Logistic Regression

Create a Classification Model that can predict whether or not a person has presence of heart disease based on physical features of that person (age,sex, cholesterol, etc...)

In [2]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [3]:

```
df = pd.read_csv('heart.csv')
df.head()
```

Out[3]:

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

Data description

This database contains 14 physical attributes based on physical testing of a patient. Blood samples are taken and the patient also conducts a brief exercise test. The "goal" field refers to the presence of heart disease in the patient. It is integer (0 for no presence, 1 for presence). In general, to confirm 100% if a patient has heart disease can be quite an invasive process, so if we can create a model that accurately predicts the likelihood of heart disease, we can help avoid expensive and invasive procedures.

Content

Attribute Information:

- age
- sex
- chest pain type (4 values)
- resting blood pressure
- serum cholestoral in mg/dl
- fasting blood sugar > 120 mg/dl
- resting electrocardiographic results (values 0,1,2)
- maximum heart rate achieved
- exercise induced angina
- oldpeak = ST depression induced by exercise relative to rest
- the slope of the peak exercise ST segment
- number of major vessels (0-3) colored by flourosopy
- thal: 3 = normal; 6 = fixed defect; 7 = reversable defect

- thal: 3 = normal; 6 = fixed defect; 7 = reversable defect
- target:0 for no presence of heart disease, 1 for presence of heart disease

Original Source: https://archive.ics.uci.edu/ml/datasets/Heart+Disease

In [8]:

```
df['target'].unique()
```

Out[8]:

```
array([1, 0])
```

In [9]:

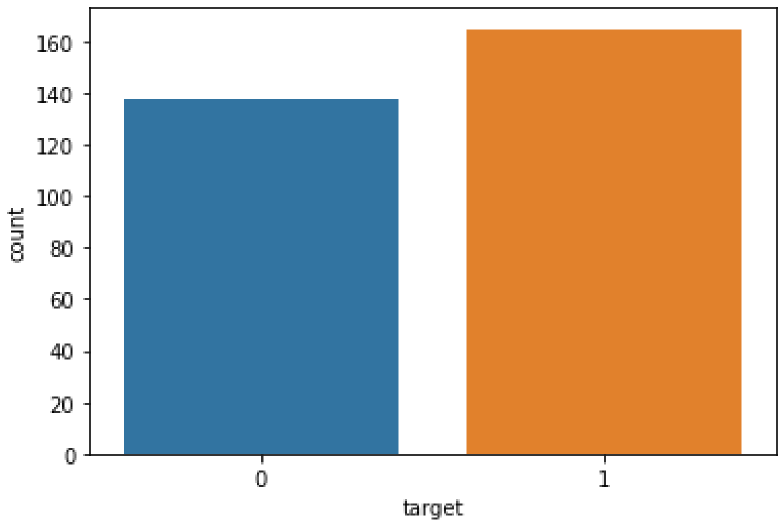
```
# The output (Target) contain only 2 possible output 0 or 1 . It is a binary
classification dataset.
```

In [10]:

```
sns.countplot(x='target',data=df)
```

Out[10]:

```
<AxesSubplot:xlabel='target', ylabel='count'>
```



In [11]:

```
# The output is evenly distributed and we can use accuracy as the performance mea
sure.
```

In [12]:

```
X = df.drop('target',axis=1)
y = df['target']
```

In [14]:

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
# We will be using stdscaller for scalling the data
```

In [15]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1,
random_state=101)
# 10% of data for test and 90% for training with 101 as random state
```

In [16]:

```
scaler = StandardScaler()
```

In [17]:

```
scaled_X_train = scaler.fit_transform(X_train)
scaled_X_test = scaler.transform(X_test)
```

In [19]:

```
from sklearn.linear_model import LogisticRegressionCV
# We will be using CV (inbuild crossvalidation logistic reg model to train out dat
a)
```

In [20]:

```
log_model = LogisticRegressionCV()
```

In [21]:

```
log_model.fit(scaled_X_train,y_train)
```

Out[21]:

```
LogisticRegressionCV()
```

In [22]:

```
log_model.coef_
```

Out[22]:

```
array([[-0.09621199, -0.39460154,  0.53534731, -0.13850191, -0.08830462,
         0.02487341,  0.08083826,  0.29914053, -0.33438151, -0.352386  ,
         0.25101033, -0.49735752, -0.37448551]])
```

In [23]:

```
#Model Performance Evaluation
```

In [24]:

```
from sklearn.metrics import
confusion_matrix,classification_report,plot_confusion_matrix
```

In [25]:

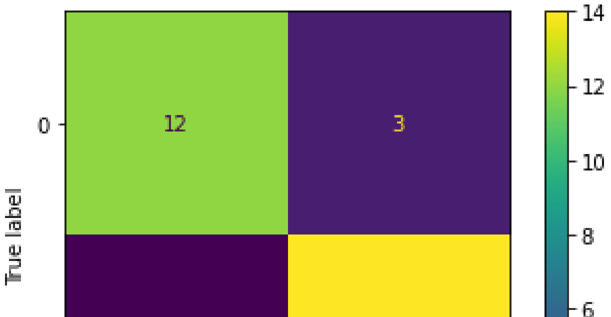
```
y_pred = log_model.predict(scaled_X_test)
```

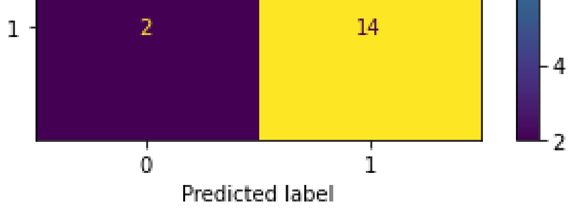
In [27]:

```
#confusion_matrix
plot_confusion_matrix(log_model,scaled_X_test,y_test)
```

Out[27]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f8509957a90>
```





In [28]:

```
# precision, recall, f1 score
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.86      0.80      0.83        15
           1       0.82      0.88      0.85        16

    accuracy                           0.84        31
   macro avg       0.84      0.84      0.84        31
weighted avg       0.84      0.84      0.84        31
```

In [30]:

```
# Prediction on new data

new_data= [[ 54. ,   1. ,   0. , 122. , 286. ,   0. ,   0. , 116. ,   1. ,
          3.2,   1. ,   2. ,   2. ]]

# As our model is trained on scaled data, we will have to scale this new data too

new_scaled_data= scaler.transform(new_data)
print(new_scaled_data)
```

```
[[-0.03345031  0.69737995 -0.94692412 -0.55319325  0.75524961 -0.42732739
  -0.99577247 -1.49008466  1.47064295  1.97686092 -0.67167968  1.23823052
  -0.4842146 ]]
```

In [32]:

```
log_model.predict(new_scaled_data)
```

Out[32]:

```
array([0])
```

In [33]:

```
log_model.predict_proba(new_scaled_data)
```

Out[33]:

```
array([[0.94751173, 0.05248827]])
```

In [ ]:

```
#For this new data, our model is 94% sure that it will be a 0 class
```