ML practice-Week 6:

Logistic Regression for binary classification

Introduction

Logistic Regression (also called Logit Regression) is commonly used to estimate the probability that an instance belongs to a particular class.

- If the estimated probability is greater than 50%, then the model predicts that the instance belongs to that class (called the positive class, labeled “1”), or else it predicts that it does not (i.e., it belongs to the negative class, labeled “0”).
- This makes it a binary classifier.

Loading the dataset

Cleveland Heart-disease dataset

Attribute Information:

1. Age (in years)
2. Sex (1 = male; 0 = female)
3. cp -chest pain type
4. trestbps - resting blood pressure (anything above 130-140 is typically cause for concern)
5. chol-serum cholestoral in mg/dl (above 200 is cause for concern)
6. fbs - fasting blood sugar (> 120 mg/dl) (1 = true; 0 = false)
7. restecg - resting electrocardiographic results (0 = normal;1 = having ST-T wave abnormality; 2 = showing probable or definite left ventricular hypertrophy by Estes' criteria)
8. thalach-maximum heart rate achieved
9. exang - exercise induced angina (1 = yes; 0 = no)
10. oldpeak - depression induced by exercise relative to rest
11. slope - slope of the peak exercise ST segment (1 = upsloping; 2 = flat Value; 3 = downsloping)
12. ca - number of major vessels (0-3) colored by flourosopy
13. thal - (3 = normal; 6 = fixed defect; 7 = reversable defect
14. **num** (target) - diagnosis of heart disease (angiographic disease status)(0: < 50% diameter narrowing ; 1: > 50% diameter narrowing)

Reference

Import basic libraries

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn import datasets
from sklearn.linear_model import LogisticRegression
from pandas.plotting import scatter_matrix
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
```

Download Heart disease dataset

```
#Define the column names
cols = ['age', 'sex', 'cp', 'trestbps', 'chol',  'fbs', 'restecg', 'thalach', 'exang', 'ol

# Load the dataset
heart_data = pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-databases/heart-
heart_data
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	c
0	63.0	1.0	1.0	145.0	233.0	1.0	2.0	150.0	0.0	2.3	3.0	0.
1	67.0	1.0	4.0	160.0	286.0	0.0	2.0	108.0	1.0	1.5	2.0	3.
2	67.0	1.0	4.0	120.0	229.0	0.0	2.0	129.0	1.0	2.6	2.0	2.
3	37.0	1.0	3.0	130.0	250.0	0.0	0.0	187.0	0.0	3.5	3.0	0.
4	41.0	0.0	2.0	130.0	204.0	0.0	2.0	172.0	0.0	1.4	1.0	0.
...	...	...	...	...	...	...	...	...	...	...	...	.
298	45.0	1.0	1.0	110.0	264.0	0.0	0.0	132.0	0.0	1.2	2.0	0.
299	68.0	1.0	4.0	144.0	193.0	1.0	0.0	141.0	0.0	3.4	2.0	2.
300	57.0	1.0	4.0	130.0	131.0	0.0	0.0	115.0	1.0	1.2	2.0	1.
301	57.0	0.0	2.0	130.0	236.0	0.0	2.0	174.0	0.0	0.0	2.0	1.
302	38.0	1.0	3.0	138.0	175.0	0.0	0.0	173.0	0.0	0.0	1.0	

303 rows × 14 columns

```
# to check the type of data variable

type(heart_data)
```

```
pandas.core.frame.DataFrame
```

```
# Display first five rows of the dataset
heart_data.head() #head is first 5 rows
```

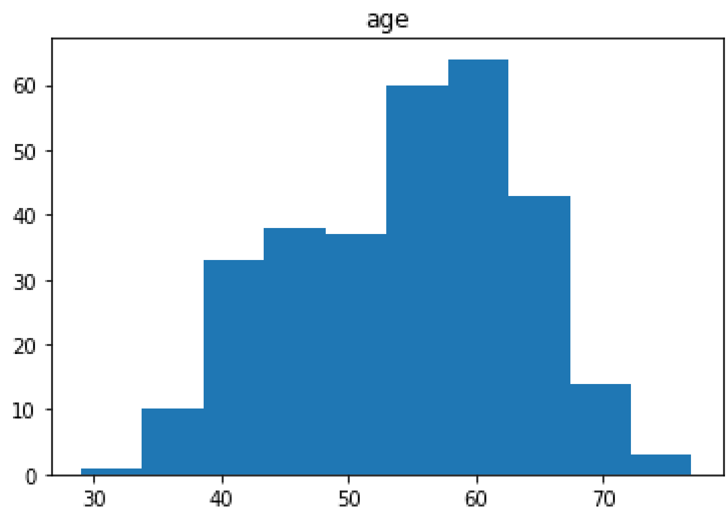
	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca
0	63.0	1.0	1.0	145.0	233.0	1.0	2.0	150.0	0.0	2.3	3.0	0.0
1	67.0	1.0	4.0	160.0	286.0	0.0	2.0	108.0	1.0	1.5	2.0	3.0
2	67.0	1.0	4.0	120.0	229.0	0.0	2.0	129.0	1.0	2.6	2.0	2.0
3	37.0	1.0	3.0	130.0	250.0	0.0	0.0	187.0	0.0	3.5	3.0	0.0
4	41.0	0.0	2.0	130.0	204.0	0.0	2.0	172.0	0.0	1.4	1.0	0.0

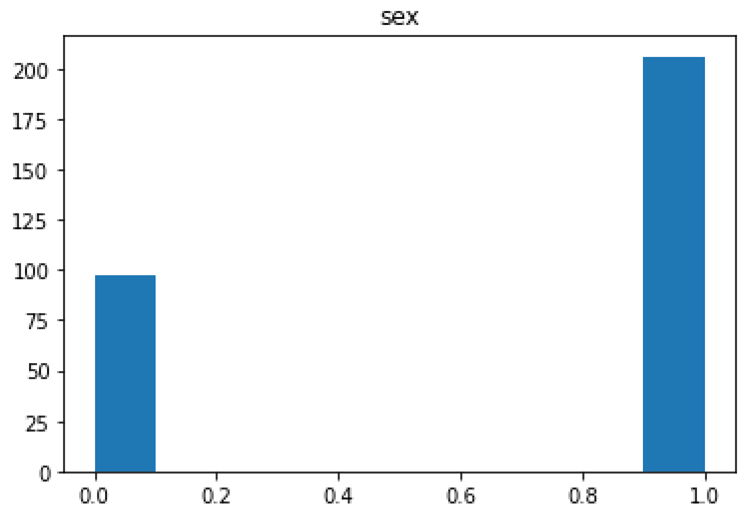
```
# Display last five rows of the dataset
heart_data.tail() #tail is last 5 rows
```

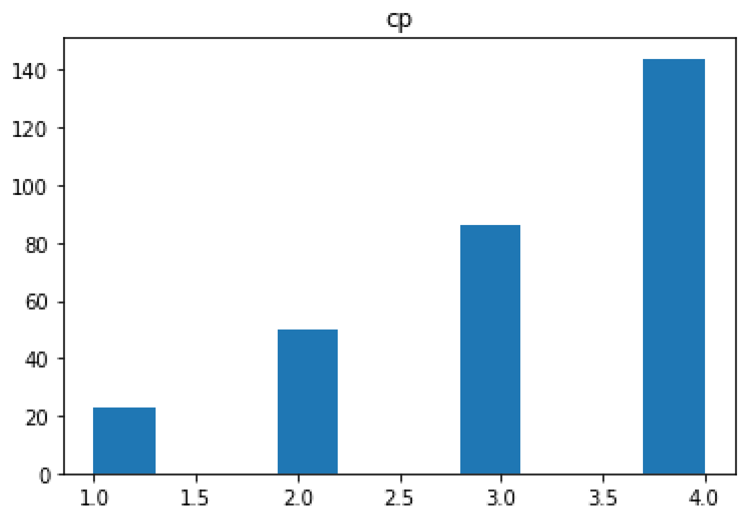
	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	c
298	45.0	1.0	1.0	110.0	264.0	0.0	0.0	132.0	0.0	1.2	2.0	0.
299	68.0	1.0	4.0	144.0	193.0	1.0	0.0	141.0	0.0	3.4	2.0	2.
300	57.0	1.0	4.0	130.0	131.0	0.0	0.0	115.0	1.0	1.2	2.0	1.
301	57.0	0.0	2.0	130.0	236.0	0.0	2.0	174.0	0.0	0.0	2.0	1.
302	38.0	1.0	3.0	138.0	175.0	0.0	0.0	173.0	0.0	0.0	1.0	

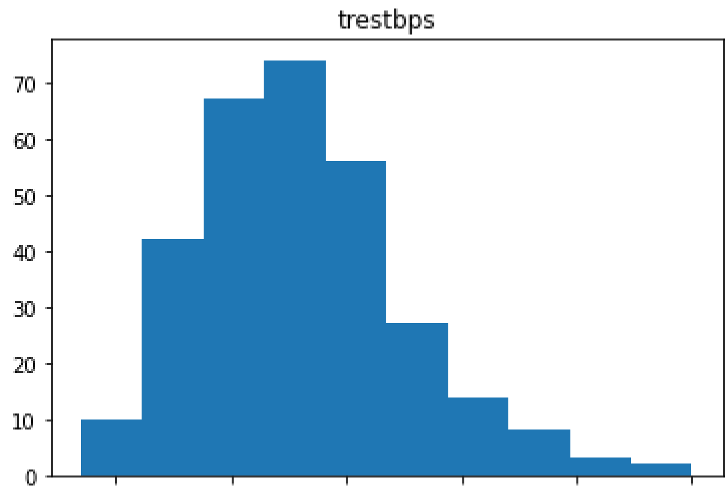
Visualizing dataset and features

```
for feature in cols:
  plt.hist(heart_data[feature])
  plt.title(feature)
  # display histogram
  plt.show()
```

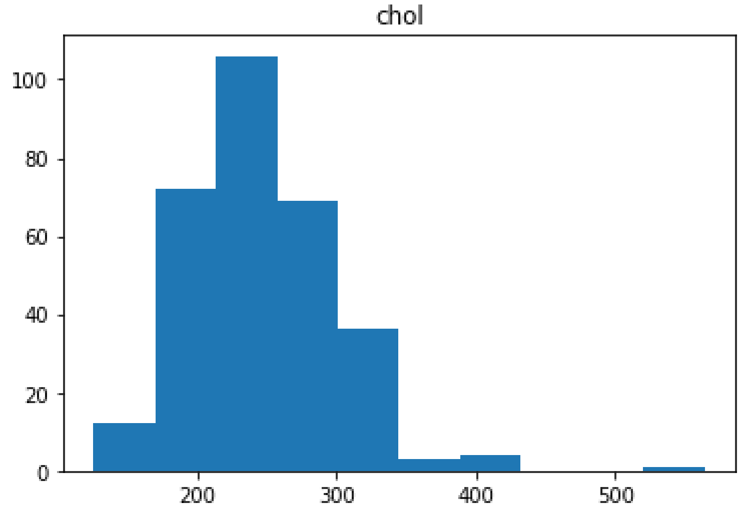

age
0
10
20
30
40
50
60
30
40
50
60
70

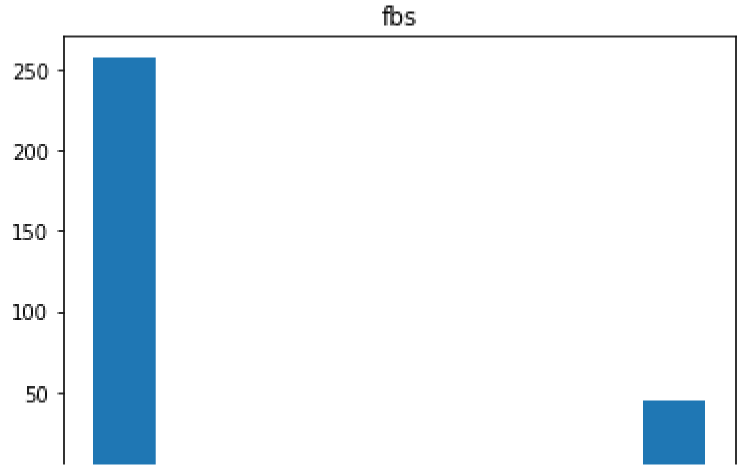

sex
0
25
50
75
100
125
150
175
200
0.0
0.2
0.4
0.6
0.8
1.0


cp
0
20
40
60
80
100
120
140
1.0
1.5
2.0
2.5
3.0
3.5
4.0


trestbps
0
10
20
30
40
50
60
70


100
120
140
160
180
200


chol
0
20
40
60
80
100
200
300
400
500


fbs
50
100
150
200
250

Preprocessing : class labels

- Experiments with the database have concentrated on simply attempting to distinguish presence (values 1,2,3,4) from absence (value 0)
- Let us change instances with labels 2,3 and to 1.

```
# converting class labels 2,3, and 4 into label 1
heart_data = heart_data.replace({"num":  {2:1,3:1, 4:1}})

# Visualize the label
heart_data
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	c
0	63.0	1.0	1.0	145.0	233.0	1.0	2.0	150.0	0.0	2.3	3.0	0.
1	67.0	1.0	4.0	160.0	286.0	0.0	2.0	108.0	1.0	1.5	2.0	3.
2	67.0	1.0	4.0	120.0	229.0	0.0	2.0	129.0	1.0	2.6	2.0	2.
3	37.0	1.0	3.0	130.0	250.0	0.0	0.0	187.0	0.0	3.5	3.0	0.
4	41.0	0.0	2.0	130.0	204.0	0.0	2.0	172.0	0.0	1.4	1.0	0.
...	...	...	...	...	...	...	...	...	...	...	...	.
298	45.0	1.0	1.0	110.0	264.0	0.0	0.0	132.0	0.0	1.2	2.0	0.
299	68.0	1.0	4.0	144.0	193.0	1.0	0.0	141.0	0.0	3.4	2.0	2.
300	57.0	1.0	4.0	130.0	131.0	0.0	0.0	115.0	1.0	1.2	2.0	1.
301	57.0	0.0	2.0	130.0	236.0	0.0	2.0	174.0	0.0	0.0	2.0	1.
302	38.0	1.0	3.0	138.0	175.0	0.0	0.0	173.0	0.0	0.0	1.0	

303 rows × 14 columns

Preprocessing : Replacing missing values

The feature 'ca' has missing values that are given as '?'. Let us replace the '?' with nan and then fill those missing values using 'mean' imputation strategy.

```
heart_data.replace('?',np.nan, inplace=True)
imputer = SimpleImputer(missing_values = np.nan, strategy ='mean')
imputer = imputer.fit(heart_data)
heart_imputed = imputer.transform(heart_data)
heart_data_imputed = pd.DataFrame(heart_imputed, columns = cols)
heart_data_imputed
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	
0	63.0	1.0	1.0	145.0	233.0	1.0	2.0	150.0	0.0	2.3	3.0	0.
1	67.0	1.0	4.0	160.0	286.0	0.0	2.0	108.0	1.0	1.5	2.0	3.
2	67.0	1.0	4.0	120.0	229.0	0.0	2.0	129.0	1.0	2.6	2.0	2.
3	37.0	1.0	3.0	130.0	250.0	0.0	0.0	187.0	0.0	3.5	3.0	0.
4	41.0	0.0	2.0	130.0	204.0	0.0	2.0	172.0	0.0	1.4	1.0	0.
...	...	...	...	...	...	...	...	...	...	...	...	
298	45.0	1.0	1.0	110.0	264.0	0.0	0.0	132.0	0.0	1.2	2.0	0.
299	68.0	1.0	4.0	144.0	193.0	1.0	0.0	141.0	0.0	3.4	2.0	2.
300	57.0	1.0	4.0	130.0	131.0	0.0	0.0	115.0	1.0	1.2	2.0	1.
301	57.0	0.0	2.0	130.0	236.0	0.0	2.0	174.0	0.0	0.0	2.0	1.
302	38.0	1.0	3.0	138.0	175.0	0.0	0.0	173.0	0.0	0.0	1.0	0.

303 rows × 14 columns

Let us first separate the input attributes and target attribute.

```
# Assign a new variable y as target

y = heart_data_imputed['num']
y = np.array(y)
y
```

```
array([0., 1., 1., 0., 0., 0., 1., 0., 1., 1., 0., 0., 1., 0., 0., 0., 1.,
       0., 0., 0., 0., 0., 1., 1., 1., 0., 0., 0., 0., 1., 0., 1., 1., 0.,
       0., 0., 1., 1., 1., 0., 1., 0., 0., 0., 1., 1., 0., 1., 0., 0., 0.,
       0., 1., 0., 1., 1., 1., 1., 0., 0., 1., 0., 1., 0., 1., 1., 1., 0.,
       1., 1., 0., 1., 1., 1., 1., 0., 1., 0., 0., 1., 0., 0., 0., 1., 0.,
       0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 1., 1., 1., 0., 0., 0., 0.,
       0., 0., 1., 0., 1., 1., 1., 1., 1., 1., 0., 1., 1., 0., 0., 0., 1.,
       1., 1., 1., 0., 1., 1., 0., 1., 1., 0., 0., 0., 0., 0., 0., 0., 0.,
       1., 1., 1., 0., 0., 1., 0., 1., 0., 1., 1., 0., 0., 0., 0., 0., 0.,
       1., 1., 1., 1., 1., 1., 0., 0., 1., 0., 0., 0., 0., 0., 0., 1., 0.,
       1., 0., 1., 0., 1., 1., 0., 1., 0., 0., 1., 1., 0., 0., 1., 0., 0.,
       1., 1., 1., 0., 1., 1., 1., 0., 1., 0., 0., 0., 1., 0., 0., 0., 0.,
       0., 1., 1., 1., 0., 1., 0., 1., 0., 1., 1., 0., 0., 0., 0., 0., 0.,
```

```
       0., 0., 1., 1., 0., 0., 0., 1., 1., 0., 1., 1., 0., 0., 1., 1., 1.,
       0., 0., 0., 0., 0., 1., 0., 1., 1., 1., 1., 0., 0., 1., 0., 0., 0.,
       0., 0., 0., 0., 1., 0., 1., 0., 0., 1., 1., 1., 1., 1., 0., 1., 0.,
       1., 0., 1., 0., 0., 0., 1., 0., 1., 0., 1., 0., 1., 1., 1., 0., 0.,
       0., 1., 0., 1., 1., 1., 0., 1., 1., 1., 1., 1., 1., 0.])
```

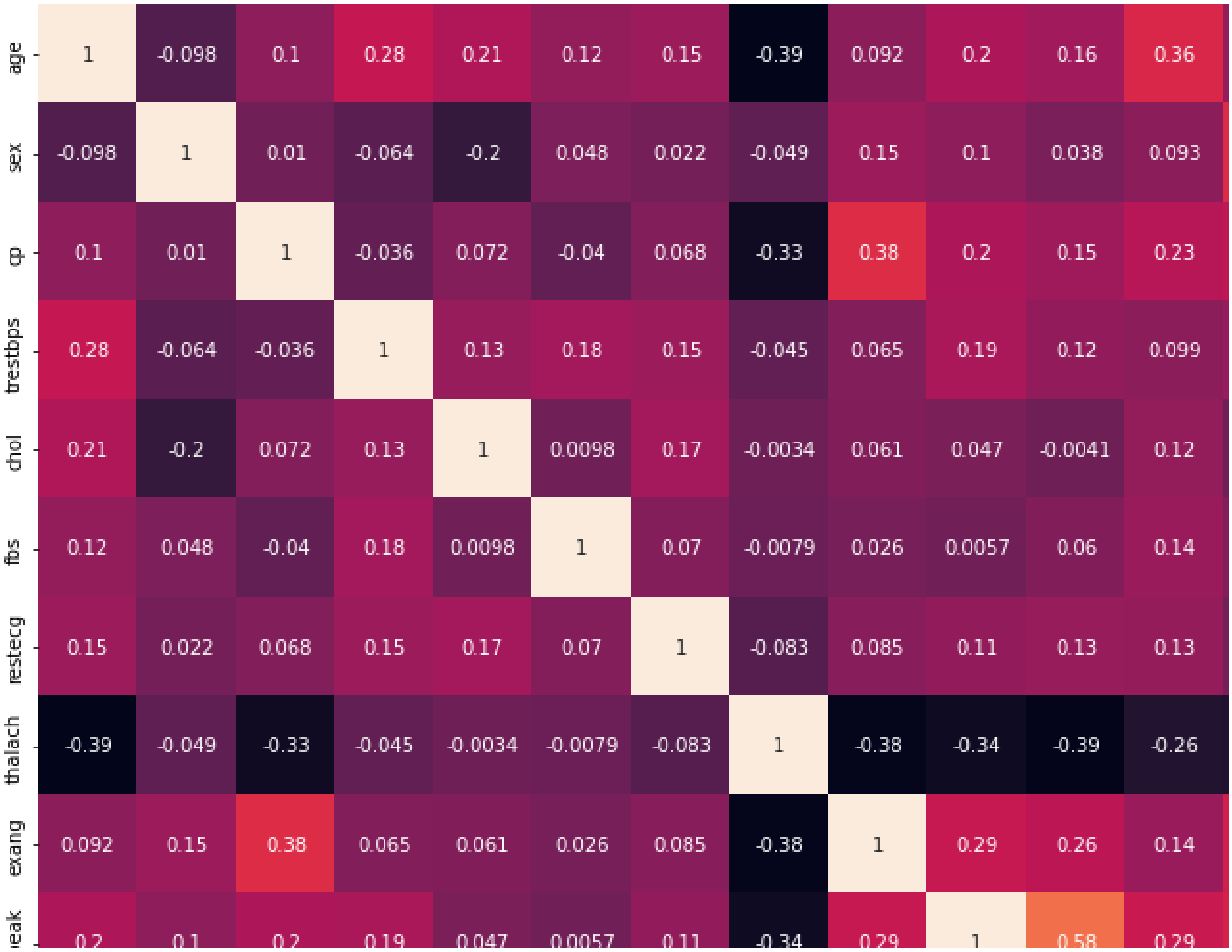
```
# Remove the target variable from heart_data

del heart_data_imputed['num']
```

```
heart_data_imputed.describe()
```

	age	sex	cp	trestbps	chol	fbs	reste
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.0000
mean	54.438944	0.679868	3.158416	131.689769	246.693069	0.148515	0.9900
std	9.038662	0.467299	0.960126	17.599748	51.776918	0.356198	0.9949
min	29.000000	0.000000	1.000000	94.000000	126.000000	0.000000	0.0000
25%	48.000000	0.000000	3.000000	120.000000	211.000000	0.000000	0.0000
50%	56.000000	1.000000	3.000000	130.000000	241.000000	0.000000	1.0000
75%	61.000000	1.000000	4.000000	140.000000	275.000000	0.000000	2.0000
max	77.000000	1.000000	4.000000	200.000000	564.000000	1.000000	2.0000

Understanding the correlation between Input features

```
plt.figure(figsize=[15,15])
sns.heatmap(heart_data_imputed.corr(),annot = True, square = True)
plt.show()
```



Train and Test data split

```
# Let us split the data for training and testing

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(heart_data_imputed, y, test_size = 0.2

print('Shape of training data',X_train.shape)
print('Shape of training labels', y_train.shape)
print('Shape of testing data', X_test.shape)
print('Shape of testing labels',y_test.shape)
```

```
Shape of training data (227, 13)
Shape of training labels (227,)
Shape of testing data (76, 13)
Shape of testing labels (76,)
```

```
X_train
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	
173	62.0	0.0	4.0	140.0	394.0	0.0	2.0	157.0	0.0	1.2	2.0	0.
261	58.0	0.0	2.0	136.0	319.0	1.0	2.0	152.0	0.0	0.0	1.0	2.
37	57.0	1.0	4.0	150.0	276.0	0.0	2.0	112.0	1.0	0.6	2.0	1.
101	34.0	1.0	1.0	118.0	182.0	0.0	2.0	174.0	0.0	0.0	1.0	0.
166	52.0	1.0	3.0	138.0	223.0	0.0	0.0	169.0	0.0	0.0	1.0	0.
...	...	...	...	...	...	...	...	...	...	...	...	
251	58.0	1.0	4.0	146.0	218.0	0.0	0.0	105.0	0.0	2.0	2.0	1.
192	43.0	1.0	4.0	132.0	247.0	1.0	2.0	143.0	1.0	0.1	2.0	0.
117	35.0	0.0	4.0	138.0	183.0	0.0	0.0	182.0	0.0	1.4	1.0	0.
47	50.0	1.0	4.0	150.0	243.0	0.0	2.0	128.0	0.0	2.6	2.0	0.
172	59.0	0.0	4.0	174.0	249.0	0.0	0.0	143.0	1.0	0.0	2.0	0.

As there is a wide variation among the numerical values between features, it is a best practice to normalize the features before training.

Normalizing features for training

```
# Instantiate the scaler to a variable and fit the train and test data

ss = StandardScaler()
X_train_norm = ss.fit_transform(X_train)
X_test_norm = ss.transform(X_test)
```

Perform Classification

```
LR = LogisticRegression()

classifier=LR.fit(X_train_norm, y_train)

score = LR.score(X_train_norm, y_train)

print("Training score: ", score)

#Make the prediction
y_pred = LR.predict(X_test_norm)
```

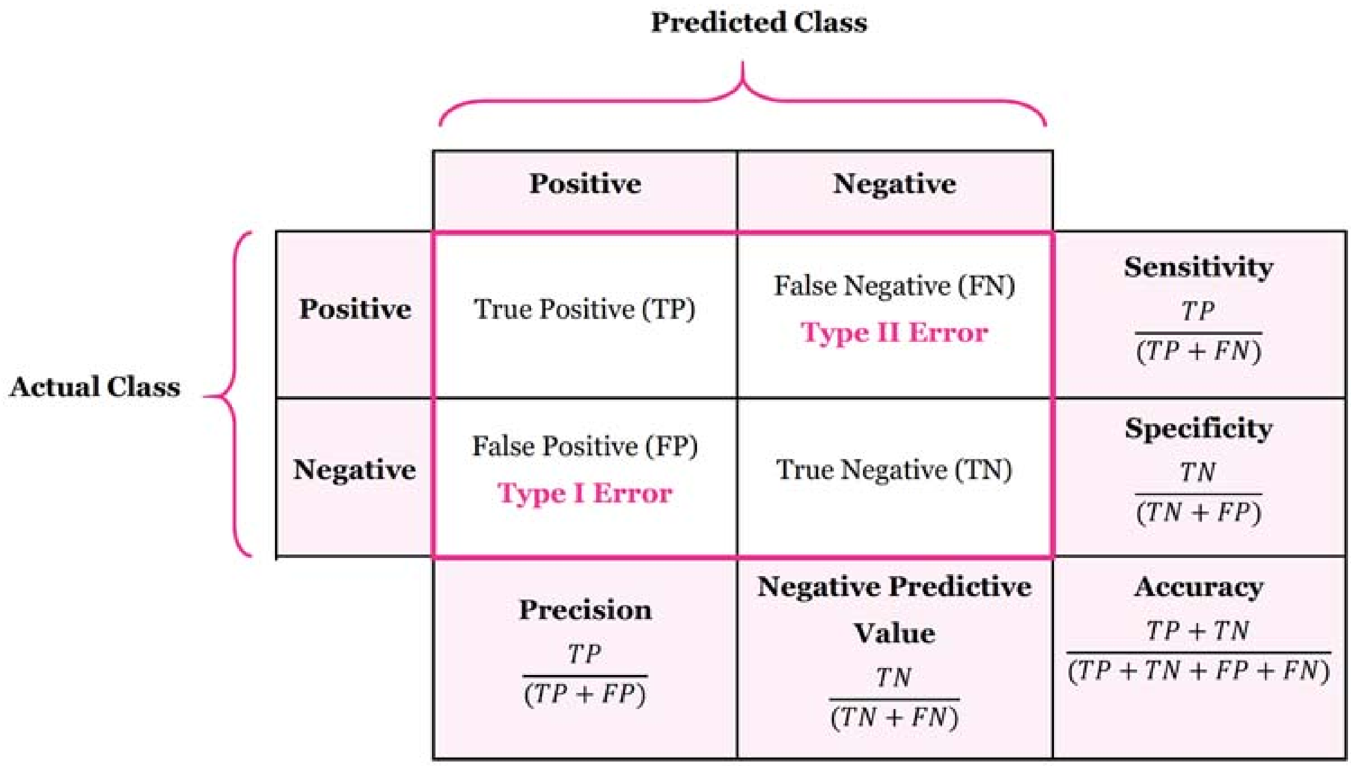
```
Training score:  0.8634361233480177
```

```
# Import the libraries
```

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

Confusion Matrix

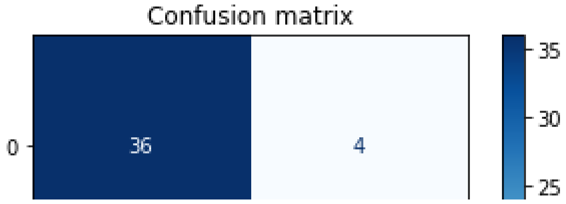
A confusion matrix is a summary of prediction results on a classification problem.



[Source]()

```
# visualizing the confusion matrix

from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import plot_roc_curve

class_names=["0","1"]
plot_confusion_matrix(classifier, X_test_norm, y_test,display_labels=class_names,cmap=plt.
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names, rotation=0)
plt.yticks(tick_marks, class_names)
plt.title('Confusion matrix')
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87: FutureWarnin
  warnings.warn(msg, category=FutureWarning)
```




```
CR = classification_report(y_test, y_pred)
print('Classification report \n')
print(CR)
```

```
Classification report

              precision    recall  f1-score   support

         0.0       0.78      0.90      0.84        40
         1.0       0.87      0.72      0.79        36

    accuracy                           0.82        76
   macro avg       0.82      0.81      0.81        76
weighted avg       0.82      0.82      0.81        76
```

Hyperparameter tuning with RandomizedSearchCV and GridSearchCV

```
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
```

RandomizedSearchCV

```
# Create a hyperparameter grid for LogisticRegression
log_reg_grid_rs = {"C": np.logspace(-4, 4, 20),
                "solver": ["liblinear"]}

# Tune LogisticRegression

np.random.seed(42)

# Setup random hypterparameter search for LogisticRegression with cross-validation
RS_log_reg = RandomizedSearchCV(LogisticRegression(),
                                param_distributions=log_reg_grid_rs,
                                cv=5,
                                n_iter=20,
                                verbose=True)

# Fit random hyperparamter search model for LogisticRegression
RS_log_reg.fit(X_train_norm, y_train)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
RandomizedSearchCV(cv=5, estimator=LogisticRegression(), n_iter=20,
                   param_distributions={'C': array([1.00000000e-04, 2.63665090e-04,
```

```
     6.95192796e-04, 1.83298071e-03,
            4.83293024e-03, 1.27427499e-02, 3.35981829e-02, 8.85866790e-02,
            2.33572147e-01, 6.15848211e-01, 1.62377674e+00, 4.28133240e+00,
            1.12883789e+01, 2.97635144e+01, 7.84759970e+01, 2.06913808e+02,
            5.45559478e+02, 1.43844989e+03, 3.79269019e+03, 1.00000000e+04]),
                                                 'solver': ['liblinear']},
                        verbose=True)
```

```
?LogisticRegression()
```

```
np.logspace(-4, 4, 20)
```

```
     array([1.00000000e-04, 2.63665090e-04, 6.95192796e-04, 1.83298071e-03,
            4.83293024e-03, 1.27427499e-02, 3.35981829e-02, 8.85866790e-02,
            2.33572147e-01, 6.15848211e-01, 1.62377674e+00, 4.28133240e+00,
            1.12883789e+01, 2.97635144e+01, 7.84759970e+01, 2.06913808e+02,
            5.45559478e+02, 1.43844989e+03, 3.79269019e+03, 1.00000000e+04])
```

```
# Find the best hyperparameters
RS_log_reg.best_params_
```

```
     {'C': 0.08858667904100823, 'solver': 'liblinear'}
```

```
RS_log_reg.score(X_train_norm, y_train)
```

```
     0.8678414096916299
```

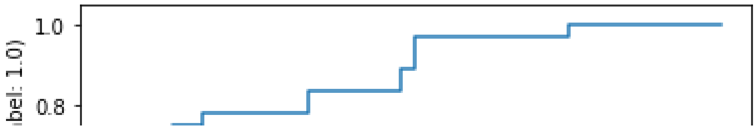
```
# Make predictions with tuned model
y_preds = RS_log_reg.predict(X_test_norm)
# Confusion matrix
print(confusion_matrix(y_test, y_preds))
```

```
     [[36  4]
      [10 26]]
```

```
?plot_roc_curve
```

```
# Plot ROC curve and calculate AUC metric
plot_roc_curve(RS_log_reg, X_test_norm, y_test)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87: FutureWarnin
  warnings.warn(msg, category=FutureWarning)
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7f8a13f6d190>
```



GridSearchCV

```
# Setup grid hyperparamter search for LogisticRegression
log_reg_grid_gs = {"C": np.logspace(-4, 4, 30),
                "solver": ["liblinear"]}

GS_log_reg = GridSearchCV(LogisticRegression(),
                          param_grid=log_reg_grid_gs,
                          cv=5,
                          verbose=True)

# Fit grid hyperparameter search model
GS_log_reg.fit(X_train_norm, y_train);
```

```
Fitting 5 folds for each of 30 candidates, totalling 150 fits
```

```
np.logspace(-4, 4, 30)
```

```
array([1.00000000e-04, 1.88739182e-04, 3.56224789e-04, 6.72335754e-04,
       1.26896100e-03, 2.39502662e-03, 4.52035366e-03, 8.53167852e-03,
       1.61026203e-02, 3.03919538e-02, 5.73615251e-02, 1.08263673e-01,
       2.04335972e-01, 3.85662042e-01, 7.27895384e-01, 1.37382380e+00,
       2.59294380e+00, 4.89390092e+00, 9.23670857e+00, 1.74332882e+01,
       3.29034456e+01, 6.21016942e+01, 1.17210230e+02, 2.21221629e+02,
       4.17531894e+02, 7.88046282e+02, 1.48735211e+03, 2.80721620e+03,
       5.29831691e+03, 1.00000000e+04])
```

```
# Check the best hyperparameters
GS_log_reg.best_params_
```

```
{'C': 0.1082636733874054, 'solver': 'liblinear'}
```

```
# Evaluate the grid search LogisticRegression model
GS_log_reg.score(X_train_norm, y_train)
```

```
0.8634361233480177
```

```
# Make predictions with tuned model
y_preds = GS_log_reg.predict(X_test_norm)
# Confusion matrix
print(confusion_matrix(y_test, y_preds))
```

```
[[36  4]
 [10 26]]
```