K-NN Classification

Source:

https://www.kaggle.com/ronitf/heart-disease-uci (https://www.kaggle.com/ronitf/heart-disease-uci)

Defining the Problem Statement

This dataset records the attributes of a group of patients and whether they have heart disease. From this dataset, we would like to be able to predict the presence of heart disease in patients.

Collecting the Data

In [1]:

```
# Adding Required Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import sklearn
import time
```

In [2]:

```
# Read in data from the file
df = pd.read_csv('heart.csv')
df.head() # show the first five values
```

Out[2]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	tar
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	

Modelling

- Output is the 'target' column.
- The goal is to identify whether a patient has heart disease or not.

In [3]:

```
df_not = df[df['target']==1]
df_yes = df[df['target']==0]
df_yes.head()
```

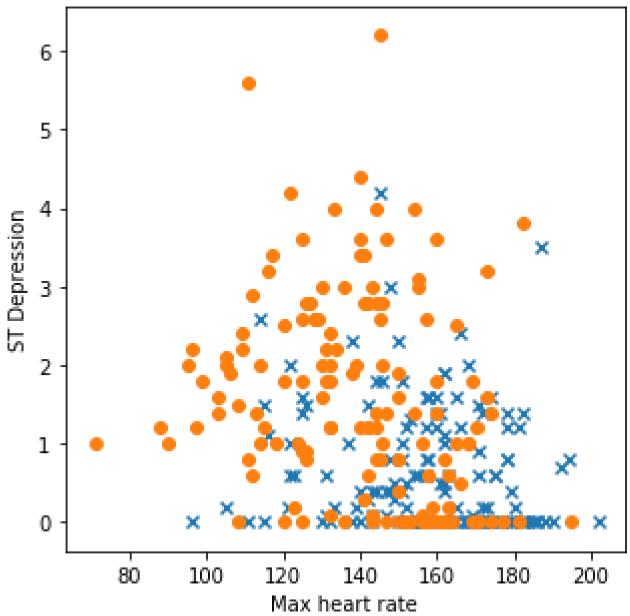
Out[3]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	t
165	67	1	0	160	286	0	0	108	1	1.5	1	3	2	
166	67	1	0	120	229	0	0	129	1	2.6	1	2	3	
167	62	0	0	140	268	0	0	160	0	3.6	0	2	2	
168	63	1	0	130	254	0	0	147	0	1.4	1	1	3	
169	53	1	0	140	203	1	0	155	1	3.1	0	0	3	

- We select **thalach (maximum heart rate)** and **oldpeak(ST Depression)** as our first set of independent variables.

In [4]:

```
fig,ax=plt.subplots(figsize=(5,5))
ax.scatter(df_not['thalach'],df_not['oldpeak'],marker='x')
ax.scatter(df_yes['thalach'],df_yes['oldpeak'],marker='o')
ax.set(xlabel='Max heart rate', ylabel='ST Depression')
plt.show()
```



In [5]:

```
# Loading Libraries required for prediction
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix

# we let k = 5 first, which means choosing 5 nearest neighbors.
knn = KNeighborsClassifier(n_neighbors = 5)
```

In [6]:

```
X= df.loc[:,['thalach','oldpeak']]
y = df.loc[:,'target']

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 42)
X_train.head()
```

Out[6]:

	thalach	oldpeak
287	164	0.0
282	134	2.2
197	163	0.2
158	144	0.4
164	173	0.0

In [7]:

```
knn_model = KNeighborsClassifier(n_neighbors = 5)
start = time.time()

knn_model.fit(X_train, y_train)
end = time.time()
print(end-start)
```

```
0.0019936561584472656
```

In [8]:

```
y_pred = knn_model.predict(X_test)
print(y_pred) # our prediction
print(y_test) # actual values
```

```
[0 0 1 1 0 1 1 0 0 1 1 0 1 0 1 1 1 0 0 0 1 0 0 0 1 1 0 1 1 0 0 1 0 1 0 1 0
 1 1 1 1 1 1 0 1 1 1 1 0 0 1 1 1 0 1 0 1 1 0 0 0 0 0 0 1 1 0 0 1 1 1 1 1 1
 0 1]
179    0
228    0
111    1
246    0
60     1
9      1
119    1
223    0
268    0
33     1
5      1
101    1
45     1
175    0
118    1
46     1
125    1
192    0
285    0
279    0
152    1
269    0
272    0
25     1
146    1
283    0
254    0
73     1
231    0
109    1
      ..
281    0
78     1
292    0
232    0
219    0
255    0
63     1
82     1
236    0
204    0
249    0
104    1
300    0
193    0
184    0
132    1
202    0
196    0
75     1
176    0
59     1
93     1
6      1
177    0
30     1
22     1
258    0
```

```
56     1
242    0
114    1
Name: target, Length: 76, dtype: int64
```

In [9]:

```
# we should test how accurate our model is
from sklearn.metrics import accuracy_score
print(accuracy_score(y_test, y_pred))
```

```
0.6578947368421053
```

We have obtained an accuracy score of **0.65789** with our first model.

Modelling Part 2: Using different k values

- To improve the accuracy score, we can test different k values for our model.
- We will try k = 1 to k = 20, as smaller k means noises have large influence and larger k means computation becomes expensive.

In [10]:

```
k_array = np.arange(1, 21, 2)

k_array
```

Out[10]:

```
array([ 1,  3,  5,  7,  9, 11, 13, 15, 17, 19])
```

In [11]:

```
# we can change k value to 1 - 20, and check the accuracy score
# Then we can choose the optimized k value

for k in k_array:
    knn_ex = KNeighborsClassifier(n_neighbors = k)
    knn_ex.fit(X_train, y_train)
    ac = accuracy_score(y_test, knn_ex.predict(X_test))
    print(k)
    print(ac)
```

```
1
0.6578947368421053
3
0.7236842105263158
5
0.6578947368421053
7
0.6973684210526315
9
0.7105263157894737
11
0.7236842105263158
13
0.7368421052631579
15
0.7236842105263158
17
0.7236842105263158
19
0.7631578947368421
```

In [12]:

```
knn_1 = KNeighborsClassifier(n_neighbors = 19)
knn_1.fit(X_train, y_train)
y_pred1 = knn_1.predict(X_test)
print(accuracy_score(y_test, y_pred1))
```

```
0.7631578947368421
```

The accuracy of the model using different values of k **varies**. Choosing a optimized value for our model is important.

Modelling Part 3: Adding independent variables

- Next, we added chest pain and exercise induced angina to our first set of independent variables (maximum heart rate and ST Depression).

In [13]:

```
x= df.loc[:,['cp','exang','thal','oldpeak']]
y = df.loc[:,'target']
X_train, X_test, y_train, y_test = train_test_split(x, y,random_state = 42)
```

In [14]:

```
knn_model = KNeighborsClassifier(n_neighbors = 15)
start = time.time()

knn_model.fit(X_train, y_train)
end = time.time()
print(end-start)
```

```
0.002956867218017578
```

In [15]:

```
y_pred = knn_model.predict(X_test)
y_pred
```

Out[15]:

```
array([0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0,
       1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0,
       1, 1, 1, 1, 1, 1, 0, 1, 1, 1], dtype=int64)
```

In [16]:

```
k_array = np.arange(1, 30, 2)

# we can change k value to 1 - 30, and check the accuracy score
# Then we can choose the optimized k value

for k in k_array:
    knn_ex = KNeighborsClassifier(n_neighbors = k)
    knn_ex.fit(X_train, y_train)
    ac = accuracy_score(y_test, knn_ex.predict(X_test))
    print(k)
    print(ac)
```

```
1
0.7763157894736842
3
0.7236842105263158
5
0.75
7
0.7763157894736842
9
0.8552631578947368
11
0.8552631578947368
13
0.8552631578947368
15
0.868421052631579
17
0.868421052631579
19
0.868421052631579
21
0.868421052631579
23
0.868421052631579
25
0.8552631578947368
27
0.8552631578947368
29
0.868421052631579
```

In [17]:

```
knn_1 = KNeighborsClassifier(n_neighbors = 15)
knn_1.fit(X_train, y_train)
y_pred1 = knn_1.predict(X_test)
print(accuracy_score(y_test, y_pred1))
```

```
0.868421052631579
```

By adding 2 features, we have obtained a higher accuracy score of **0.86842**.

Validation with Confusion Matrix

In [18]:

```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test, y_pred)
```

Out[18]:

```
array([[29,  6],
       [ 4, 37]], dtype=int64)
```

In [19]:

```
# The confusion matrix when k = 1
confusion_matrix(y_test, y_pred1)
```

Out[19]:

```
array([[29,  6],
       [ 4, 37]], dtype=int64)
```

In [20]:

```
# The F1 score can be interpreted as a weighted average of the precision and recall,
# where an F1 score reaches its best value at 1 and worst score at 0.
from sklearn.metrics import f1_score
f1_score(y_test, y_pred1, average = 'micro')
```

Out[20]:

```
0.868421052631579
```

Conclusion

With an increase in independent variables from 2 to 4, we have improved the accuracy score from 76.3% to 86.8%. However, training duration has increased slightly by 0.001 second as the dataset is quite large (303 rows of data) and it is taxing on computing recources to use K-NN model.

In [ ]:

```

```