In [1]:

- 1 # Importing Pandas and NumPy
- 2 import pandas as pd
- 3 import numpy as np

In [2]:

- 1 # Importing dataset
- data = pd.read_csv('D:/Python/Dataset/nrippner-titanic-disaster-dataset/titanic.csv')

In [3]:

1 data

Out[3]:

	pclass	survived	name	sex	age	sibsp	parch	ticket	fare	cabin	е
0	1.0	1.0	Allen, Miss. Elisabeth Walton	female	29.0000	0.0	0.0	24160	211.3375	B5	
1	1.0	1.0	Allison, Master. Hudson Trevor	male	0.9167	1.0	2.0	113781	151.5500	C22 C26	
2	1.0	0.0	Allison, Miss. Helen Loraine	female	2.0000	1.0	2.0	113781	151.5500	C22 C26	
3	1.0	0.0	Allison, Mr. Hudson Joshua Creighton	male	30.0000	1.0	2.0	113781	151.5500	C22 C26	
4	1.0	0.0	Allison, Mrs. Hudson J C (Bessie Waldo Daniels)	female	25.0000	1.0	2.0	113781	151.5500	C22 C26	
1305	3.0	0.0	Zabour, Miss. Thamine	female	NaN	1.0	0.0	2665	14.4542	NaN	
1306	3.0	0.0	Zakarian, Mr. Mapriededer	male	26.5000	0.0	0.0	2656	7.2250	NaN	
1307	3.0	0.0	Zakarian, Mr. Ortin	male	27.0000	0.0	0.0	2670	7.2250	NaN	
1308	3.0	0.0	Zimmerman, Mr. Leo	male	29.0000	0.0	0.0	315082	7.8750	NaN	
1309	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

1310 rows × 14 columns

•

In [4]:

```
1 data.describe()
```

Out[4]:

	pclass	survived	age	sibsp	parch	fare	bo
count	1309.000000	1309.000000	1046.000000	1309.000000	1309.000000	1308.000000	121.0000
mean	2.294882	0.381971	29.881135	0.498854	0.385027	33.295479	160.8099
std	0.837836	0.486055	14.413500	1.041658	0.865560	51.758668	97.6969
min	1.000000	0.000000	0.166700	0.000000	0.000000	0.000000	1.0000
25%	2.000000	0.000000	21.000000	0.000000	0.000000	7.895800	72.0000
50%	3.000000	0.000000	28.000000	0.000000	0.000000	14.454200	155.0000
75%	3.000000	1.000000	39.000000	1.000000	0.000000	31.275000	256.0000
max	3.000000	1.000000	80.000000	8.000000	9.000000	512.329200	328.0000
4							•

In [5]:

1 data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1310 entries, 0 to 1309
Data columns (total 14 columns):
             1309 non-null float64
pclass
survived
             1309 non-null float64
name
             1309 non-null object
             1309 non-null object
sex
             1046 non-null float64
age
             1309 non-null float64
sibsp
parch
             1309 non-null float64
             1309 non-null object
ticket
             1308 non-null float64
fare
             295 non-null object
cabin
             1307 non-null object
embarked
boat
             486 non-null object
             121 non-null float64
body
home.dest
             745 non-null object
dtypes: float64(7), object(7)
memory usage: 143.4+ KB
```

In [6]:

```
1 data['sex'].value_counts()
```

Out[6]:

male 843 female 466

Name: sex, dtype: int64

In [7]:

```
# Converting Male to 1 and Female to 0
data['sex'] = data['sex'].map({'male': 1, 'female': 0})
#The varaible was imported as a string we need to convert it to float
#data['sex'] =pd.to_numeric(data['sex'],errors='coerce')
```

In [8]:

1 data

Out[8]:

	pclass	survived	name	sex	age	sibsp	parch	ticket	fare	cabin	em
0	1.0	1.0	Allen, Miss. Elisabeth Walton	0.0	29.0000	0.0	0.0	24160	211.3375	В5	
1	1.0	1.0	Allison, Master. Hudson Trevor	1.0	0.9167	1.0	2.0	113781	151.5500	C22 C26	
2	1.0	0.0	Allison, Miss. Helen Loraine	0.0	2.0000	1.0	2.0	113781	151.5500	C22 C26	
3	1.0	0.0	Allison, Mr. Hudson Joshua Creighton	1.0	30.0000	1.0	2.0	113781	151.5500	C22 C26	
4	1.0	0.0	Allison, Mrs. Hudson J C (Bessie Waldo Daniels)	0.0	25.0000	1.0	2.0	113781	151.5500	C22 C26	
1305	3.0	0.0	Zabour, Miss. Thamine	0.0	NaN	1.0	0.0	2665	14.4542	NaN	
1306	3.0	0.0	Zakarian, Mr. Mapriededer	1.0	26.5000	0.0	0.0	2656	7.2250	NaN	
1307	3.0	0.0	Zakarian, Mr. Ortin	1.0	27.0000	0.0	0.0	2670	7.2250	NaN	
1308	3.0	0.0	Zimmerman, Mr. Leo	1.0	29.0000	0.0	0.0	315082	7.8750	NaN	
1309	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

1310 rows × 14 columns

localhost:8888/notebooks/Logistic Regression Titanic dataset.ipynb

In [9]:

1 data.describe()

Out[9]:

	pclass	survived	sex	age	sibsp	parch	1
count	1309.000000	1309.000000	1309.000000	1046.000000	1309.000000	1309.000000	1308.000
mean	2.294882	0.381971	0.644003	29.881135	0.498854	0.385027	33.295
std	0.837836	0.486055	0.478997	14.413500	1.041658	0.865560	51.758
min	1.000000	0.000000	0.000000	0.166700	0.000000	0.000000	0.000
25%	2.000000	0.000000	0.000000	21.000000	0.000000	0.000000	7.895
50%	3.000000	0.000000	1.000000	28.000000	0.000000	0.000000	14.454
75%	3.000000	1.000000	1.000000	39.000000	1.000000	0.000000	31.275
max	3.000000	1.000000	1.000000	80.000000	8.000000	9.000000	512.329
4							•

In [10]:

- 1 # Creating a dummy variable for the variable 'Contract' and dropping the first one.
- cont = pd.get_dummies(data['embarked'],prefix='embarked',drop_first=True)
- 3 #Adding the results to the master dataframe
- 4 data = pd.concat([data,cont],axis=1)

In [11]:

1 data

Out[11]:

	pclass	survived	name	sex	age	sibsp	parch	ticket	fare	cabin	em
0	1.0	1.0	Allen, Miss. Elisabeth Walton	0.0	29.0000	0.0	0.0	24160	211.3375	В5	
1	1.0	1.0	Allison, Master. Hudson Trevor	1.0	0.9167	1.0	2.0	113781	151.5500	C22 C26	
2	1.0	0.0	Allison, Miss. Helen Loraine	0.0	2.0000	1.0	2.0	113781	151.5500	C22 C26	
3	1.0	0.0	Allison, Mr. Hudson Joshua Creighton	1.0	30.0000	1.0	2.0	113781	151.5500	C22 C26	
4	1.0	0.0	Allison, Mrs. Hudson J C (Bessie Waldo Daniels)	0.0	25.0000	1.0	2.0	113781	151.5500	C22 C26	
1305	3.0	0.0	Zabour, Miss. Thamine	0.0	NaN	1.0	0.0	2665	14.4542	NaN	
1306	3.0	0.0	Zakarian, Mr. Mapriededer	1.0	26.5000	0.0	0.0	2656	7.2250	NaN	
1307	3.0	0.0	Zakarian, Mr. Ortin	1.0	27.0000	0.0	0.0	2670	7.2250	NaN	
1308	3.0	0.0	Zimmerman, Mr. Leo	1.0	29.0000	0.0	0.0	315082	7.8750	NaN	
1309	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

1310 rows × 16 columns

localhost:8888/notebooks/Logistic Regression Titanic dataset.ipynb

In [12]:

```
1 data.describe()
```

Out[12]:

1	parch	sibsp	age	sex	survived	pclass	
1308.000	1309.000000	1309.000000	1046.000000	1309.000000	1309.000000	1309.000000	count
33.295	0.385027	0.498854	29.881135	0.644003	0.381971	2.294882	mean
51.758	0.865560	1.041658	14.413500	0.478997	0.486055	0.837836	std
0.000	0.000000	0.000000	0.166700	0.000000	0.000000	1.000000	min
7.895	0.000000	0.000000	21.000000	0.000000	0.000000	2.000000	25%
14.454	0.000000	0.000000	28.000000	1.000000	0.000000	3.000000	50%
31.275	0.000000	1.000000	39.000000	1.000000	1.000000	3.000000	75%
512.329	9.000000	8.000000	80.000000	1.000000	1.000000	3.000000	max

→

In [13]:

```
1 data['ticket'].value_counts()
```

Out[13]:

```
CA. 2343
                 11
1601
                  8
CA 2144
                  8
347077
                  7
S.O.C. 14879
364850
                  1
315083
                  1
350035
                  1
350404
                  1
31028
```

Name: ticket, Length: 929, dtype: int64

In [14]:

```
# We have created dummies for the below variables, so we can drop them
data = data.drop(['embarked'], 1)
```

In [15]:

1 data

Out[15]:

	pclass	survived	name	sex	age	sibsp	parch	ticket	fare	cabin	boa
0	1.0	1.0	Allen, Miss. Elisabeth Walton	0.0	29.0000	0.0	0.0	24160	211.3375	В5	
1	1.0	1.0	Allison, Master. Hudson Trevor	1.0	0.9167	1.0	2.0	113781	151.5500	C22 C26	1
2	1.0	0.0	Allison, Miss. Helen Loraine	0.0	2.0000	1.0	2.0	113781	151.5500	C22 C26	Nal
3	1.0	0.0	Allison, Mr. Hudson Joshua Creighton	1.0	30.0000	1.0	2.0	113781	151.5500	C22 C26	Nal
4	1.0	0.0	Allison, Mrs. Hudson J C (Bessie Waldo Daniels)	0.0	25.0000	1.0	2.0	113781	151.5500	C22 C26	Nal
1305	3.0	0.0	Zabour, Miss. Thamine	0.0	NaN	1.0	0.0	2665	14.4542	NaN	Nal
1306	3.0	0.0	Zakarian, Mr. Mapriededer	1.0	26.5000	0.0	0.0	2656	7.2250	NaN	Nal
1307	3.0	0.0	Zakarian, Mr. Ortin	1.0	27.0000	0.0	0.0	2670	7.2250	NaN	Nal
1308	3.0	0.0	Zimmerman, Mr. Leo	1.0	29.0000	0.0	0.0	315082	7.8750	NaN	Nal
1309	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Nal

1310 rows × 15 columns



In [16]:

```
# Checking outliers at 25%,50%,75%,90%,95% and 99%
data.describe(percentiles=[.25,.5,.75,.90,.95,.99])
```

Out[16]:

	pclass	survived	sex	age	sibsp	parch	1
count	1309.000000	1309.000000	1309.000000	1046.000000	1309.000000	1309.000000	1308.000
mean	2.294882	0.381971	0.644003	29.881135	0.498854	0.385027	33.295
std	0.837836	0.486055	0.478997	14.413500	1.041658	0.865560	51.758
min	1.000000	0.000000	0.000000	0.166700	0.000000	0.000000	0.000
25%	2.000000	0.000000	0.000000	21.000000	0.000000	0.000000	7.895
50%	3.000000	0.000000	1.000000	28.000000	0.000000	0.000000	14.454
75%	3.000000	1.000000	1.000000	39.000000	1.000000	0.000000	31.275
90%	3.000000	1.000000	1.000000	50.000000	1.000000	2.000000	78.050
95%	3.000000	1.000000	1.000000	57.000000	2.000000	2.000000	133.650
99%	3.000000	1.000000	1.000000	65.000000	5.000000	4.000000	262.375
max	3.000000	1.000000	1.000000	80.000000	8.000000	9.000000	512.329

In [17]:

```
# Adding up the missing values (column-wise)
data.isnull().sum()
```

Out[17]:

pclass	1
survived	1
name	1
sex	1
age	264
sibsp	1
parch	1
ticket	1
fare	2
cabin	1015
boat	824
body	1189
home.dest	565
embarked_Q	0
embarked_S	0
dtype: int64	

In [18]:

```
# Checking the percentage of missing values
round(100*(data.isnull().sum()/len(data.index)), 2)
```

Out[18]:

pclass	0.08
survived	0.08
name	0.08
sex	0.08
age	20.15
sibsp	0.08
parch	0.08
ticket	0.08
fare	0.15
cabin	77.48
boat	62.90
body	90.76
home.dest	43.13
embarked_Q	0.00
embarked_S	0.00
dtype: float64	1

```
In [88]:
```

data['home.dest'].value counts()

```
______
                                          Traceback (most recent call last)
KevError
~\Anaconda3\lib\site-packages\pandas\core\indexes\base.py in get_loc(self, k
ey, method, tolerance)
  2896
                   try:
-> 2897
                        return self._engine.get_loc(key)
  2898
                    except KeyError:
pandas\_libs\index.pyx in pandas._libs.index.IndexEngine.get_loc()
pandas\_libs\index.pyx in pandas._libs.index.IndexEngine.get_loc()
pandas\_libs\hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHa
shTable.get item()
pandas\_libs\hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHa
shTable.get_item()
KeyError: 'home.dest'
During handling of the above exception, another exception occurred:
KeyError
                                          Traceback (most recent call last)
<ipython-input-88-114bb5a0bd52> in <module>
---> 1 data['home.dest'].value_counts()
~\Anaconda3\lib\site-packages\pandas\core\frame.py in getitem (self, key)
                   if self.columns.nlevels > 1:
  2978
  2979
                        return self._getitem_multilevel(key)
                    indexer = self.columns.get_loc(key)
-> 2980
                    if is_integer(indexer):
  2981
  2982
                        indexer = [indexer]
~\Anaconda3\lib\site-packages\pandas\core\indexes\base.py in get loc(self, k
ey, method, tolerance)
  2897
                        return self._engine.get_loc(key)
  2898
                    except KeyError:
                        return self. engine.get loc(self. maybe cast indexer
-> 2899
(key))
               indexer = self.get indexer([key], method=method, tolerance=t
  2900
olerance)
  2901
               if indexer.ndim > 1 or indexer.size > 1:
pandas\ libs\index.pyx in pandas. libs.index.IndexEngine.get loc()
pandas\ libs\index.pyx in pandas. libs.index.IndexEngine.get loc()
pandas\_libs\hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHa
shTable.get item()
pandas\ libs\hashtable class helper.pxi in pandas. libs.hashtable.PyObjectHa
shTable.get item()
KeyError: 'home.dest'
```

In [20]:

```
# We have some unwanted columns , so we can drop them
data = data.drop(['home.dest','cabin','boat'], 1)
```

In [21]:

1 data

Out[21]:

	pclass	survived	name	sex	age	sibsp	parch	ticket	fare	body	eml
0	1.0	1.0	Allen, Miss. Elisabeth Walton	0.0	29.0000	0.0	0.0	24160	211.3375	NaN	
1	1.0	1.0	Allison, Master. Hudson Trevor	1.0	0.9167	1.0	2.0	113781	151.5500	NaN	
2	1.0	0.0	Allison, Miss. Helen Loraine	0.0	2.0000	1.0	2.0	113781	151.5500	NaN	
3	1.0	0.0	Allison, Mr. Hudson Joshua Creighton	1.0	30.0000	1.0	2.0	113781	151.5500	135.0	
4	1.0	0.0	Allison, Mrs. Hudson J C (Bessie Waldo Daniels)	0.0	25.0000	1.0	2.0	113781	151.5500	NaN	
1305	3.0	0.0	Zabour, Miss. Thamine	0.0	NaN	1.0	0.0	2665	14.4542	NaN	
1306	3.0	0.0	Zakarian, Mr. Mapriededer	1.0	26.5000	0.0	0.0	2656	7.2250	304.0	
1307	3.0	0.0	Zakarian, Mr. Ortin	1.0	27.0000	0.0	0.0	2670	7.2250	NaN	
1308	3.0	0.0	Zimmerman, Mr. Leo	1.0	29.0000	0.0	0.0	315082	7.8750	NaN	
1309	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

1310 rows × 12 columns

```
In [22]:
```

```
1 data['age'].tail(50)
Out[22]:
1260
        18.0
        63.0
1261
1262
         NaN
1263
        11.5
        40.5
1264
1265
        10.0
1266
        36.0
1267
        30.0
1268
         NaN
1269
        33.0
1270
        28.0
1271
        28.0
        47.0
1272
1273
        18.0
1274
        31.0
        16.0
1275
1276
        31.0
1277
        22.0
1278
        20.0
        14.0
1279
1280
        22.0
1281
        22.0
1282
         NaN
1283
         NaN
1284
         NaN
1285
        32.5
1286
        38.0
1287
        51.0
1288
        18.0
1289
        21.0
1290
        47.0
1291
         NaN
1292
         NaN
1293
         NaN
1294
        28.5
1295
        21.0
1296
        27.0
1297
         NaN
1298
        36.0
1299
        27.0
1300
        15.0
1301
        45.5
         NaN
1302
1303
         NaN
        14.5
1304
1305
         NaN
        26.5
1306
1307
        27.0
1308
        29.0
1309
         NaN
Name: age, dtype: float64
```

In [23]:

1 data.describe()

Out[23]:

	pclass	survived	sex	age	sibsp	parch	1
count	1309.000000	1309.000000	1309.000000	1046.000000	1309.000000	1309.000000	1308.000
mean	2.294882	0.381971	0.644003	29.881135	0.498854	0.385027	33.295
std	0.837836	0.486055	0.478997	14.413500	1.041658	0.865560	51.758
min	1.000000	0.000000	0.000000	0.166700	0.000000	0.000000	0.000
25%	2.000000	0.000000	0.000000	21.000000	0.000000	0.000000	7.895
50%	3.000000	0.000000	1.000000	28.000000	0.000000	0.000000	14.454
75%	3.000000	1.000000	1.000000	39.000000	1.000000	0.000000	31.275
max	3.000000	1.000000	1.000000	80.000000	8.000000	9.000000	512.329
4							>

In [24]:

data.describe(percentiles=[.25,.5,.75,.90,.95,.99])

Out[24]:

	pclass	pclass survived sex		age	sibsp	parch	1
count	1309.000000	1309.000000	1309.000000	1046.000000	1309.000000	1309.000000	1308.000
mean	2.294882	0.381971	0.644003	29.881135	0.498854	0.385027	33.295
std	0.837836	0.486055	0.478997	14.413500	1.041658	0.865560	51.758
min	1.000000	0.000000	0.000000	0.166700	0.000000	0.000000	0.000
25%	2.000000	0.000000	0.000000	21.000000	0.000000	0.000000	7.895
50%	3.000000	0.000000	1.000000	28.000000	0.000000	0.000000	14.454
75%	3.000000	1.000000	1.000000	39.000000	1.000000	0.000000	31.275
90%	3.000000	3.000000 1.000000 1.000000 50.00		50.000000	1.000000	2.000000	78.050
95%	3.000000	1.000000	1.000000	57.000000	2.000000	2.000000	133.650
99%	3.000000	1.000000	1.000000	65.000000	5.000000	4.000000	262.375
max	3.000000	1.000000	1.000000	80.000000	8.000000	9.000000	512.329
4							•

```
In [25]:
 1 data.isnull().sum()
Out[25]:
pclass
                 1
survived
                 1
                 1
name
                 1
sex
               264
age
sibsp
                 1
                 1
parch
ticket
                 1
fare
                 2
              1189
body
embarked_Q
                 0
embarked_S
                 0
dtype: int64
In [26]:
 1 data['age'].fillna(data['age'].mean(),inplace=True)
In [27]:
 1 data['fare'].fillna(data['fare'].mean(),inplace=True)
In [28]:
 1 data.isnull().sum()
Out[28]:
                 1
pclass
                 1
survived
                 1
name
                 1
sex
age
                 1
sibsp
parch
                 1
ticket
fare
              1189
body
embarked_Q
                 0
embarked S
                 0
dtype: int64
In [29]:
   # Normalising continuous features
 1
    df = data[['sex','age','fare']]
In [30]:
    normalized_df=(df-df.mean())/df.std()
```

```
In [31]:
 1 data = data.drop(['sex', 'age', 'fare'], 1)
In [32]:
    data = pd.concat([data,normalized_df],axis=1)
In [33]:
    data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1310 entries, 0 to 1309
Data columns (total 12 columns):
              1309 non-null float64
pclass
              1309 non-null float64
survived
              1309 non-null object
name
              1309 non-null float64
sibsp
parch
              1309 non-null float64
              1309 non-null object
ticket
              121 non-null float64
body
              1310 non-null uint8
embarked_Q
embarked S
              1310 non-null uint8
              1309 non-null float64
sex
              1310 non-null float64
age
fare
              1310 non-null float64
dtypes: float64(8), object(2), uint8(2)
memory usage: 105.0+ KB
In [34]:
 1 # Removing NaN in Survived rows
   data = data[~np.isnan(data['survived'])]
In [35]:
    survived = (sum(data['survived'])/len(data['survived'].index))*100
In [36]:
    survived
Out[36]:
38.19709702062643
In [37]:
    from sklearn.model_selection import train_test_split
```

```
In [38]:
```

```
# Putting feature variable to X
X = data.drop(['name','survived','ticket','body'],axis=1)
# Putting response variable to y
y = data['survived']
```

In [39]:

```
1 X.isnull().sum()
```

Out[39]:

```
pclass 0
sibsp 0
parch 0
embarked_Q 0
embarked_S sex 0
age 0
fare 0
dtype: int64
```

In [40]:

```
# Splitting the data into train and test
X_train, X_test, y_train, y_test = train_test_split(X,y, train_size=0.7,test_size=0.3,
```

In [41]:

```
1 import statsmodels.api as sm
```

In [42]:

```
# Let's run the model using the selected variables
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
logsk = LogisticRegression()
logsk.fit(X_train, y_train)
```

C:\Users\Vicky\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
432: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Speci
fy a solver to silence this warning.
 FutureWarning)

Out[42]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True, intercept_scaling=1, l1_ratio=None, max_iter=100, multi_class='warn', n_jobs=None, penalty='l2', random_state=None, solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

In [43]:

```
# Predicted probabilities
y_pred = logsk.predict_proba(X_test)
```

In [44]:

```
1 # Predicted probabilities
2 y_pred1 = logsk.predict(X_test)
```

In [45]:

```
from sklearn import metrics
metrics.accuracy_score( y_test, y_pred1)*100
```

Out[45]:

76.33587786259542

In [46]:

```
logsk1 = LogisticRegression(C=10000,penalty='l1')
logsk1.fit(X_train, y_train)
```

C:\Users\Vicky\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
432: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Speci
fy a solver to silence this warning.
 FutureWarning)

Out[46]:

In [47]:

```
1 # Predicted probabilities
2 y_pred1 = logsk1.predict_proba(X_test)
```

```
In [48]:
    y_pred1
Out[48]:
array([[0.39286987, 0.60713013],
       [0.92442351, 0.07557649],
       [0.91191923, 0.08808077],
       [0.39401712, 0.60598288],
       [0.03604694, 0.96395306],
       [0.78627565, 0.21372435],
       [0.85648477, 0.14351523],
       [0.49035479, 0.50964521],
       [0.88571314, 0.11428686],
       [0.51616802, 0.48383198],
       [0.09139541, 0.90860459],
       [0.4032952, 0.5967048],
       [0.84052779, 0.15947221],
       [0.55398624, 0.44601376],
       [0.45654732, 0.54345268],
       [0.18422854, 0.81577146],
       [0.91236422, 0.08763578],
       [0.96045032. 0.03954968].
In [49]:
   metrics.accuracy_score( y_test, y_pred1)*100
______
                                         Traceback (most recent call last)
ValueError
<ipython-input-49-eddbce20593e> in <module>
----> 1 metrics.accuracy_score( y_test, y_pred1)*100
~\Anaconda3\lib\site-packages\sklearn\metrics\classification.py in accuracy_
score(y_true, y_pred, normalize, sample_weight)
    174
           # Compute accuracy for each possible representation
   175
           y_type, y_true, y_pred = _check_targets(y_true, y_pred)
--> 176
           check_consistent_length(y_true, y_pred, sample_weight)
    177
    178
           if y_type.startswith('multilabel'):
~\Anaconda3\lib\site-packages\sklearn\metrics\classification.py in check ta
rgets(y_true, y_pred)
    79
           if len(y_type) > 1:
               raise ValueError("Classification metrics can't handle a mix
    80
of {0} "
                                "and {1} targets".format(type true, type pr
---> 81
ed))
    82
           # We can't have more than one value on y_type => The set is no m
    83
ore needed
ValueError: Classification metrics can't handle a mix of binary and continuo
us-multioutput targets
In [50]:
    y_pred2 = logsk.predict(X_test)
```

```
In [51]:
```

```
1 metrics.accuracy_score( y_test, y_pred2)*100
```

Out[51]:

76.33587786259542

In [52]:

```
logsk2 = LogisticRegression(C=100,penalty='elasticnet',solver='saga',l1_ratio=0)
logsk2.fit(X_train, y_train)
```

Out[52]:

```
LogisticRegression(C=100, class_weight=None, dual=False, fit_intercept=True, intercept_scaling=1, l1_ratio=0, max_iter=100, multi_class='warn', n_jobs=None, penalty='elasticnet', random_state=None, solver='saga', tol=0.0001, verbose=0, warm_start=False)
```

In [53]:

```
1 y_pred3 = logsk.predict(X_test)
```

In [54]:

```
1 metrics.accuracy_score( y_test, y_pred3)*100
```

Out[54]:

76.33587786259542

In [55]:

```
logsk3 = LogisticRegression(C=10,penalty='elasticnet',solver='saga',l1_ratio=1)
logsk3.fit(X_train, y_train)
```

Out[55]:

```
LogisticRegression(C=10, class_weight=None, dual=False, fit_intercept=True, intercept_scaling=1, l1_ratio=1, max_iter=100, multi_class='warn', n_jobs=None, penalty='elasticnet', random_state=None, solver='saga', tol=0.0001, verbose=0, warm_start=False)
```

In [56]:

```
1 y_pred4 = logsk.predict(X_test)
```

In [57]:

```
1 metrics.accuracy_score( y_test, y_pred4)*100
```

Out[57]:

76.33587786259542

In [59]:

```
# Converting y_pred to a dataframe which is an array
y_pred_df = pd.DataFrame(y_pred1)
```

In [60]:

```
# Converting to column dataframe
y_pred_1 = y_pred_df.iloc[:,[1]]
```

In [61]:

```
1 # Let's see the head
2 y_pred_1.head()
```

Out[61]:

1

- 0 0.607130
- 1 0.075576
- 2 0.088081
- 3 0.605983
- 4 0.963953

In [62]:

```
1 # Converting y_test to dataframe
2 y_test_df = pd.DataFrame(y_test)
```

In [63]:

```
1 # Putting CustID to index
2 y_test_df['name'] = y_test_df.index
```

In [64]:

```
1 y_test_df
```

Out[64]:

	survived	name
173	0.0	173
843	0.0	843
996	0.0	996
992	0.0	992
12	1.0	12
1191	0.0	1191
165	1.0	165
588	1.0	588
270	1.0	270
61	1.0	61

393 rows × 2 columns

In [65]:

```
# Removing index for both dataframes to append them side by side
y_pred_1.reset_index(drop=True, inplace=True)
y_test_df.reset_index(drop=True, inplace=True)
```

In [66]:

```
1 # Appending y_test_df and y_pred_1
2 y_pred_final = pd.concat([y_test_df,y_pred_1],axis=1)
```

In [67]:

```
# Renaming the column
y_pred_final= y_pred_final.rename(columns={ 1 : 'Survived_Prob'})
```

In [68]:

```
1 # Let's see the head of y_pred_final
2 y_pred_final.head()
```

Out[68]:

	survived	name	Survived_Prob
0	0.0	173	0.607130
1	0.0	843	0.075576
2	0.0	996	0.088081
3	0.0	992	0.605983
4	1.0	12	0.963953

In [69]:

```
# Creating new column 'predicted' with 1 if Churn_Prob>0.5 else 0
y_pred_final['predicted'] = y_pred_final.Survived_Prob.map( lambda x: 1 if x > 0.5 else
```

In [70]:

```
1 # Let's see the head
2 y_pred_final.head()
```

Out[70]:

	survived	name	Survived_Prob	predicted
0	0.0	173	0.607130	1
1	0.0	843	0.075576	0
2	0.0	996	0.088081	0
3	0.0	992	0.605983	1
4	1.0	12	0.963953	1

In [71]:

```
1 from sklearn import metrics
```

In [74]:

```
# Confusion matrix
confusion = metrics.confusion_matrix( y_pred_final.survived, y_pred_final.predicted )
confusion
```

Out[74]:

```
array([[208, 45],
        [46, 94]], dtype=int64)
```

```
In [75]:
```

```
#Let's check the overall accuracy.
metrics.accuracy_score( y_pred_final.survived, y_pred_final.predicted)
```

Out[75]:

0.7684478371501272

In [76]:

```
1  TP = confusion[0,0] # true positive
2  TN = confusion[1,1] # true negatives
3  FP = confusion[0,1] # false positives
4  FN = confusion[1,0] # false negatives
```

In [77]:

```
1 # Let's see the sensitivity of our logistic regression model
2 TP / float(TP+FN)
```

Out[77]:

0.8188976377952756

In [78]:

```
1 # Let us calculate specificity
2 TN / float(TN+FP)
```

Out[78]:

0.6762589928057554

In [80]:

```
# Calculate false postive rate - predicting survived when customer does not survived
print(FP/ float(TN+FP))
```

0.3237410071942446

In [81]:

```
1 # positive predictive value
2 print (TP / float(TP+FP))
```

0.8221343873517787

In [82]:

```
1 # Negative predictive value
2 print (TN / float(TN+ FN))
```

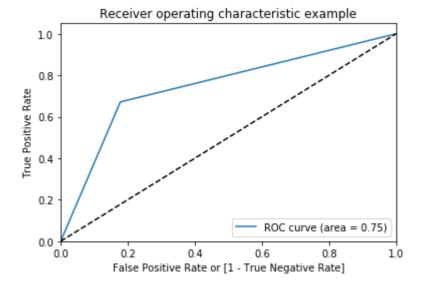
0.6714285714285714

In [85]:

```
def draw roc( actual, probs ):
 1
        fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
 2
 3
                                                   drop_intermediate = False )
        auc score = metrics.roc auc score( actual, probs )
 4
 5
        plt.figure(figsize=(6, 4))
 6
        plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
 7
        plt.plot([0, 1], [0, 1], 'k--')
        plt.xlim([0.0, 1.0])
 8
 9
        plt.ylim([0.0, 1.05])
        plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
10
        plt.ylabel('True Positive Rate')
11
        plt.title('Receiver operating characteristic example')
12
        plt.legend(loc="lower right")
13
        plt.show()
14
15
        return fpr, tpr, thresholds
16
```

In [87]:

```
# Importing matplotlib and seaborn
import matplotlib.pyplot as plt
import seaborn as sns
// matplotlib inline
draw_roc(y_pred_final.survived, y_pred_final.predicted)
```



Out[87]:

```
(array([0. , 0.17786561, 1. ]),
array([0. , 0.67142857, 1. ]),
array([2, 1, 0], dtype=int64))
```

In [91]:

```
# Let's create columns with different probability cutoffs
numbers = [float(x)/10 for x in range(10)]
for i in numbers:
    y_pred_final[i] = y_pred_final.Survived_Prob.map( lambda x: 1 if x > i else 0)
y_pred_final.head()
```

Out[91]:

	survived	name	Survived_Prob	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	8.0	0.9	
0	0.0	173	0.607130	1	1	1	1	1	1	1	1	0	0	0	
1	0.0	843	0.075576	0	1	0	0	0	0	0	0	0	0	0	
2	0.0	996	0.088081	0	1	0	0	0	0	0	0	0	0	0	
3	0.0	992	0.605983	1	1	1	1	1	1	1	1	0	0	0	
4	1.0	12	0.963953	1	1	1	1	1	1	1	1	1	1	1	_
4														 	

In [92]:

```
# Now let's calculate accuracy sensitivity and specificity for various probability cut
   cutoff_df = pd.DataFrame( columns = ['prob', 'accuracy', 'sensi', 'speci'])
   from sklearn.metrics import confusion_matrix
   num = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9]
 5
    for i in num:
        cm1 = metrics.confusion_matrix( y_pred_final.survived, y_pred_final[i] )
 6
 7
        total1=sum(sum(cm1))
8
        accuracy = (cm1[0,0]+cm1[1,1])/total1
        sensi = cm1[0,0]/(cm1[0,0]+cm1[0,1])
9
10
        speci = cm1[1,1]/(cm1[1,0]+cm1[1,1])
11
        cutoff_df.loc[i] =[ i ,accuracy,sensi,speci]
    print(cutoff_df)
12
```

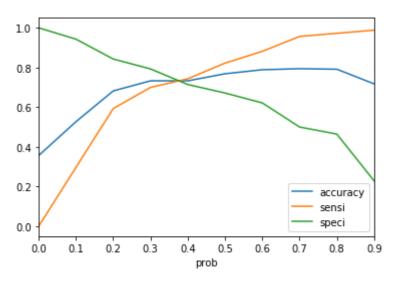
```
prob
         accuracy
                       sensi
                                speci
     0.0
         0.356234 0.000000 1.000000
0.0
0.1
     0.1
         0.526718 0.296443 0.942857
0.2
     0.2 0.681934 0.592885 0.842857
0.3
     0.3 0.732824 0.699605 0.792857
     0.4 0.732824 0.743083 0.714286
0.4
0.5
     0.5 0.768448
                   0.822134 0.671429
     0.6 0.788804 0.881423 0.621429
0.6
     0.7 0.793893 0.956522 0.500000
0.7
0.8
     0.8 0.791349
                   0.972332 0.464286
     0.9 0.717557 0.988142 0.228571
0.9
```

In [93]:

```
# Let's plot accuracy sensitivity and specificity for various probabilities.
cutoff_df.plot.line(x='prob', y=['accuracy','sensi','speci'])
```

Out[93]:

<matplotlib.axes._subplots.AxesSubplot at 0x215b1629e88>



In [95]:

1 y_pred_final['final_predicted'] = y_pred_final.Survived_Prob.map(lambda x: 1 if x > 0

In [96]:

1 y_pred_final.head()

Out[96]:

	survived	name	Survived_Prob	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	8.0	0.9	fin
0	0.0	173	0.607130	1	1	1	1	1	1	1	1	0	0	0	
1	0.0	843	0.075576	0	1	0	0	0	0	0	0	0	0	0	
2	0.0	996	0.088081	0	1	0	0	0	0	0	0	0	0	0	
3	0.0	992	0.605983	1	1	1	1	1	1	1	1	0	0	0	
4	1.0	12	0.963953	1	1	1	1	1	1	1	1	1	1	1	
4															•

```
In [98]:
```

```
#Let's check the overall accuracy.
metrics.accuracy_score( y_pred_final.survived, y_pred_final.final_predicted)
```

Out[98]:

0.732824427480916

In [100]:

```
metrics.confusion_matrix( y_pred_final.survived, y_pred_final.final_predicted )
```

Out[100]:

In []:

1