146201  0.102173  0.037533  0.093185
cp        0.067505 -0.334422  0.384060  0.202277  0.152050  0.233214
```

```
trestbps  0.146560 -0.045351  0.064762  0.189171  0.117382  0.098773
chol      0.171043 -0.003432  0.061310  0.046564 -0.004062  0.119000
fbs       0.069564 -0.007854  0.025665  0.005747  0.059894  0.145478
restecg   1.000000 -0.083389  0.084867  0.114133  0.133946  0.128343
thalach  -0.083389  1.000000 -0.378103 -0.343085 -0.385601 -0.264246
exang     0.084867 -0.378103  1.000000  0.288223  0.257748  0.145570
oldpeak   0.114133 -0.343085  0.288223  1.000000  0.577537  0.295832
slope     0.133946 -0.385601  0.257748  0.577537  1.000000  0.110119
ca        0.128343 -0.264246  0.145570  0.295832  0.110119  1.000000
thal      0.024531 -0.279631  0.329680  0.341004  0.287232  0.256382
num       0.169202 -0.417167  0.431894  0.424510  0.339213  0.460442
```

```
              thal       num
age       0.127389  0.223120
sex       0.380936  0.276816
cp        0.265246  0.414446
trestbps  0.133554  0.150825
chol      0.014214  0.085164
fbs       0.071358  0.025264
restecg   0.024531  0.169202
thalach  -0.279631 -0.417167
exang     0.329680  0.431894
oldpeak   0.341004  0.424510
slope     0.287232  0.339213
ca        0.256382  0.460442
thal      1.000000  0.525689
num       0.525689  1.000000
```



From the correlation matrix, we can see that the features are not highly correlated with each other. The top-3 variable with highest correlation with num is thal, ca, and exang.

(6)

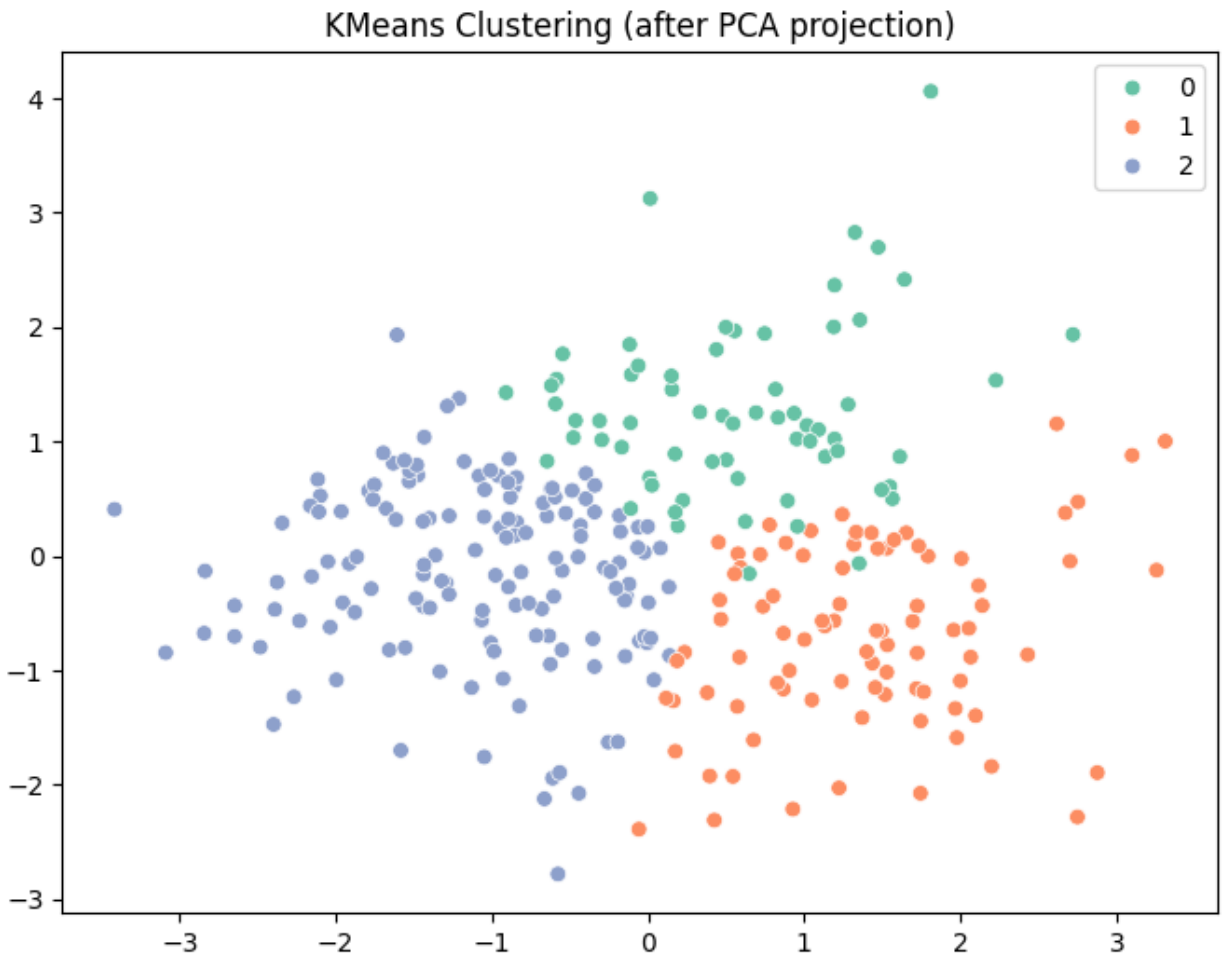
```
scaled_data.dropna(inplace=True)
num_observations_after_drop = scaled_data.shape[0]


print(num_observations_after_drop)
```

297

There are 297 observations after dropping the missing values.

(7)

```
categorical_cols = ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca',
 ↪  'thal', 'num']
X_cluster = scaled_data.drop(columns = categorical_cols)

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_cluster)



kmeans = KMeans(n_clusters = 3, random_state = 1) #choose the number of clusters
 ↪  = 3 due to previous knowledge
clusters = kmeans.fit_predict(X_scaled)

pca = PCA(n_components = 2)
X_pca = pca.fit_transform(X_scaled)

plt.figure(figsize = (8,6))
sns.scatterplot(x = X_pca[:, 0], y = X_pca[:, 1], hue = clusters, palette =
 ↪  'Set2' , s = 40)

plt.title('KMeans Clustering (after PCA projection)')
plt.show()
```



(8)

```
X = scaled_data.drop(columns=["num"])
y = scaled_data["num"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=1, stratify=y
)

print(f"Training set size: {X_train.shape[0]}")
print(f"Testing set size: {X_test.shape[0]}")
```

```
Training set size: 207
```

```
Testing set size: 90
```

(9)

We select:

1. Logistic Regression

Logistic regression always used for binary classification problems. Because it is really efficiency for small/medium datasets. The structure of it is easy and has great interpretability. In this case we are analysising the heart disease dataset, and by previous knowledge we know logistic regression is suitale for this kind of dataset. So the first one we choose is logistic regression.

2. Decision Tree

Decision tree is a very well understood model that divides data into different categories step by step by constantly making "yes" and "no" judgments on features. It is very easy to operate because we don't need to standardize the data in advance, and it can handle different types of data at the same time. I think its biggest advantage is that it has a clear structure, and it can draw very graphical diagrams to see how to make decisions at each step, which is very helpful for medical data analysis, because the model is very explanatory and easy to understand. For example, let's judge each item in this data on a finger-by-finger basis.

(10)

We choose accuracy and precision.

1. Accuracy:

formula when calculating 'Accuracy = (TP + TN) / (TP + TN + FP + FN)' TP is True Positive, TN is True Negative; FP is False Positive, FN is False Negative.

It is one of the most commonly used metrics to measure the overall performance of a classification model. It shows how many times the model predicted correctly and what percentage of the total predictions were made.

2. Sensitivity:

Formula when calculating 'Sensitivity = TP / (TP + FN)'

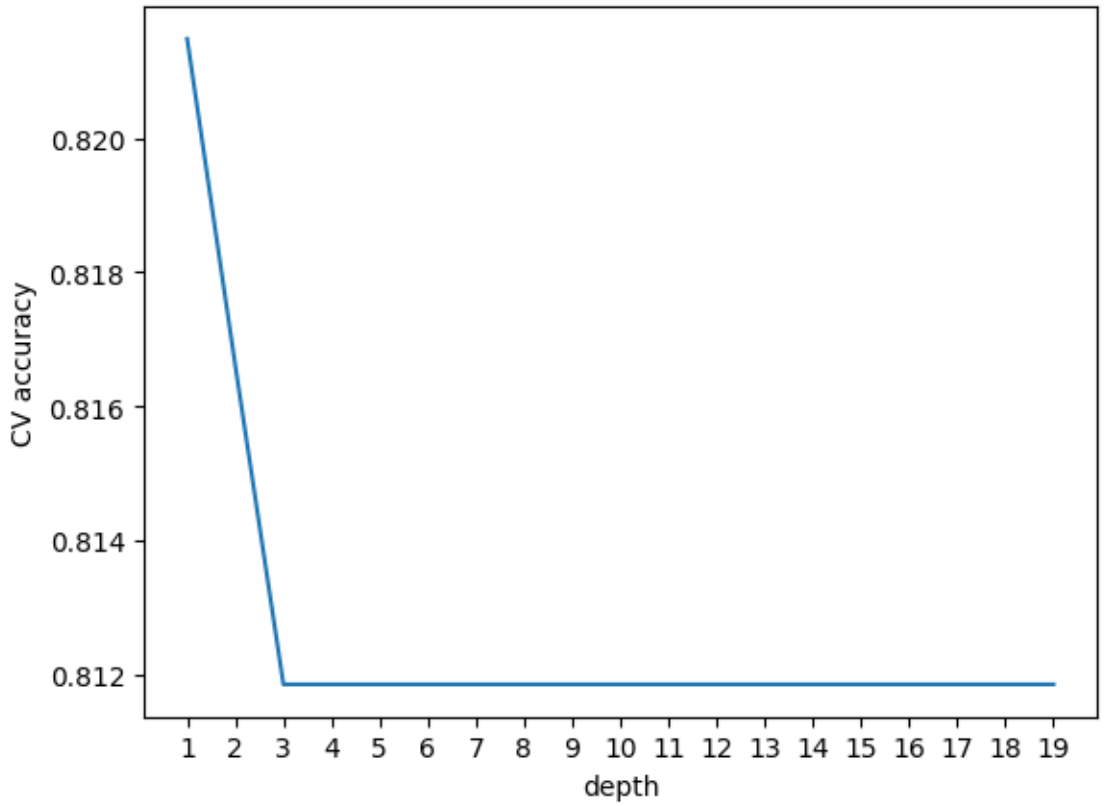
TP is True Positive, FN is False Negative.

Sensitivity measures how well the model identifies actual positive cases. In other words, sensitivity shows what proportion of people who are actually "have problem" were correctly predicted as "have problem/sick" by the model. A high sensitivity means the model is good at detecting all real cases, even sometimes it maybe too sensitive. But if we cannot identify someone is actual "have problem" it may lead to very bad situation.

(11)

```
# identify optimal tuning parameters using cross validation
depth_range = range(1, 20)
cv_scores = []
for k in depth_range:
    heart_disease_log = LogisticRegression(max_iter=120, C=k)
# 5-fold cross-validation using accuracy
    cv_scores_k = cross_val_score(
        heart_disease_log,
        X_train,
        y_train,
        cv=5,
        scoring='accuracy'
    )
# append the average accuracy across all folds
    cv_scores.append(np.mean(cv_scores_k))
plt.plot(depth_range, cv_scores)
plt.xlabel('depth')
plt.ylabel('CV accuracy')
plt.xticks(range(1,20))
plt.show()

optimal_depth_index = np.argmax(cv_scores)
```

```
optimal_depth = depth_range[optimal_depth_index]

print("Optimal max_depth: ", optimal_depth)

# train logistic regression model
heart_disease_log = LogisticRegression(max_iter=120, C=optimal_depth)
heart_disease_log.fit(X_train, y_train)
```

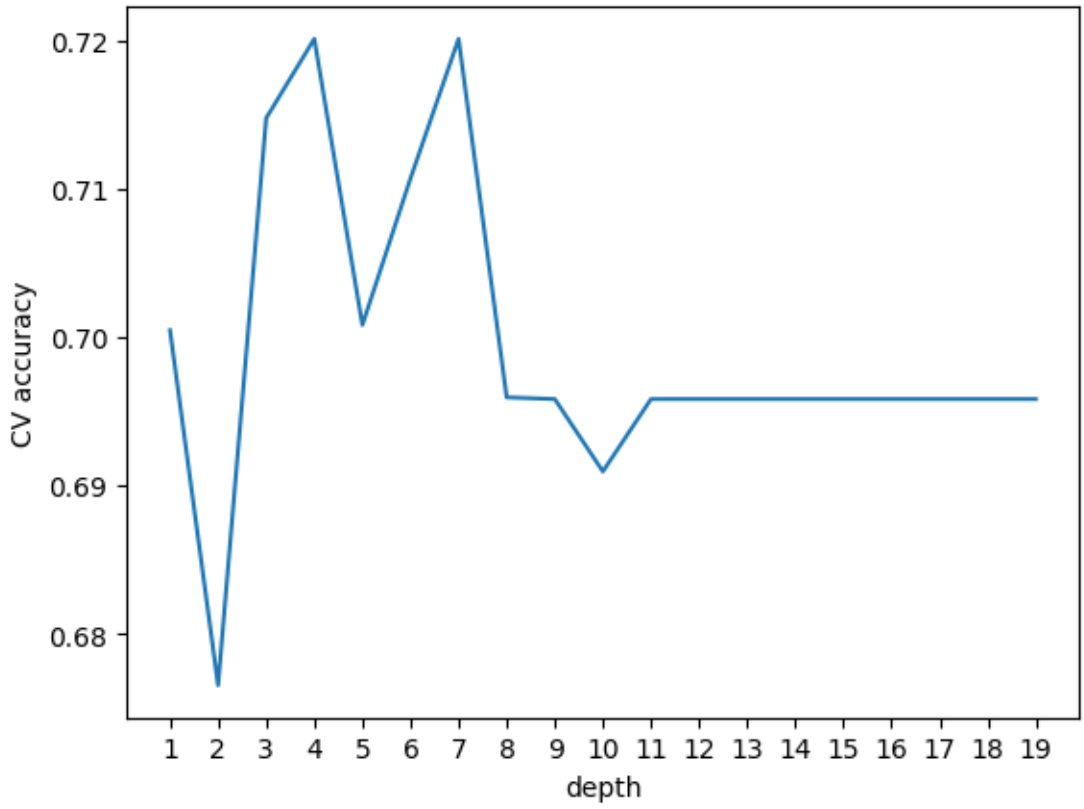



```
Optimal max_depth:  1

LogisticRegression(C=1, max_iter=120)
```

The optimal tuning parameter for logistic regression is max depth k: 1.

```
# identify optimal tuning parameters using cross validation
depth_range = range(1, 20)
cv_scores = []
for k in depth_range:
    dt = DecisionTreeClassifier(
    criterion='gini',
    random_state=0,
    max_depth=k
    )

    cv_scores_k = cross_val_score(
        dt,
        X_train,
        y_train,
        cv=5,
        scoring='accuracy'
    )
    cv_scores.append(np.mean(cv_scores_k))
plt.plot(depth_range, cv_scores)
plt.xlabel('depth')
plt.ylabel('CV accuracy')
plt.xticks(range(1,20))
plt.show()

optimal_depth_index = np.argmax(cv_scores)
optimal_depth = depth_range[optimal_depth_index]

print("Optimal max_depth: ", optimal_depth)

# train decision tree model
heart_disease_dt = DecisionTreeClassifier(
```

```
    criterion='gini',
    random_state=0,
    max_depth=3
)
heart_disease_dt.fit(X_train, y_train)
```




```
Optimal max_depth:  7
```

```
DecisionTreeClassifier(max_depth=3, random_state=0)
```

The optimal tuning parameter for decision tree is optimal max depth: 7.

(12)

```
# Apply Step-wise subset selection to descision tree
sfs = SFS(
    estimator=heart_disease_dt,
    k_features=(1, 8),
    forward=True,
    floating=False,
    scoring='accuracy',
    cv=5,
)
sfs.fit(X_train, y_train)

# identify optimal tuning parameters
selected_features = X_train.columns[list(sfs.k_feature_idx_)]
X_train_sfs = X_train[selected_features]
X_test_sfs = X_test[selected_features]

depth_range = range(1, 20)
cv_scores = []
for k in depth_range:
    dt = DecisionTreeClassifier(
    criterion='gini',
    random_state=0,
    max_depth=k
    )

    cv_scores_k = cross_val_score(
        dt,
        X_train_sfs,
        y_train,
        cv=5,
        scoring='accuracy'
```

```
    )
    cv_scores.append(np.mean(cv_scores_k))

optimal_depth_index = np.argmax(cv_scores)
optimal_depth = depth_range[optimal_depth_index]

print("Optimal max_depth: ", optimal_depth)

# train decision tree model with selected features
m_sfs = DecisionTreeClassifier(
    criterion='gini',
    random_state=0,
    max_depth=optimal_depth
)
m_sfs.fit(X_train_sfs, y_train)
```

```
Optimal max_depth:  3
```

```
DecisionTreeClassifier(max_depth=3, random_state=0)
```

The optimal tuning parameter for decision tree is optimal max depth: 3.

(13)

```
# confusion matrix for logistic regression
y_test_hat = heart_disease_log.predict(X_test)
cm_log = confusion_matrix(y_test, y_test_hat)
total1 = sum(sum(cm_log))
accuracy_log = (cm_log[0,0]+cm_log[1,1])/total1
print("Logistic Regression Accuracy: ", accuracy_log)
sensitivity_log = cm_log[1,1]/(cm_log[1,0]+cm_log[1,1])
print("Logistic Regression Sensitivity: ", sensitivity_log)
```

```
y_pred_dt = heart_disease_dt.predict(X_test)
# confusion matrix for decision tree
cm_dt = confusion_matrix(y_test, y_pred_dt)
total2 = sum(sum(cm_dt))
accuracy_dt = (cm_dt[0,0]+cm_dt[1,1])/total2
print("Decision Tree Accuracy: ", accuracy_dt)
sensitivity_dt = cm_dt[1,1]/(cm_dt[1,0]+cm_dt[1,1])
print("Decision Tree Sensitivity: ", sensitivity_dt)

y_pred_sfs = m_sfs.predict(X_test_sfs)
# confusion matrix for decision tree with selected features
cm_sfs = confusion_matrix(y_test, y_pred_sfs)
total3 = sum(sum(cm_sfs))
accuracy_sfs = (cm_sfs[0,0]+cm_sfs[1,1])/total3
print("Decision Tree with Selected Features Accuracy: ", accuracy_sfs)
sensitivity_sfs = cm_sfs[1,1]/(cm_sfs[1,0]+cm_sfs[1,1])
print("Decision Tree with Selected Features Sensitivity: ", sensitivity_sfs)
```

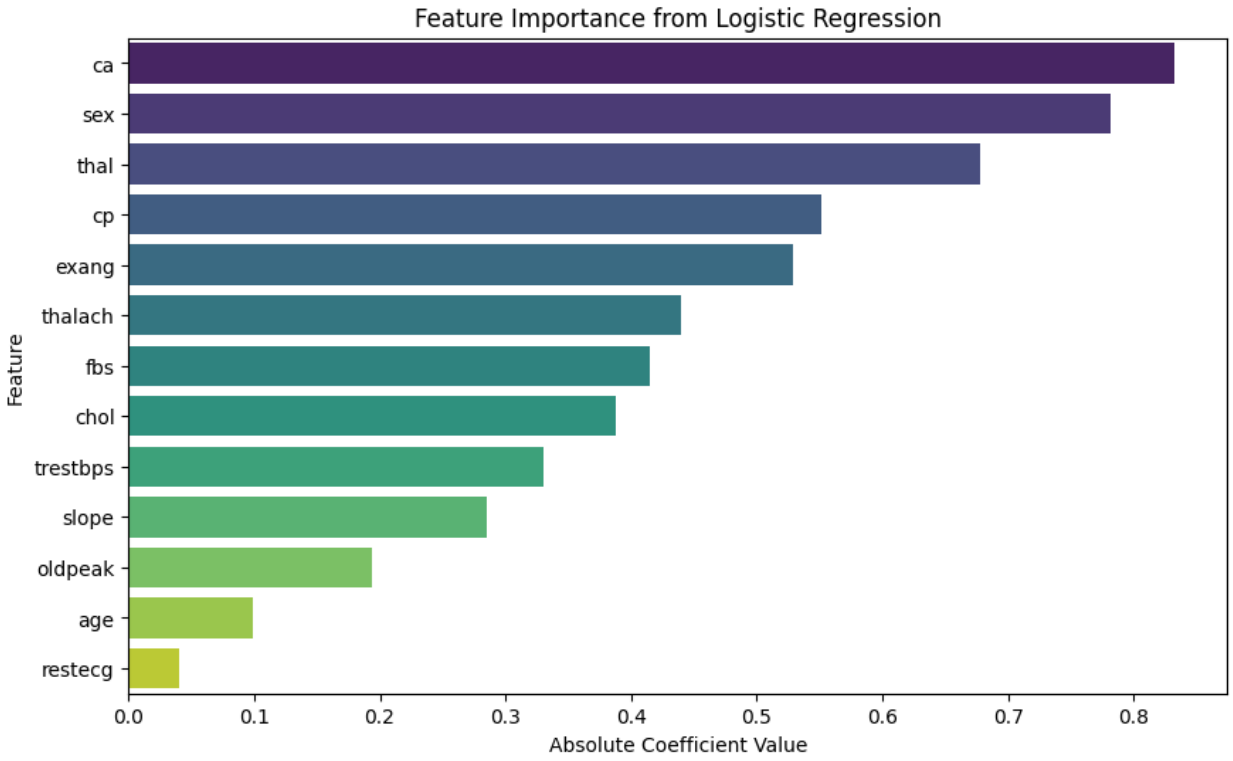
```
Logistic Regression Accuracy:  0.8444444444444444
Logistic Regression Sensitivity:  0.7619047619047619
Decision Tree Accuracy:  0.7444444444444445
Decision Tree Sensitivity:  0.7857142857142857
Decision Tree with Selected Features Accuracy:  0.7555555555555555
Decision Tree with Selected Features Sensitivity:  0.8095238095238095
```

The Logistic Regression model has a higher accuracy than the Decision Tree model. However, the Decision Tree model has a higher sensitivity, which means it is better at identifying positive cases. Both accuracy and sensitivity for Decision Tree model with SFS are bit higher than the original Decision Tree model. This indicates that feature selection has improved the performance of the classifier.

(14)

```
# The best interpretable model identified in (13) is logistic regression.
coefficients = heart_disease_log.coef_[0]
feature_importance = pd.DataFrame(
    {'Feature': X_train.columns,
     'Coefficient': coefficients}
)
feature_importance['Importance'] = np.abs(feature_importance['Coefficient'])
feature_importance = feature_importance.sort_values(by='Importance',
 ↪  ascending=False)
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importance,
 ↪  palette='viridis')
plt.title('Feature Importance from Logistic Regression')
plt.xlabel('Absolute Coefficient Value')
plt.ylabel('Feature')
plt.show()
```

```
/tmp/ipykernel_698439/1559183592.py:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign

  sns.barplot(x='Importance', y='Feature', data=feature_importance, palette='viridis')
```



The most important predictor variables is 'ca', which is the number of major vessels (0-3) colored by fluoroscopy. This variable has a positive coefficient, indicating that as the number of major vessels increases, the likelihood of having heart disease also increases. This suggests that individuals with more major vessels are at a higher risk of heart disease.

(15)

From (7), we can see there are subgroups of patients with and without heart disease. We can further improve the linear regression model by adding interaction terms between the features. For example, we can create a new feature that is the product of 'ca' and 'thal', which may capture the interaction between these two variables. We can also try polynomial regression to capture non-linear relationships between the features and the target variable. Additionally, we can use regularization techniques such as Lasso or Ridge regression to prevent overfitting and improve the model's performance.

```
# Logistic regression with interaction terms
X_train_interaction = X_train.copy()
X_test_interaction = X_test.copy()
```

```
X_train_interaction['ca_thal'] = X_train['ca'] * X_train['thal']
X_test_interaction['ca_thal'] = X_test['ca'] * X_test['thal']
heart_disease_log_interaction = LogisticRegression(max_iter=120, C=optimal_depth)
heart_disease_log_interaction.fit(X_train_interaction, y_train)
y_test_hat_interaction =
 ↪  heart_disease_log_interaction.predict(X_test_interaction)
cm_log_interaction = confusion_matrix(y_test, y_test_hat_interaction)
total4 = sum(sum(cm_log_interaction))
accuracy_log_interaction =
 ↪  (cm_log_interaction[0,0]+cm_log_interaction[1,1])/total4
print("Logistic Regression with Interaction Terms Accuracy: ",
 ↪  accuracy_log_interaction)
sensitivity_log_interaction =
 ↪  cm_log_interaction[1,1]/(cm_log_interaction[1,0]+cm_log_interaction[1,1])
print("Logistic Regression with Interaction Terms Sensitivity: ",
 ↪  sensitivity_log_interaction)
```

```
Logistic Regression with Interaction Terms Accuracy:  0.8666666666666667
Logistic Regression with Interaction Terms Sensitivity:  0.7857142857142857
```

The original logistic regression model has accuracy 0.84 and sensitivity 0.76. With the new feature, the new logistic regression model has acfuracy 0.86 and sensitivity 0.78. This indicates that the new feature has improved the model's performance, as it has a higher accuracy and sensitivity than the original model.

(16)

Contributions:

Yixin Ma: 11, 12, 13, 14

Runhan Huang: 6, 7, 8, 9, 10

Kunhan Liang: 1, 2, 3, 4, 5, 15

(17)

Link to the public repository: https://github.com/SweetIceLolly/3da-a6

References

GitHub Copilot was used as a code assistant for some of the questions.