We have a data set named- titanic.csv, we have to classify wheather the passenger survived or not.

These are the variables in this data set

PassengerId- some id associated with each passenger

```
survival-        Passenger Survived or Not
pclass -          Ticktet Class
Sex-               Gender of Passenger
Age-         Age in years
sibsp-             No. of siblings / sposes aboard
parch-            No. of parents / children aboard
ticket-      Ticket Number
fare-        Passenger fare
cabin-       Canbin Number
Embarked-    Port of Embarkation
```

We imported necessary libraries.

In [1574]:

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import math
```

Adding data set

In [1575]:

```
ds = pd.read_csv('/content/titanic.csv')
```

In [1576]:

```
ds.head()
```

Out[1576]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

Now let's see the statistical measures.

In [1577]:

```
ds.describe()
```

Out[1577]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

We will check for missing values in the columns.

In [1578]:

```
ds.isna().sum()
```

Out[1578]:

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

We can see the coloumn "Embarked" has only 2 NaN value. So we can remove the 2 rows. Also we see for the coloumn "Cabin" there are 687 out of 891 columns. So we can also drop this column "Cabin"

In [1579]:

```
ds.drop(axis="rows", labels = ds.index[ds['Embarked'].isna()], inplace = True)
ds.drop(axis="columns", labels="Cabin", inplace=True)
```

In [1580]:

```
ds.isna().sum()
```

Out[1580]:

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Embarked         0
dtype: int64
```

Now we are filling median in the 177 rows of Age column as removing 177 rows is not feasible

In [1581]:

```
ds["Age"].fillna(ds["Age"].median(), inplace=True)
```

In [1582]:

```
ds.head()
```

Out[1582]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	S

As instructed in the assignment to Not consider Passenger ID

In [1583]:

```
ds.drop(axis="columns", labels="PassengerId", inplace=True)
```

In [1584]:

```
ds.head()
```

Out[1584]:

	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
1	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C
2	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S
3	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	S
4	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	S

We see "Name" has too many unique columns.

In [1585]:

```
ds["Name"].value_counts()
```

Out[1585]:

```
Braund, Mr. Owen Harris                1
Boulos, Mr. Hanna                      1
Frolicher-Stehli, Mr. Maxmillian       1
Gilinski, Mr. Eliezer                  1
Murdlin, Mr. Joseph                    1
                                      ..
McCoy, Mr. Bernard                     1
Johnson, Mr. William Cahoone Jr        1
Keane, Miss. Nora A                    1
Williams, Mr. Howard Hugh "Harry"      1
Dooley, Mr. Patrick                    1
Name: Name, Length: 889, dtype: int64
```

Checking for "Ticket" how many unique values are there.

In [1586]:

```
ds["Ticket"].value_counts()
```

Out[1586]:

```
347082      7
CA. 2343    7
1601        7
3101295     6
CA 2144     6
           ..
9234        1
19988       1
2693        1
PC 17612    1
370376      1
Name: Ticket, Length: 680, dtype: int64
```

In [1587]:

```
ds.drop(axis="columns", labels="Ticket", inplace=True)
```

In [1588]:

```
ds.drop(axis="columns", labels="Name", inplace=True)
```

In [1589]:

```
ds.head()
```

Out[1589]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	22.0	1	0	7.2500	S
1	1	1	female	38.0	1	0	71.2833	C
2	1	3	female	26.0	0	0	7.9250	S
3	1	1	female	35.0	1	0	53.1000	S
4	0	3	male	35.0	0	0	8.0500	S

Now we see "Sex" as male and female. So we can use label encoding.

In [1590]:

```
ds["Sex"].value_counts()
```

Out[1590]:

```
male      577
female    312
Name: Sex, dtype: int64
```

Encoding male and female in Sex column

In [1591]:

```
ds['Sex'] = ds["Sex"].map({"male": 0, "female": 1})
ds["Sex"].value_counts()
```

Out[1591]:

```
0    577
1    312
Name: Sex, dtype: int64
```

In [1592]:

```
ds.head()
```

Out[1592]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	0	22.0	1	0	7.2500	S
1	1	1	1	38.0	1	0	71.2833	C
2	1	3	1	26.0	0	0	7.9250	S
3	1	1	1	35.0	1	0	53.1000	S
4	0	3	0	35.0	0	0	8.0500	S

Now we will check for Embarked Column and Pclass

In [1593]:

```
ds["Embarked"].value_counts()
```

Out[1593]:

```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

In [1594]:

```
ds["Pclass"].value_counts()
```

Out[1594]:

```
3    491
1    214
2    184
Name: Pclass, dtype: int64
```

One Hot Encoding

Here we see 3 unique values "S", "C", "Q" for "Embarked" So doing one-hot Encoding. Also for Pclass, we have 1, 2, 3 values but to know which class has higher priority and which has low we will do one-hot encoding.

In [1595]:

```
ds = pd.get_dummies(ds, columns=["Embarked", "Pclass"])
```

Duplicate Cell

Now we are going to check for duplicate rows and remove them

In [1596]:

```
ds.duplicated().sum()
```

Out[1596]:

```
116
```

In [1597]:

```
ds.drop(axis="rows", labels=ds.index[ds.duplicated()], inplace=True)
ds.duplicated().sum()
```

Out[1597]:

```
0
```

In [1598]:

```
ds.describe()
```

Out[1598]:

	Survived	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Embarked_S	P
count	773.000000	773.000000	773.000000	773.000000	773.000000	773.000000	773.000000	773.000000	773.00000	773
mean	0.411384	0.375162	29.528357	0.530401	0.421734	34.761659	0.200517	0.075032	0.72445	0.
std	0.492403	0.484478	13.731264	0.991241	0.841380	52.425906	0.400647	0.263614	0.44708	0.
min	0.000000	0.000000	0.420000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000	0.
25%	0.000000	0.000000	21.000000	0.000000	0.000000	8.050000	0.000000	0.000000	0.00000	0.
50%	0.000000	0.000000	28.000000	0.000000	0.000000	15.900000	0.000000	0.000000	1.00000	0.
75%	1.000000	1.000000	36.000000	1.000000	1.000000	33.500000	0.000000	0.000000	1.00000	1.
max	1.000000	1.000000	80.000000	8.000000	6.000000	512.329200	1.000000	1.000000	1.00000	1.

In [1599]:

```
ds.loc[:20,:]
```

Out[1599]:

	Survived	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Embarked_S	Pclass_1	Pclass_2	Pclass_3
0	0	0	22.0	1	0	7.2500	0	0	1	0	0	1
1	1	1	38.0	1	0	71.2833	1	0	0	1	0	0
2	1	1	26.0	0	0	7.9250	0	0	1	0	0	1
3	1	1	35.0	1	0	53.1000	0	0	1	1	0	0
4	0	0	35.0	0	0	8.0500	0	0	1	0	0	1
5	0	0	28.0	0	0	8.4583	0	1	0	0	0	1
6	0	0	54.0	0	0	51.8625	0	0	1	1	0	0
7	0	0	2.0	3	1	21.0750	0	0	1	0	0	1
8	1	1	27.0	0	2	11.1333	0	0	1	0	0	1
9	1	1	14.0	1	0	30.0708	1	0	0	0	1	0
10	1	1	4.0	1	1	16.7000	0	0	1	0	0	1
11	1	1	58.0	0	0	26.5500	0	0	1	1	0	0
12	0	0	20.0	0	0	8.0500	0	0	1	0	0	1
13	0	0	39.0	1	5	31.2750	0	0	1	0	0	1
14	0	1	14.0	0	0	7.8542	0	0	1	0	0	1
15	1	1	55.0	0	0	16.0000	0	0	1	0	1	0
16	0	0	2.0	4	1	29.1250	0	1	0	0	0	1
17	1	0	28.0	0	0	13.0000	0	0	1	0	1	0
18	0	1	31.0	1	0	18.0000	0	0	1	0	0	1
19	1	1	28.0	0	0	7.2250	1	0	0	0	0	1
20	0	0	35.0	0	0	26.0000	0	0	1	0	1	0

Feature Scaling

Now using Min-Max Normalization on Age and Fare columns

In [1600]:

```
x = ds["Age"] - np.min(ds["Age"])
y = np.max(ds["Age"]) - np.min(ds["Age"])
ds["Age"] = x/y
ds.loc[:20,:]
```

Out[1600]:

	Survived	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Embarked_S	Pclass_1	Pclass_2	Pclass_3
0	0	0	0.271174	1	0	7.2500	0	0	1	0	0	1
1	1	1	0.472229	1	0	71.2833	1	0	0	1	0	0
2	1	1	0.321438	0	0	7.9250	0	0	1	0	0	1
3	1	1	0.434531	1	0	53.1000	0	0	1	1	0	0
4	0	0	0.434531	0	0	8.0500	0	0	1	0	0	1
5	0	0	0.346569	0	0	8.4583	0	1	0	0	0	1
6	0	0	0.673285	0	0	51.8625	0	0	1	1	0	0
7	0	0	0.019854	3	1	21.0750	0	0	1	0	0	1
8	1	1	0.334004	0	2	11.1333	0	0	1	0	0	1
9	1	1	0.170646	1	0	30.0708	1	0	0	0	1	0
10	1	1	0.044986	1	1	16.7000	0	0	1	0	0	1
11	1	1	0.723549	0	0	26.5500	0	0	1	1	0	0
12	0	0	0.246042	0	0	8.0500	0	0	1	0	0	1
13	0	0	0.484795	1	5	31.2750	0	0	1	0	0	1
14	0	1	0.170646	0	0	7.8542	0	0	1	0	0	1
15	1	1	0.685851	0	0	16.0000	0	0	1	0	1	0
16	0	0	0.019854	4	1	29.1250	0	1	0	0	0	1
17	1	0	0.346569	0	0	13.0000	0	0	1	0	1	0
18	0	1	0.384267	1	0	18.0000	0	0	1	0	0	1
19	1	1	0.346569	0	0	7.2250	1	0	0	0	0	1
20	0	0	0.434531	0	0	26.0000	0	0	1	0	1	0

In [1601]:

```
x = ds["Fare"] - np.min(ds["Fare"])
y = np.max(ds["Fare"]) - np.min(ds["Fare"])
ds["Fare"] = x/y
ds.loc[:20,:]
```

Out[1601]:

	Survived	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Embarked_S	Pclass_1	Pclass_2	Pclass_3
0	0	0	0.271174	1	0	0.014151	0	0	1	0	0	1
1	1	1	0.472229	1	0	0.139136	1	0	0	1	0	0
2	1	1	0.321438	0	0	0.015469	0	0	1	0	0	1
3	1	1	0.434531	1	0	0.103644	0	0	1	1	0	0
4	0	0	0.434531	0	0	0.015713	0	0	1	0	0	1
5	0	0	0.346569	0	0	0.016510	0	1	0	0	0	1
6	0	0	0.673285	0	0	0.101229	0	0	1	1	0	0
7	0	0	0.019854	3	1	0.041136	0	0	1	0	0	1
8	1	1	0.334004	0	2	0.021731	0	0	1	0	0	1
9	1	1	0.170646	1	0	0.058694	1	0	0	0	1	0
10	1	1	0.044986	1	1	0.032596	0	0	1	0	0	1

	Survived	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Embarked_S	Pclass_1	Pclass_2	Pclass_3
10	1	1	0.044986	1	1	0.032596	0	0	1	0	0	1
11	1	1	0.723549	0	0	0.051822	0	0	1	1	0	0
12	0	0	0.246042	0	0	0.015713	0	0	1	0	0	1
13	0	0	0.484795	1	5	0.061045	0	0	1	0	0	1
14	0	1	0.170646	0	0	0.015330	0	0	1	0	0	1
15	1	1	0.685851	0	0	0.031230	0	0	1	0	1	0
16	0	0	0.019854	4	1	0.056848	0	1	0	0	0	1
17	1	0	0.346569	0	0	0.025374	0	0	1	0	1	0
18	0	1	0.384267	1	0	0.035134	0	0	1	0	0	1
19	1	1	0.346569	0	0	0.014102	1	0	0	0	0	1
20	0	0	0.434531	0	0	0.050749	0	0	1	0	1	0

Correlation

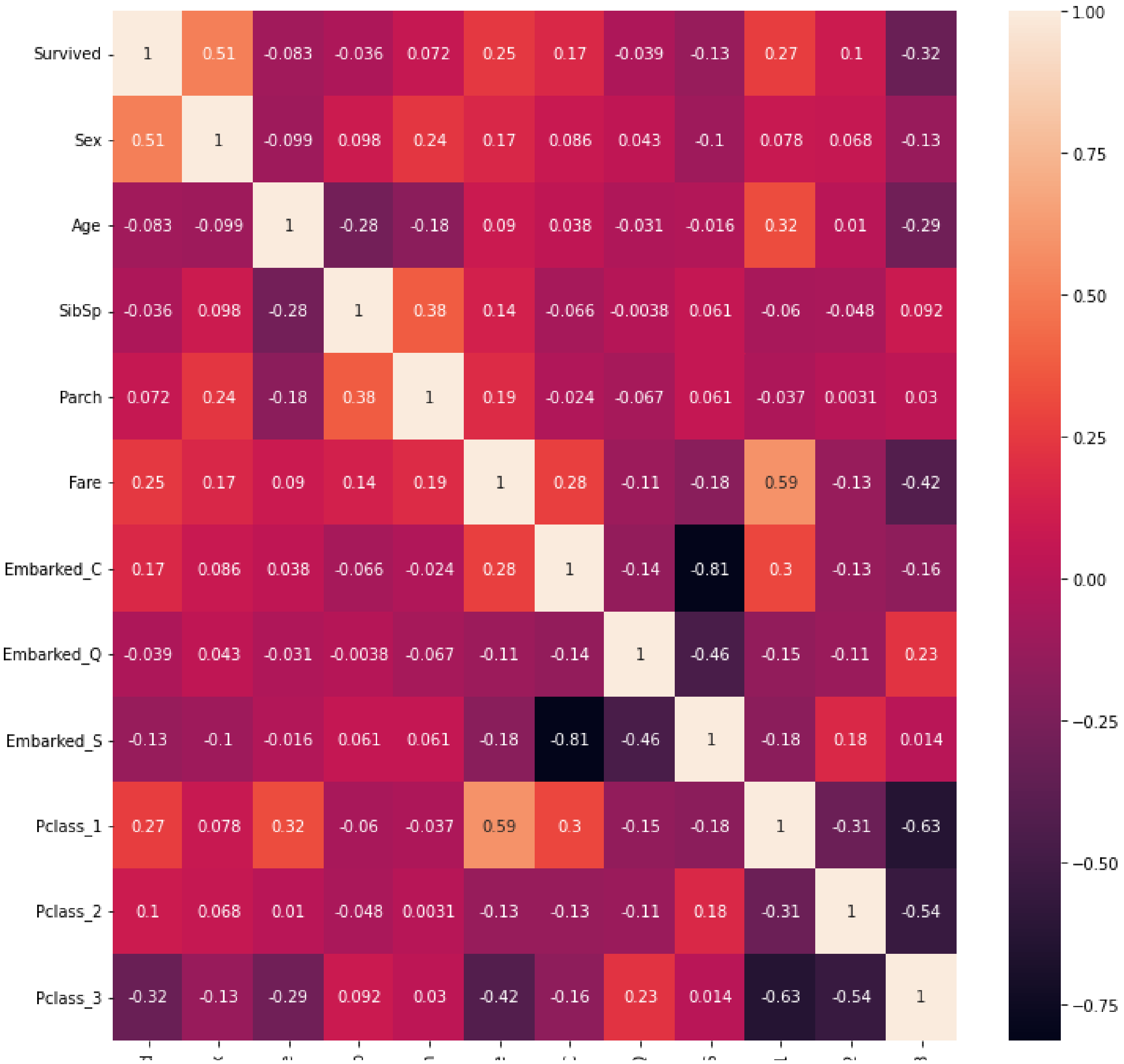
Now we are going to find the Correlation Matrix

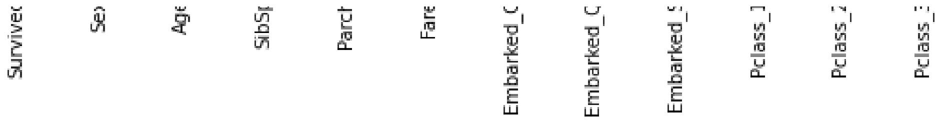
In [1602]:

```
plt.figure(figsize=(12,12))
sns.heatmap(ds.corr(), annot=True)
```

Out[1602]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f52c3476a50>
```





Here in the matrix, we see there is not that much dependency between cloumns. If column1 and column2 has a value close or equal to 1 or -1, there is a high dependency between them.

If that value is close to 0 then, there is no dependency.

In [1603]:

```
ds.loc[:6,:]
```

Out[1603]:

	Survived	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Embarked_S	Pclass_1	Pclass_2	Pclass_3
0	0	0	0.271174	1	0	0.014151	0	0	1	0	0	1
1	1	1	0.472229	1	0	0.139136	1	0	0	1	0	0
2	1	1	0.321438	0	0	0.015469	0	0	1	0	0	1
3	1	1	0.434531	1	0	0.103644	0	0	1	1	0	0
4	0	0	0.434531	0	0	0.015713	0	0	1	0	0	1
5	0	0	0.346569	0	0	0.016510	0	1	0	0	0	1
6	0	0	0.673285	0	0	0.101229	0	0	1	1	0	0

Now we will split our data in training and testing set.

In [1604]:

```
train = ds.sample(frac =0.77, replace = False)
test = ds.drop(train.index)

#convert dataframe to numpy array
train = train.to_numpy()
test = test.to_numpy()

#Remove Survived column
x_train = np.delete(train, 0, 1)
x_test = np.delete(test, 0, 1)

#Survived column
y_train = train[:,0]
y_test = test[:,0]
```

In [1605]:

```
x_train
```

Out[1605]:

```
array([[0.        , 0.13294798, 5.        , ..., 0.        , 0.        ,
        1.        ],
       [1.        , 0.17692888, 1.        , ..., 0.        , 0.        ,
        1.        ],
       [0.        , 0.19577783, 0.        , ..., 0.        , 0.        ,
        1.        ],
       ...,
       [0.        , 0.2083438 , 1.        , ..., 0.        , 0.        ,
        1.        ],
       [0.        , 0.39683338, 0.        , ..., 0.        , 0.        ,
        1.        ],
       [0.        , 0.560191  , 0.        , ..., 1.        , 0.        ,
        0.        ]])
```

Checking the dimensions of our x_test, x_train and y_test, y_train

In [1606]:

```
x_test.shape
```

Out[1606]:

```
(178, 11)
```

In [1607]:

```
x_train.shape
```

Out[1607]:

```
(595, 11)
```

In [1608]:

```
y_train.shape
```

Out[1608]:

```
(595,)
```

In [1609]:

```
y_test.shape
```

Out[1609]:

```
(178,)
```

In [1610]:

```
x_train = x_train.T
y_train = y_train.reshape((1, 595))

x_test = x_test.T
y_test = y_test.reshape((1, 178))
```

Logistic Regression

w = weight matrix (n x 1)

b = parameter (1 x 1)

x_train (n x m) n= features m= rows

y_train (1 x m) m= rows

A(y-predicted) = sigmoid(wT * x_train + b)

In [1611]:

```
def sigmoidFunction(w, x, b):                    #Parameters => weight matrix and b
  z = np.dot(w.T, x) + b                         #output => 1/1+e^-{wTx + b}
  return (1.0/(1+np.exp(-z)))
```

In [1612]:

```
def costFunc(m, Y, A):
  c = -(1/m)*np.sum( Y*np.log(A) + (1-Y)*np.log(1-A))
  return c
```

In [1613]:

```
def logistic_regression(X, Y, alpha, itr, rows, col):

    m = rows
```

```
    n = col

    w = np.zeros((n,1))    # w = n x 1
    b = 0

    cost_list = []

    for i in range(itr):

        y_cap = sigmoidFunction(w, X, b)

        # cost function
        c = costFunc(m, Y, y_cap)


        dw = (1/m)*np.dot(y_cap - Y, X.T)          #d(cost)/dw = (y_cap - Y)*X.Transpose
        db = (1/m)*np.sum(y_cap - Y)               #d(cost)/db = (y_cap - Y)

        # Gradient Descent
        w = w - alpha*dw.T
        b = b - alpha*db

        cost_list.append(c)

        if(i%100 == 0):
            print("cost after ", i, "iteration is : ", c)

    return w, b, cost_list
```

In [1614]:

```
x_train.shape
```

Out[1614]:

```
(11, 595)
```

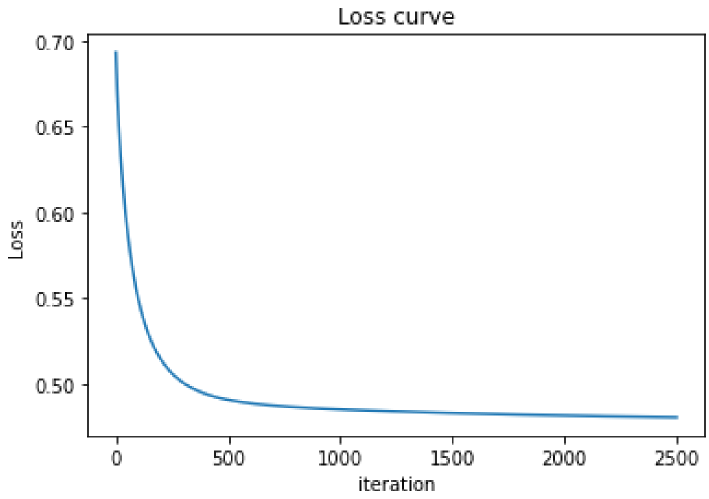
In [1615]:

```
iterations = 2500
alpha = 0.1
W, B, cost_list = logistic_regression(x_train, y_train, alpha, iterations, x_train.shape
[1], x_train.shape[0])
```

```
cost after  0 iteration is :  0.6931471805599453
cost after  100 iteration is :  0.5491700468871189
cost after  200 iteration is :  0.5143330373001338
cost after  300 iteration is :  0.5006129160019058
cost after  400 iteration is :  0.49414552685488006
cost after  500 iteration is :  0.4907140362136465
cost after  600 iteration is :  0.48869241374391537
cost after  700 iteration is :  0.4873742444433834
cost after  800 iteration is :  0.48642970146623676
cost after  900 iteration is :  0.4856966122893298
cost after  1000 iteration is :  0.48509176697706613
cost after  1100 iteration is :  0.4845707499675112
cost after  1200 iteration is :  0.4841088687152078
cost after  1300 iteration is :  0.48369175990374846
cost after  1400 iteration is :  0.48331062195136615
cost after  1500 iteration is :  0.48295973339598114
cost after  1600 iteration is :  0.4826351318491952
cost after  1700 iteration is :  0.4823338958043605
cost after  1800 iteration is :  0.48205374585313804
cost after  1900 iteration is :  0.481792818177986
cost after  2000 iteration is :  0.4815495325490751
cost after  2100 iteration is :  0.48132251305397167
cost after  2200 iteration is :  0.48111053879172216
cost after  2300 iteration is :  0.4809125119433079
cost after  2400 iteration is :  0.4807274361571433
```

In [1616]:

```
plt.plot(np.arange(iterations), cost_list)
plt.xlabel('iteration')
plt.ylabel('Loss')
plt.title('Loss curve')
plt.show()
```



Taking thresold at 0.5

For the test set, we will now see the predicted and actual y values

In [1617]:

```
y_pred = sigmoidFunction(W, x_test, B)
y_pred = y_pred > 0.5
y_pred = np.array(y_pred, dtype = 'int64')
y_pred  # probabilities (if greater than 0.5 it is 1 or True,  else 0 or False)
```

Out[1617]:

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

In [1618]:

```
y_test = np.array(y_test, dtype = 'int64')
y_test
```

Out[1618]:

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

Caluclating f1_score

Let us assume following variables

TN(true negative):- actual = 0, predicted = 0

TP(ture positive):- actual = 1, predicted = 1

FP(false positive):- actual = 0, predicted = 1

FN(false negative):- actual = 1, predicted = 0

Precision : TP / (TP+FP)

Recall : TP / (TP+FN)

F1 Score : (2 *Precision* Recall) / (Precision+Recall)

In [1619]:

```
def computeVariables(y_test, y_pred):
  tp = np.sum((y_test == 1) & (y_pred == 1))
  tn = np.sum((y_test == 0) & (y_pred == 0))
  fp = np.sum((y_test == 0) & (y_pred == 1))
  fn = np.sum((y_test == 1) & (y_pred == 0))
  return tp, tn, fp, fn
```

In [1620]:

```
tp, tn, fp, fn = computeVariables(y_test, y_pred)
print("true positive = ", tp)
print("true negative = ", tn)
print("false positive = ", fp)
print("false negative = ", fn)
```

```
true positive =  54
true negative =  81
false positive =  20
false negative =  23
```

In [1621]:

```
def f1_score(tp, tn, fp, fn):
  precision = tp / (tp+fp)
  recall = tp / (tp+fn)
  f1_score = (2 * precision * recall) / (precision + recall)
  print("F1_Score Percentage = ",f1_score*100)
```

In [1622]:

```
f1_score(tp, tn, fp, fn)
```

```
F1_Score Percentage =  71.523178807947
```

Naive Bayes

Reshaping again our x_test, x_train and y_test, y_train

We need rows x cols

In [1623]:

```
x_train = x_train.T
y_train = y_train.T

x_test = x_test.T
y_test = y_test.T
```

In [1624]:

```
print("x_train",x_train.shape)
print("x_test",x_test.shape)
print("y_train",y_train.shape)
print("y_test",y_test.shape)
```

```
x_train (595, 11)
```

```
x_test (178, 11)
y_train (595, 1)
y_test (178, 1)
```

In [1624]:

```

```

Calculating P(Y = yi)

probability (y = Survived) = no. of people survived / m

m = rows

In [1625]:

```
p_survived = np.count_nonzero(y_train)/len(y_train)
p_survived
```

Out[1625]:

```
0.4050420168067227
```

Computing the guassian function

In [1626]:

```
def GaussianFunction(mean, variance, x):
  power = -1.0*(x-mean)*(x-mean)/(2.0*variance)

  #product of all the denominators for all X= x0, x1, x2, ...
  deno = np.prod(np.sqrt(2.0*np.pi*variance))

  #         product of all the numerators / denominator
  return np.prod(np.exp(power))/deno
```

In [1627]:

```
x_train
```

Out[1627]:

```
array([[0.        , 0.13294798, 5.        , ..., 0.        , 0.        ,
        1.        ],
       [1.        , 0.17692888, 1.        , ..., 0.        , 0.        ,
        1.        ],
       [0.        , 0.19577783, 0.        , ..., 0.        , 0.        ,
        1.        ],
       ...,
       [0.        , 0.2083438 , 1.        , ..., 0.        , 0.        ,
        1.        ],
       [0.        , 0.39683338, 0.        , ..., 0.        , 0.        ,
        1.        ],
       [0.        , 0.560191  , 0.        , ..., 1.        , 0.        ,
        0.        ]])
```

Training our Model

In [1628]:

```
x_trainSurvived = []
x_trainNotSurvived = []
for i in range(len(y_train)):
  if(y_train[i] == 1):
    x_trainSurvived.append(x_train[i])
  else:
    x_trainNotSurvived.append(x_train[i])
```

Mean and Variance

In [1629]:

```
Survived_Mean = np.mean(x_trainSurvived, axis=0)
Survived_var = np.var(x_trainSurvived, axis=0)
NotSurvived_Mean = np.mean(x_trainNotSurvived, axis=0)
NotSurvived_var = np.var(x_trainNotSurvived, axis=0)
```

In [1630]:

```
print("Mean Survived",Survived_Mean)
print("Variance Survived",Survived_var)
print("Mean Not Survived",NotSurvived_Mean)
print("Var Not Survived",NotSurvived_var)
```

```
Mean Survived [0.66804979 0.33927445 0.51037344 0.52282158 0.09286224 0.24481328
 0.0746888  0.68049793 0.37759336 0.26970954 0.3526971 ]
Variance Survived [0.22175927 0.03198349 0.56524509 0.63122191 0.01434704 0.18487974
 0.06911038 0.2174205  0.23501661 0.19696631 0.22830185]
Mean Not Survived [0.16101695 0.37313906 0.56497175 0.34745763 0.04658771 0.1440678
 0.07909605 0.77683616 0.16949153 0.18644068 0.6440678 ]
Var Not Survived [0.13509049 0.02748019 1.38137189 0.68435794 0.00409281 0.12331227
 0.07283986 0.17336174 0.14076415 0.15168055 0.22924447]
```

In [1631]:

```
def Probability(meanSurvived, varSurvived, meanNotSurvived, varNotSurvived, x, pSurvived
):

  P_X_given_Survived = GaussianFunction(meanSurvived, varSurvived, x)

  P_X_given_NotSurvived = GaussianFunction(meanNotSurvived, varNotSurvived, x)

  pSur_liklihood = pSurvived*P_X_given_Survived

  pNotSur_liklihood = (1-pSurvived)*P_X_given_NotSurvived
  if(pSur_liklihood > pNotSur_liklihood):
    return 1
  return 0
```

In [1632]:

```
x_test.shape
```

Out[1632]:

```
(178, 11)
```

Testing Naive Bayes

In [1633]:

```
def testNaiveBayes(rows):
  y_predict = []
  for i in range(rows):
    y_predict.append(Probability(Survived_Mean, Survived_var, NotSurvived_Mean, NotSurvi
ved_var, x_test[i], p_survived))
  return y_predict
```

In [1634]:

```
rows = len(x_test)
y_predict = testNaiveBayes(rows)
y_predict = np.array(y_predict, dtype = 'int64')
y_predict
```

Out[1634]:

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

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

Making y_test in same dimension as y_predict

In [1635]:

```
y_test = y_test.T
```

In [1636]:

```
tp, tn, fp, fn = computeVariables(y_test, y_predict)
print("true positive = ", tp)
print("true negative = ", tn)
print("false positive = ", fp)
print("false negative = ", fn)
```

```
true positive =  53
true negative =  84
false positive =  17
false negative =  24
```

In [1637]:

```
f1_score(tp, tn, fp, fn)
```

```
F1_Score Percentage =  72.10884353741497
```