STATS 3DA3

Homework Assignment 6

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```
import pandas as pd
import numpy as np

heart_disease = pd.read_csv('https://raw.githubusercontent.com/PratheepaJ/datasets/refs/heads/m
```

1. Define and describe a classification problem using the dataset.

Want to see if we can create a possible coding solution that can predict whether an individual has a heart disease based off of previous samples and the patient's current results to a consultation.

2. Apply any chosen data transformations, or explain why no transformations were necessary.

```
#question 6 has to be done in question 2 to avoid tedious coding.
heart_diseaseD = heart_disease.dropna()

#question 2 is now done applying transformations to the data
response_var = heart_diseaseD['num']

from sklearn.preprocessing import scale, StandardScaler
#KNN requires scaling
KNN_Predictor = heart_diseaseD.drop(columns=['num'])
scaler = StandardScaler()
KNN_PredictorV = pd.DataFrame(scaler.fit_transform(
    heart_diseaseD.drop(columns=['num'])), columns=heart_diseaseD.columns[:-1])

#Tree Classification does not require scaling
Tree_Predictor = heart_diseaseD.drop(columns=['num'])
```

3. Provide a detailed description of the dataset, including variables, summaries, number of observations, data types, and distributions (include at least three statements).

The categorical variables in the dataset are sex, cp, fbs, restecg, exang, slope and thal. The other variables are all integers. Our target variable will be "num", the diagnosis of heart disease. The thal and ca variables both contain missing values.

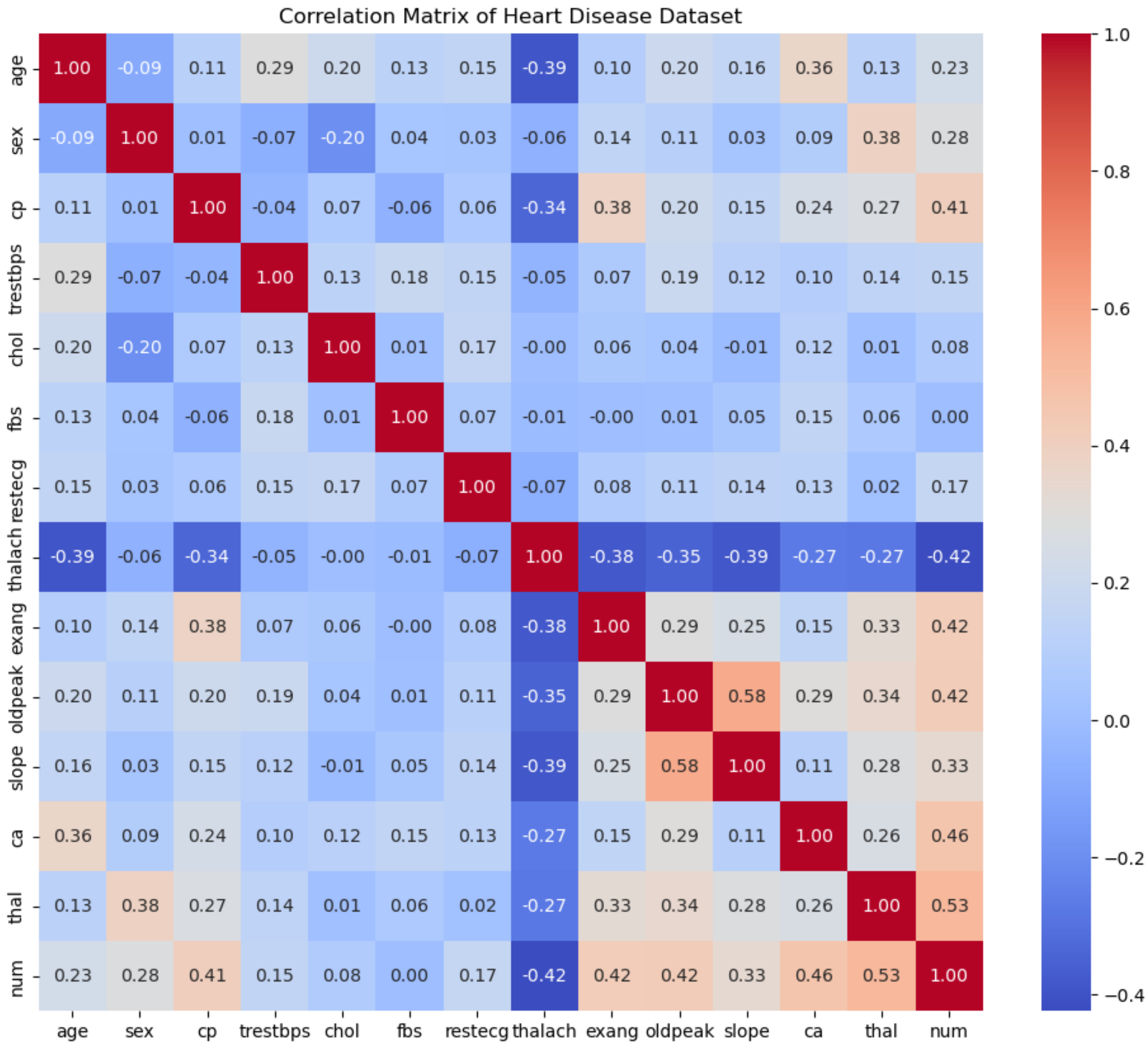
4.

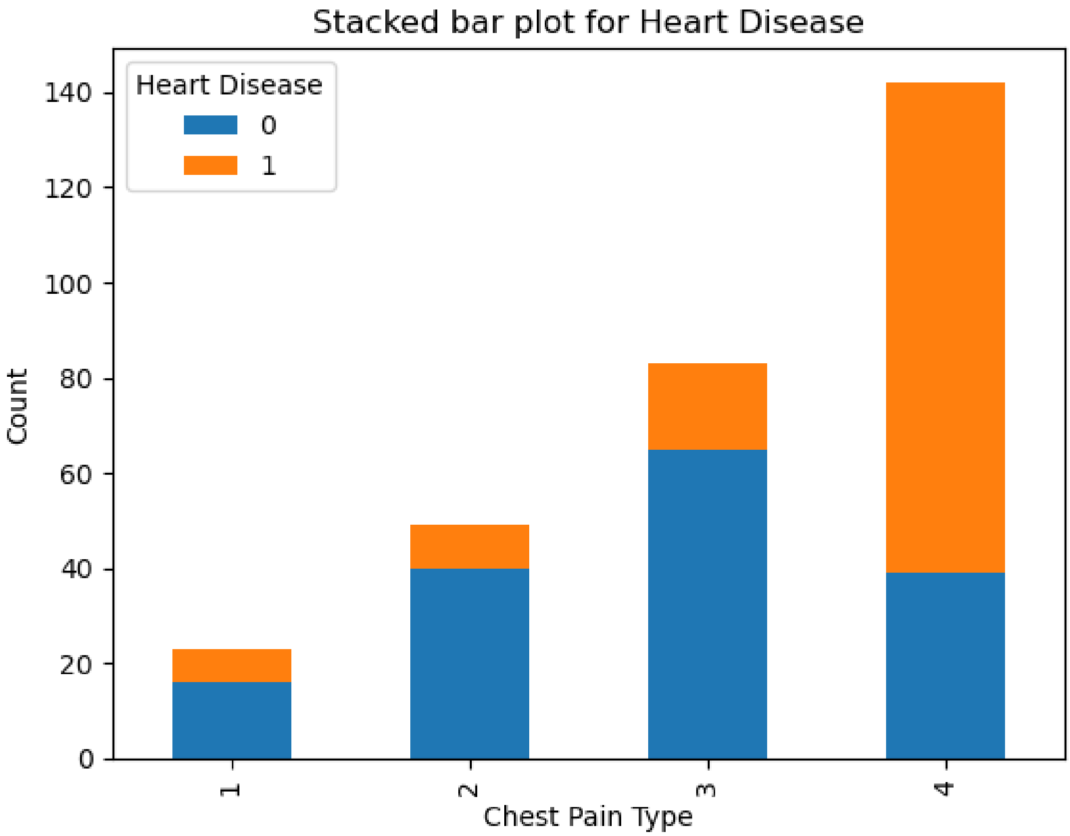
```
heart_diseaseD = heart_diseaseD.replace({'num': { 2: 1, 3: 1, 4: 1}})
ResponseVar = response_var.replace({2:1,3:1,4:1})

ResponseVar.head(5)
```

```
0    0
1    1
2    1
3    0
4    0
Name: num, dtype: int64
```

5.

```
import matplotlib.pyplot as plt
import seaborn as sns
correlation_matrix = heart_diseaseD.corr()
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix of Heart Disease Dataset')
plt.show()

stacked_data = heart_diseaseD.groupby(['cp','num']).size().unstack().fillna(0)
stacked_data.plot(kind='bar', stacked=True)
plt.ylabel('Count')
plt.xlabel('Chest Pain Type')
plt.title('Stacked bar plot for Heart Disease')
plt.legend(title='Heart Disease')
plt.show()
```


Correlation Matrix of Heart Disease Dataset
age
sex
cp
trestbps
chol
fbs
restecg
thalach
exang
oldpeak
slope
ca
thal
num
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4



Using a correlation matrix for the Heart Disease dataset we can see how well the features correlate with the response variable 'num'. Based on the results, thal has the highest correlation with the other variables and the highest correlation (0.53) to the response variable indicating its potential significance in feature selection. On the other hand, fbs and chol have very low correlation with the other variables and the response variable suggesting they may not be significant features.

The stacked bar graph shows the amount of people that do or don't have a heart disease with each chest pain type. Clearly as the chest pain type increases the amount of people with heart disease also increases. This indicates that chest pain type is a significant feature in predicting heart disease.

6.

```
heart_diseaseD.shape
```

```
(297, 14)
```

now 297 oberservations remain from the original 303.

7.

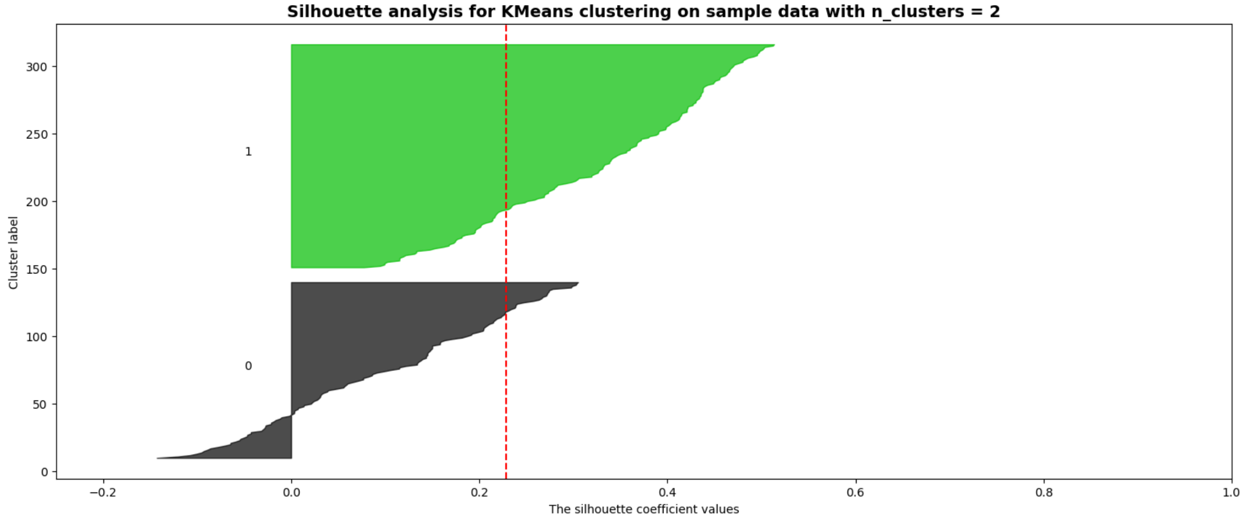
```
#need to drop categorical variables

from sklearn.preprocessing import StandardScaler

heart_diseaseDrop = heart_diseaseD.drop(
    columns=['sex','slope','thal','cp','restecg','fbs','num','exang'])

scalar = StandardScaler()
scalar.fit_transform(heart_diseaseDrop)
heart_diseaseDrop = pd.DataFrame(scalar.transform(
    heart_diseaseDrop),columns=heart_diseaseDrop.columns)
```

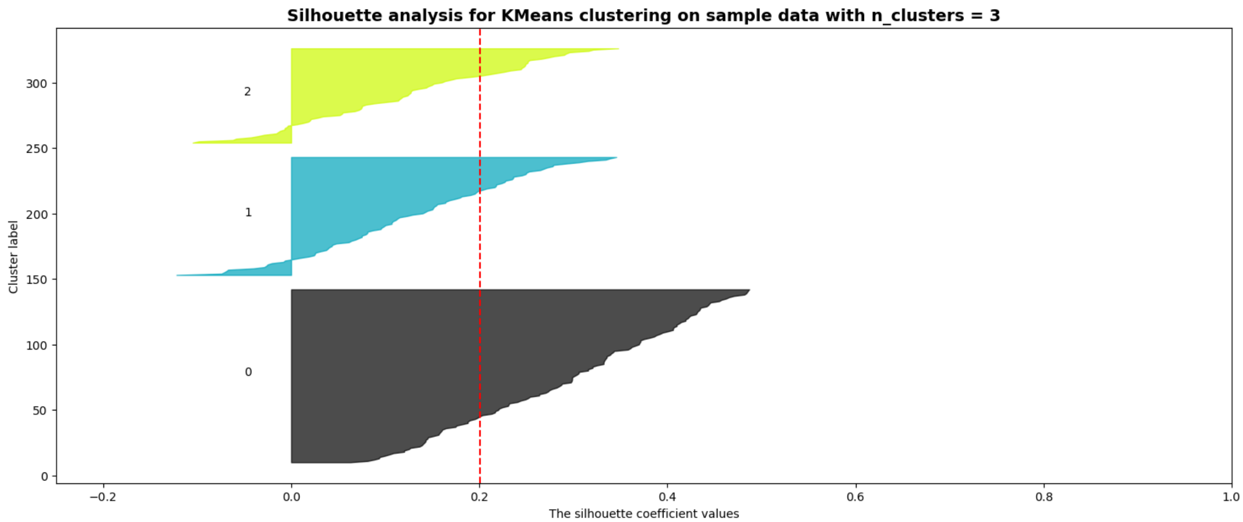
```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_samples, silhouette_score
import matplotlib.cm as cm

range_n_clusters = range(2,7)
for n_clusters in range_n_clusters:
    km = KMeans(n_clusters = n_clusters, n_init = 20, random_state=0)
    cluster_labels_km = km.fit_predict(heart_diseaseDrop)
    silhouette_avg_km = silhouette_score(heart_diseaseDrop, cluster_labels_km)

    sample_silhouette_values = silhouette_samples(heart_diseaseDrop, cluster_labels_km)
    fig, ax1 = plt.subplots(1, 1)
    fig.set_size_inches(18, 7)
    ax1.set_xlim([-0.25, 1])

    y_lower = 10
```

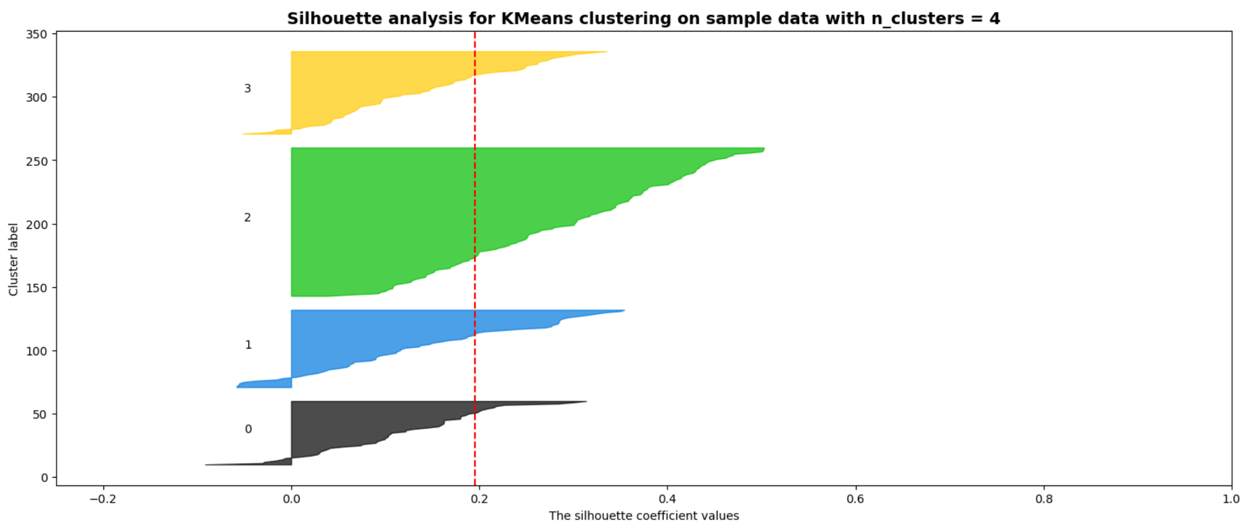
```python
for i in range(n_clusters):

    ith_cluster_silhouette_values = sample_silhouette_values[cluster_labels_km == i]

    ith_cluster_silhouette_values.sort()

    size_cluster_i = ith_cluster_silhouette_values.shape[0]
    y_upper = y_lower + size_cluster_i

    color = cm.nipy_spectral(float(i) / n_clusters)
    ax1.fill_betweenx(
        np.arange(y_lower, y_upper),
        0,
        ith_cluster_silhouette_values,
        facecolor=color,
        edgecolor=color,
        alpha=0.7,
    )



    ax1.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))



    y_lower = y_upper + 10

ax1.set_title("The silhouette plot for various cluster")
ax1.set_xlabel("The silhouette coefficient values")
ax1.set_ylabel("Cluster label")



ax1.axvline(x=silhouette_avg_km, color="red", linestyle="--")
```

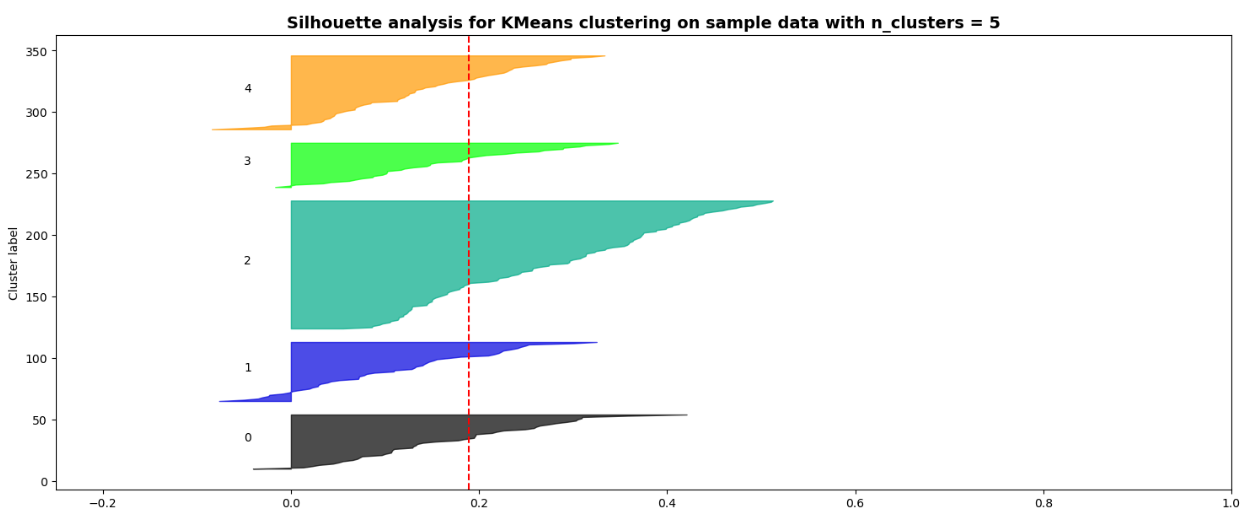
```
    plt.title(
        "Silhouette analysis for KMeans clustering on sample data with n_clusters = %d"
        % n_clusters,
        fontsize=14,
        fontweight="bold",
    )
```

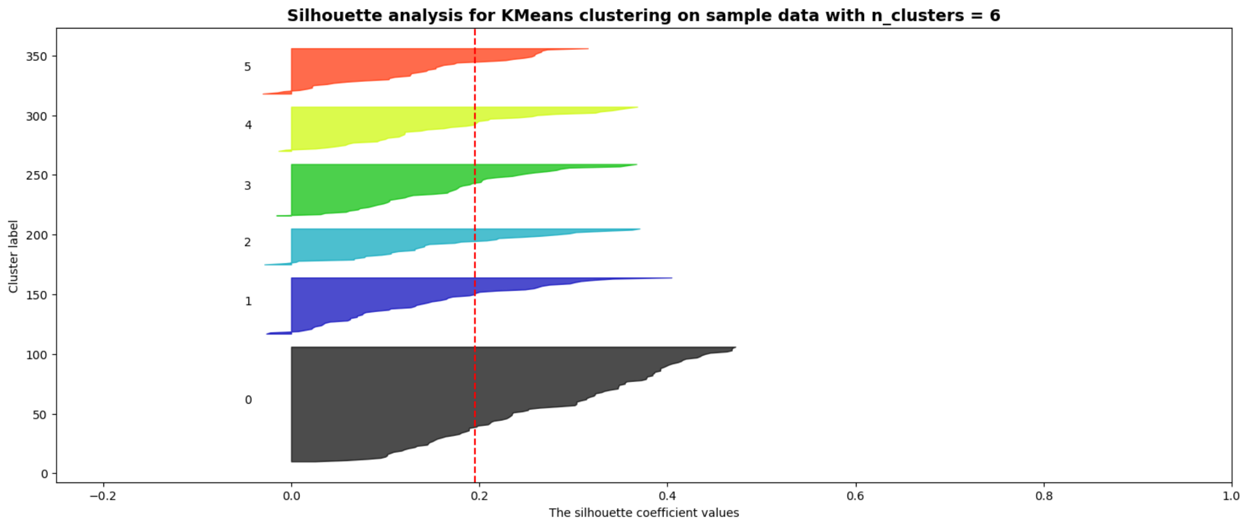
```
g:\Visual Studio\Projects\.conda\Lib\site-packages\sklearn\cluster\_kmeans.py:1419: UserWarning
  warnings.warn(
g:\Visual Studio\Projects\.conda\Lib\site-packages\sklearn\cluster\_kmeans.py:1419: UserWarning
  warnings.warn(
g:\Visual Studio\Projects\.conda\Lib\site-packages\sklearn\cluster\_kmeans.py:1419: UserWarning
  warnings.warn(
g:\Visual Studio\Projects\.conda\Lib\site-packages\sklearn\cluster\_kmeans.py:1419: UserWarning
  warnings.warn(
g:\Visual Studio\Projects\.conda\Lib\site-packages\sklearn\cluster\_kmeans.py:1419: UserWarning
  warnings.warn(
```




Silhouette analysis for KMeans clustering on sample data with n_clusters = 3
Cluster label
The silhouette coefficient values
0
1
2
0
50
100
150
200
250
300
−0.2
0.0
0.2
0.4
0.6
0.8
1.0


Silhouette analysis for KMeans clustering on sample data with n_clusters = 4
Cluster label
The silhouette coefficient values
0
1
2
3
0
50
100
150
200
250
300
350
−0.2
0.0
0.2
0.4
0.6
0.8
1.0

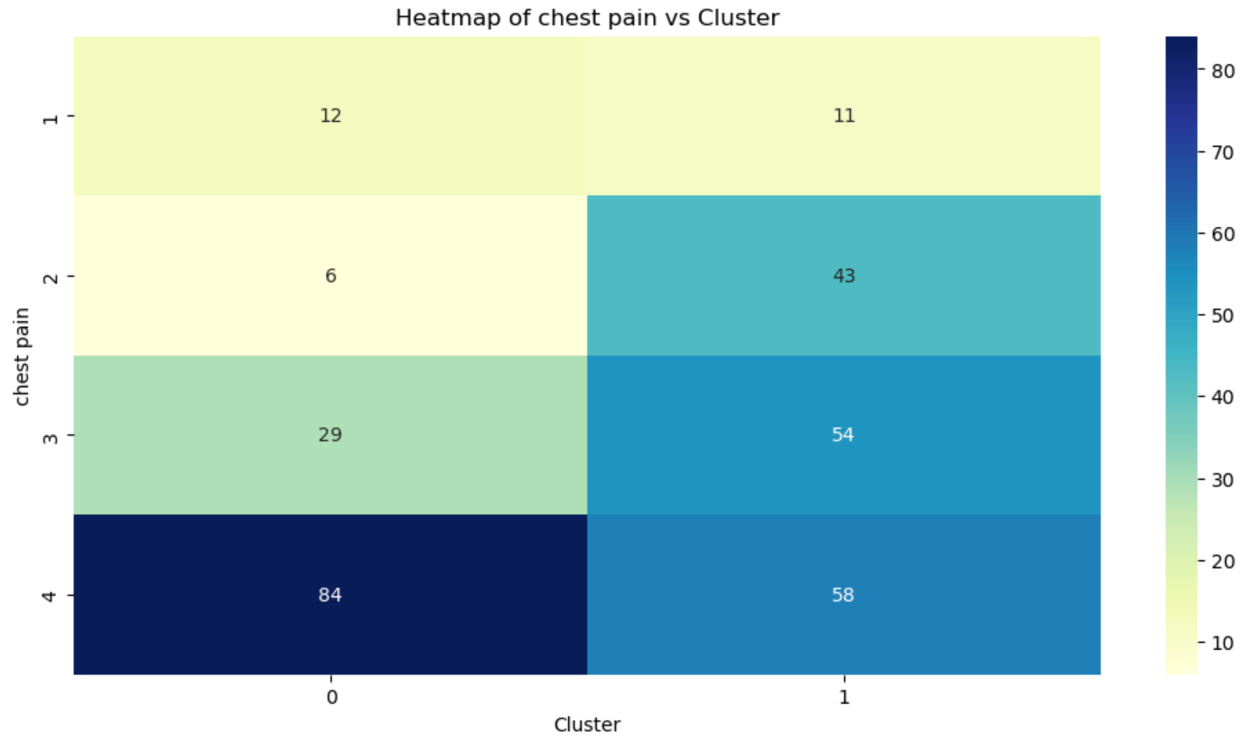

Silhouette analysis for KMeans clustering on sample data with n_clusters = 5
Cluster label
The silhouette coefficient values
0
1
2
3
4
0
50
100
150
200
250
300
350
−0.2
0.0
0.2
0.4
0.6
0.8
1.0



2 clusters seems like a good choice.

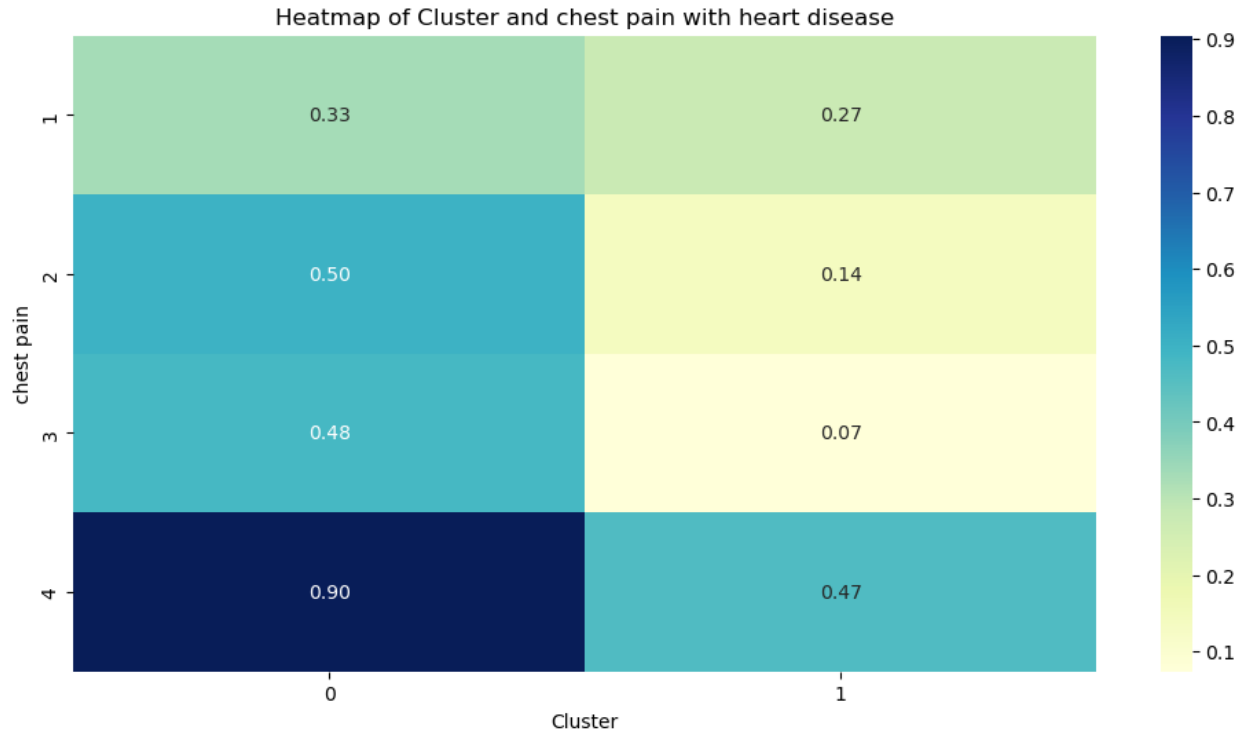
```
chest_pain = [1,2,3,4]
heart_diseaseD['cp']=  pd.Categorical(
    heart_diseaseD['cp'], categories=chest_pain, ordered=True)

km = KMeans(n_clusters = 2, n_init = 20, random_state=0)
km.fit_predict(heart_diseaseDrop)
heart_diseaseD['cluster'] = km.labels_
heart_diseaseD['cluster'] = heart_diseaseD['cluster'].astype('category')

plt.figure(figsize=(12, 6))
sns.heatmap(pd.crosstab(heart_diseaseD['cp'],
                        heart_diseaseD['cluster']), annot=True, fmt='d', cmap='YlGnBu')
plt.title('Heatmap of chest pain vs Cluster')
plt.xlabel('Cluster')
plt.ylabel('chest pain')
plt.show()
```

```
g:\Visual Studio\Projects\.conda\Lib\site-packages\sklearn\cluster\_kmeans.py:1419: UserWarning
  warnings.warn(
```




```
plt.figure(figsize=(12, 6))
pivot_table = heart_diseaseD.pivot_table(
    values='num', index='cp', columns='cluster', aggfunc='mean')
sns.heatmap(pivot_table, annot=True, fmt=".2f", cmap='YlGnBu')
plt.title('Heatmap of Cluster and chest pain with heart disease')
plt.xlabel('Cluster')
plt.ylabel('chest pain')
plt.show()
```

```
C:\Users\4xrol\AppData\Local\Temp\ipykernel_33992\328208271.py:2: FutureWarning: The default va
  pivot_table = heart_diseaseD.pivot_table(values='num', index='cp', columns='cluster', aggfunc
```



From the above heatmap Chest pain 4 seems to have a significant correlation to having some type of heart disease.

8.

```
from sklearn.model_selection import train_test_split, cross_val_score
#make the test and train groups
#need to make a test set for KNN and for Tree classification

X_train, X_test, y_train, y_test = train_test_split(
    KNN_PredictorV,
    ResponseVar,
    test_size=0.3,
    random_state=1,
    stratify=ResponseVar
    )

X_trainT, X_testT, y_trainT, y_testT = train_test_split(
```

```
    Tree_Predictor,
    ResponseVar,
    test_size=0.3,
    random_state=1,
    stratify=ResponseVar
)
```

9.

The two classifiers we have chosen are KNN and Decision Tree Classification. We chose KNN and Decision tree classification as there are simple but easily interpretable models. The decision tree model is also more robust to outliers within the data making it a good choice for this dataset.

10.

We will use the classifiers accuracy scores and sensitivity to compare the preformance of the two chosen classifiers. The accuaracy score is the number of correct predictions divied by the total number of predictions. The sesitivity score is the number of positives predicted divided by the number of actual positives.

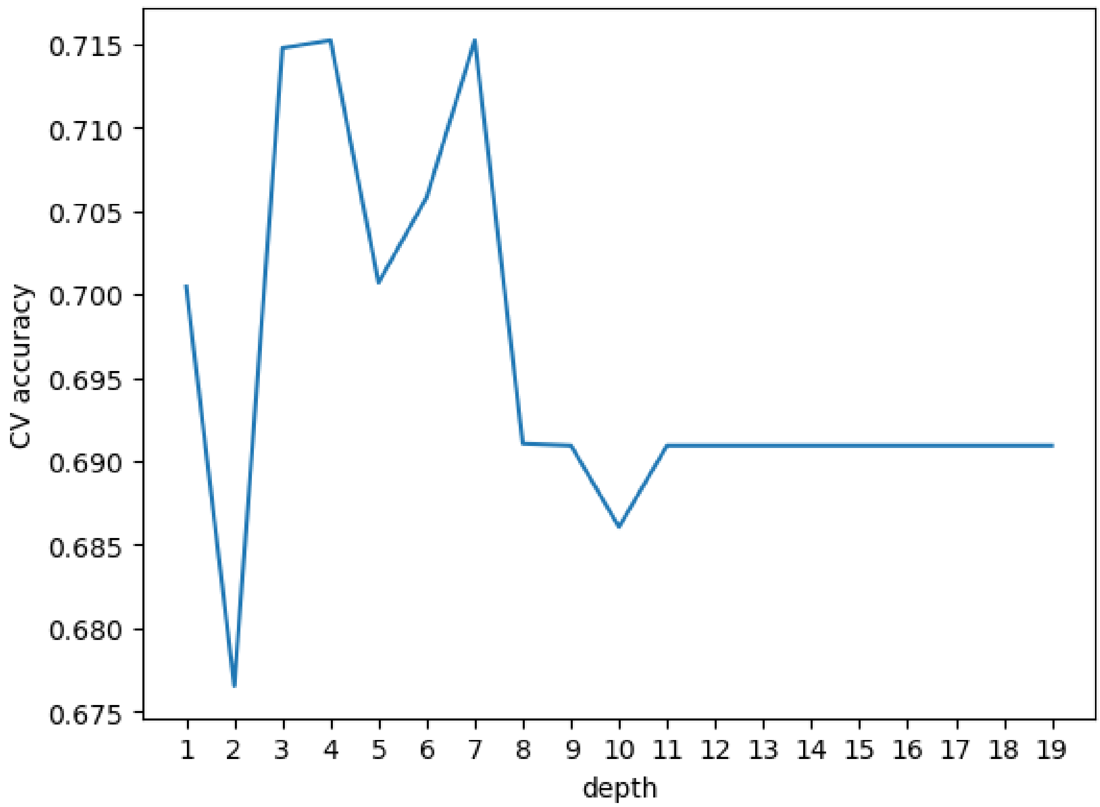
11.

```
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor, plot_tree

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

    # 5-fold cross-validation using accuracy
```

```
    cv_scores_k = cross_val_score(
        dt,
        X_trainT,
        y_trainT,
        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))
```

```
([<matplotlib.axis.XTick at 0x21fb24c49d0>,
  <matplotlib.axis.XTick at 0x21fb2a72a10>,
  <matplotlib.axis.XTick at 0x21fae037c10>,
  <matplotlib.axis.XTick at 0x21faebf9d50>,
  <matplotlib.axis.XTick at 0x21faedc6550>,
  <matplotlib.axis.XTick at 0x21fae2639d0>,
  <matplotlib.axis.XTick at 0x21fadf186d0>,
  <matplotlib.axis.XTick at 0x21fadfcfb90>,
  <matplotlib.axis.XTick at 0x21fadec2e50>,
  <matplotlib.axis.XTick at 0x21fadfcdc90>,
  <matplotlib.axis.XTick at 0x21fae0450d0>,
  <matplotlib.axis.XTick at 0x21faed3fad0>,
  <matplotlib.axis.XTick at 0x21faed3c8d0>,
  <matplotlib.axis.XTick at 0x21fadfce350>,
  <matplotlib.axis.XTick at 0x21faed97450>,
```

```
 <matplotlib.axis.XTick at 0x21faed65b10>,
 <matplotlib.axis.XTick at 0x21faed67a90>,
 <matplotlib.axis.XTick at 0x21faee7d8d0>,
 <matplotlib.axis.XTick at 0x21faed65cd0>],
[Text(1, 0, '1'),
 Text(2, 0, '2'),
 Text(3, 0, '3'),
 Text(4, 0, '4'),
 Text(5, 0, '5'),
 Text(6, 0, '6'),
 Text(7, 0, '7'),
 Text(8, 0, '8'),
 Text(9, 0, '9'),
 Text(10, 0, '10'),
 Text(11, 0, '11'),
 Text(12, 0, '12'),
 Text(13, 0, '13'),
 Text(14, 0, '14'),
 Text(15, 0, '15'),
 Text(16, 0, '16'),
 Text(17, 0, '17'),
 Text(18, 0, '18'),
 Text(19, 0, '19')])
```



Based on the graph above we choose depth 4 as the best depth for the decision tree before overfitting occurs.

```
from sklearn import neighbors
from sklearn import metrics

k_range = range(2, 8)
scores = []

for k in k_range:
    knn = neighbors.KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    scores.append(round(metrics.accuracy_score(y_test, y_pred),2))
```

Now we plot the K value test scores.

```
plt.plot(k_range, scores,color = 'purple')
plt.xlabel('K')
plt.ylabel('Test set accuracy')
plt.xticks(range(2,8))
plt.title("K Values vs Test Scores")
plt.show()
```

If we look at the graph we choose k = 5 as it is a simpler model with the highest test score.

12.

```
from mlxtend.feature_selection import SequentialFeatureSelector as SFS
import sklearn.neighbors as neighbors
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
knn = neighbors.KNeighborsClassifier(n_neighbors=5)
```

```
sfs = SFS(
    estimator=knn,
    k_features=(1, 8),
    forward=True,
    floating=False,
    scoring='accuracy',
    cv=5,
)

sfs.fit(X_train, y_train)

selected_features = X_train.columns[list(sfs.k_feature_idx_)]
selected_features

X_train_sfs = X_train[selected_features]
X_test_sfs = X_test[selected_features]
m_sfs = LogisticRegression(
    solver='saga',
    max_iter=10000
)
m_sfs.fit(X_train_sfs, y_train)
m_sfs_pre = m_sfs.predict(X_test_sfs)
accuracy_score(y_test, m_sfs_pre)
```

```
0.8
```

13.

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
#for the tree prediction
dt_best = DecisionTreeClassifier(
```

```
    max_depth = 4,
    random_state=0
    )
dt_best.fit(X_trainT, y_trainT)
test_accuracyT = dt_best.score(X_testT, y_testT)
print("The accuracy score for the decision tree is ",
      round(test_accuracyT,2))



print("The accuracy score for the KNN classifier is ",
       round(accuracy_score(y_test, y_pred),2))





print("The accuracy score for stepwise subset selection based on the KNN is ",
       round(accuracy_score(y_test, m_sfs_pre),2))

y_predT = dt_best.predict(X_testT)

con_mat = pd.DataFrame(metrics.confusion_matrix(
    y_testT, y_predT),index=['Positive Test', 'Negative Test'], columns=['Positive', 'Negative
print(con_mat)



con_mat = pd.DataFrame(metrics.confusion_matrix(
    y_test, y_pred),index=['Positive Test', 'Negative Test'], columns=['Positive', 'Negative']]
print(con_mat)

con_mat = pd.DataFrame(metrics.confusion_matrix(
    y_test, m_sfs_pre),index=['Positive Test', 'Negative Test'], columns=['Positive', 'Negativ
print(con_mat)
```

```
print("The sensitivity score for the decision tree is ", round(41/57,2))


print("The sensitivity score for KNN classifier is", round(43/54,2))


print("The sensitivity score for stepwise subset selection based on the KNN is" , round(41/52,2
```

```
The accuracy score for the decision tree is  0.74
The accuracy score for the KNN classifier is  0.82
The accuracy score for stepwise subset selection based on the KNN is  0.8
               Positive  Negative
Positive Test        41         7
Negative Test        16        26
               Positive  Negative
Positive Test        43         5
Negative Test        11        31
               Positive  Negative
Positive Test        41         7
Negative Test        11        31
The sensitivity score for the decision tree is  0.72
The sensitivity score for KNN classifier is 0.8
The sensitivity score for stepwise subset selection based on the KNN is 0.79
```

14.

```
#Fit a Decision Tree Classifier
dt_importance = DecisionTreeClassifier(max_depth=4, random_state=0)
dt_importance.fit(X_trainT, y_trainT)


#Extract feature importances
feature_importances = pd.DataFrame({
    'Feature': X_trainT.columns,
    'Importance': dt_importance.feature_importances_
```

```python
}).sort_values(by='Importance', ascending=False)

print(feature_importances)

#generated with help of copilot
```

```
     Feature  Importance
12      thal    0.499709
2         cp    0.127229
9    oldpeak    0.099146
11        ca    0.075309
7    thalach    0.054671
4       chol    0.052244
0        age    0.046330
1        sex    0.045363
3   trestbps    0.000000
8      exang    0.000000
6    restecg    0.000000
5        fbs    0.000000
10     slope    0.000000
```

Since all scores were extremely similar in value we used the decision tree function feature importance to calculate the importance of features when calculating a target variable. The most important feature with a dependable score (0.499) was thal, a blood condition in which the body has difficulty producing red blood cells. the other variables all had a 0.13 or below and so were not nearly as important in the context of predicting heart disease.

16.

Robert Questions 1,2,3,4,5

Parker Questions 6,7,8,9,14

Wesley Questions 10,11,12,13

17. https://github.com/West3104/Assignment-6/tree/main

Parker downloaded git smc from the lab and it did not work so I uploaded his questions on his behalf.

Grading scheme

1.	Answer [1]
2.	Codes (variable type transformation, etc.) [1]
	OR rationale for no transformation [1]
3.	Codes [3] and three statements [2]
4.	Codes for transforming the response variable [1]
5.	Codes for association [2] and interpretation of figures or tables [2]
6.	Codes [1]
	answer [1]
7.	Codes to identify sub groups [3] and Plot the sub groups [1]
8.	Codes [1]
9.	classifiers and justification [2]
10.	Describe the two metrics [2]
11.	Codes for training two classifiers [2]
	Codes for tuning parameters (if any) [1]
12.	Codes for feature selection or feature extraction [1]
	Codes for training the third classifier with the selected or extracted features [1]
	Codes for tuning parameters (if any) [1]
13.	Codes for evaluating three classifiers on the test set using two metrics in (10) [3]
	Two statements for the findings [2]
	One statement for the impact of feature selection or extraction [1]
14.	Codes finding the important variables [1]
	Two statements for the analysis and interpretation of the most important predictor variables [2]

15.	Codes for the sub-group improvement strategy (training and tuning parameters, if any) [Bonus 2] Comparison of the performance with the results from (13) [Bonus 1] **Bonus 3 points will be added to the final grade**
16.	Document each team member's specific contributions
17.	Link to the public GitHub repository

The maximum point for this assignment is 39. We will convert this to 100%. The bonus 3 points will be added to the final grade.

All group members will receive the same grade if they contribute to the same.