In [35]:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import sklearn
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
plt.rcParams["figure.figsize"] = [10,5]
# Ignore warnings

import warnings
# Set the warning filter to ignore FutureWarning
warnings.simplefilter(action = "ignore", category = FutureWarning)
```

In [36]:

```python
df = pd.read_csv('C:\\Users\Super\\Downloads\\titanic_dataset.csv')
df
```

Out[36]:

	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
...	...	...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN	Q

891 rows × 12 columns

In [3]:

```
df.head()
```

Out[3]:

	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

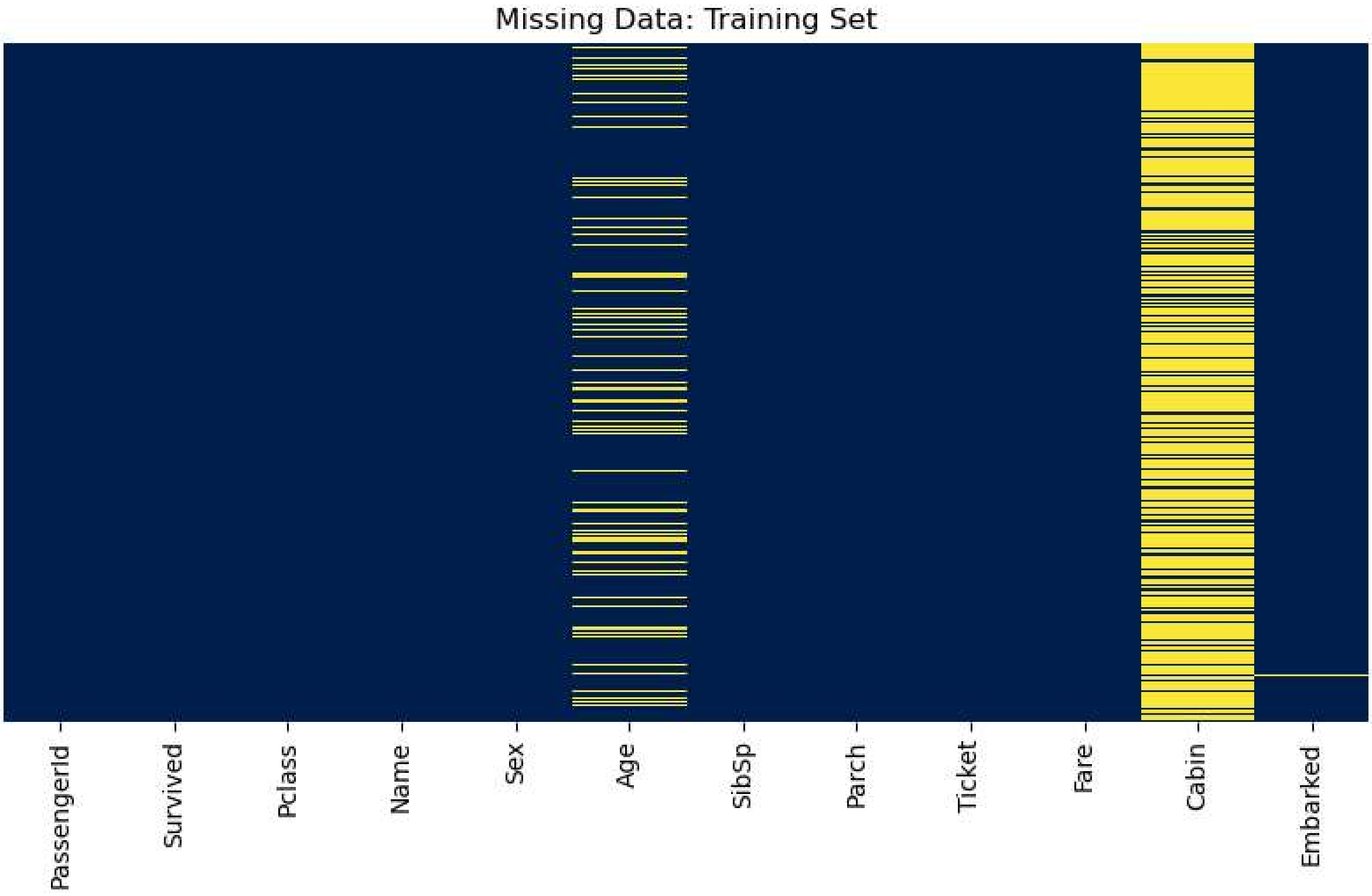
In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

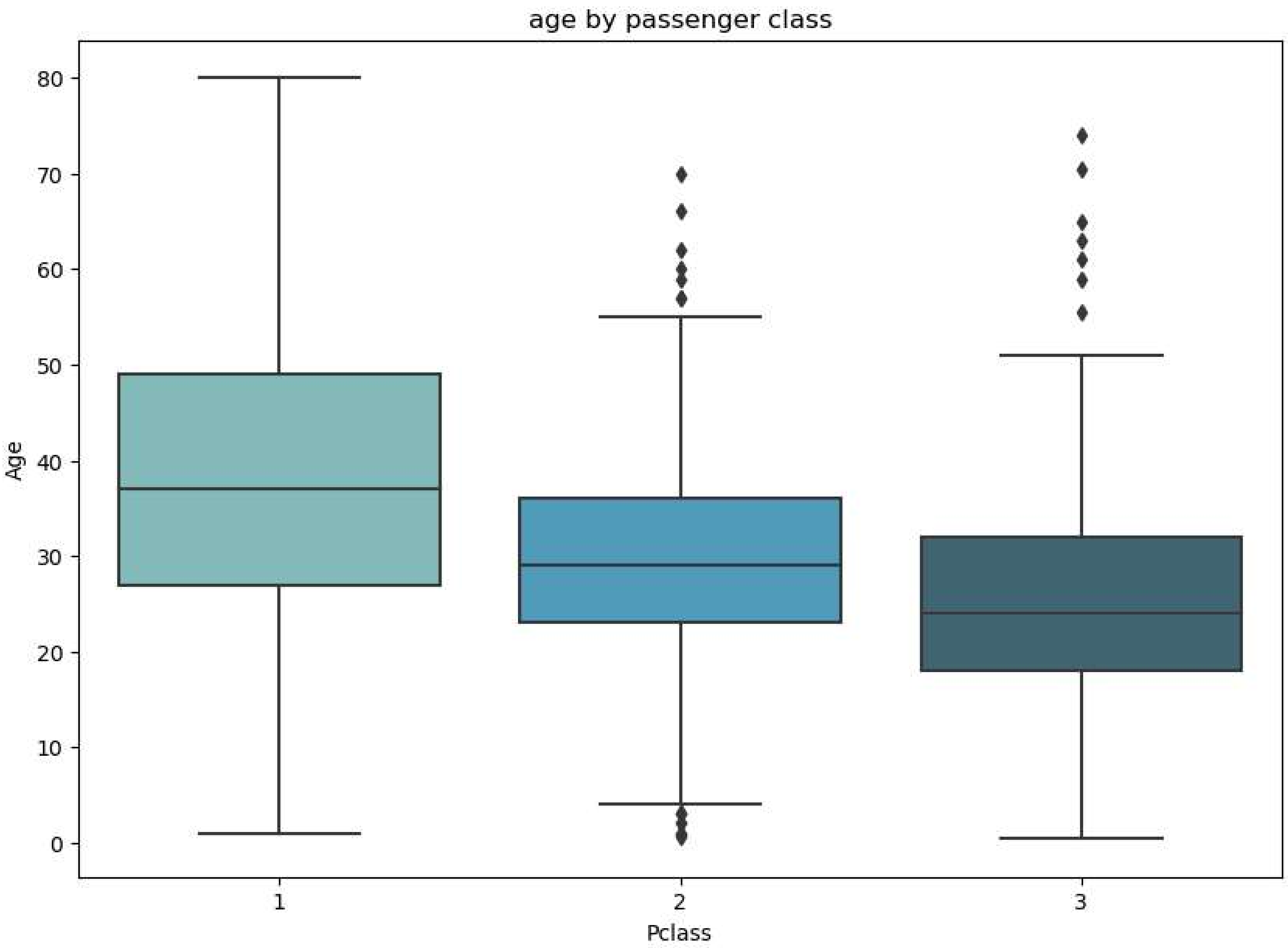
In [5]:

```
# Heatmap
sns.heatmap(df.isnull(),yticklabels = False, cbar = False,cmap = 'cividis')
plt.title('Missing Data: Training Set')
plt.show()
```



In [6]:

```
plt.figure(figsize=(10,7))
sns.boxplot(x='Pclass',y='Age',data=df,palette='GnBu_d').set_title('age by passenger class')
plt.show()
```



In [7]:

```
#Imputation function
def impute_age(cols):
    Age=cols[0]
    Pclass=cols[1]
    if pd.isnull(Age):
        if Pclass==1:
            return 37
        elif Pclass==2:
            return 29
        else:
            return 24
    else:
         return Age



# apply the function to the age column

df['Age']=df[['Age','Pclass']].apply(impute_age,axis=1)

```

In [ ]:

```
df.drop('Cabin', axis = 1, inplace = True)
```

In [39]:

```
#remove rows with missing data
df.dropna(inplace=True)
```

In [10]:

```
#remove unnecessary columns
df.drop(['Name','Ticket'],axis=1,inplace=True)
```

In [11]:

```
#convert objects to category data type
object=['Sex','Embarked']
for colname in object:
    df[colname]=df[colname].astype('category')
```

```
In [12]: df
```

```
Out[12]:
     PassengerId  Survived  Pclass     Sex   Age  SibSp  Parch     Fare  Embarked
  0            1         0       3    male  22.0      1      0   7.2500         S
  1            2         1       1  female  38.0      1      0  71.2833         C
  2            3         1       3  female  26.0      0      0   7.9250         S
  3            4         1       1  female  35.0      1      0  53.1000         S
  4            5         0       3    male  35.0      0      0   8.0500         S
...          ...       ...     ...     ...   ...    ...    ...      ...       ...
886          887         0       2    male  27.0      0      0  13.0000         S
887          888         1       1  female  19.0      0      0  30.0000         S
888          889         0       3  female  24.0      1      2  23.4500         S
889          890         1       1    male  26.0      0      0  30.0000         C
890          891         0       3    male  32.0      0      0   7.7500         Q

889 rows × 9 columns
```

```
In [13]: df.drop('PassengerId',inplace=True,axis=1)
```

```
In [14]: df.head()
```

```
Out[14]:
   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
```

In [15]:

```
df.describe()
```

Out[15]:

	Survived	Pclass	Age	SibSp	Parch	Fare
count	889.000000	889.000000	889.000000	889.000000	889.000000	889.000000
mean	0.382452	2.311586	29.019314	0.524184	0.382452	32.096681
std	0.486260	0.834700	13.209814	1.103705	0.806761	49.697504
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	22.000000	0.000000	0.000000	7.895800
50%	0.000000	3.000000	26.000000	0.000000	0.000000	14.454200
75%	1.000000	3.000000	36.500000	1.000000	0.000000	31.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [16]:

```
#identify categorical features
df.select_dtypes(['category']).columns
```

Out[16]:

```
Index(['Sex', 'Embarked'], dtype='object')
```

In [17]:

```
# convert categorical variable into dummy or indicator variable
sex=pd.get_dummies(df['Sex'],drop_first=True)
embarked=pd.get_dummies(df['Embarked'],drop_first=True)
```

In [18]:

```
# add new dummy columns to dataframe
df=pd.concat([df,sex,embarked],axis=1)
df.head()
```

Out[18]:

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

In [19]:

```python
df.drop(['Sex','Embarked'],inplace=True,axis=1)
```

In [20]:

```python
df.head()
```

Out[20]:

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

Target Variable Splitting

In [21]:

```python
#We will spilt the Full dataset into Input and target variables

#Input is also called Feature Variables Output referes to Target variables


```

In [22]:

```python
#create matix of features
x=df.drop('Survived',axis=1) # x represent features

#create target variable
y=df['Survived'] # y is the column we are trying to predict
```

In [23]:

```python
x.shape
```

Out[23]:

```
(889, 8)
```

In [24]:

```python
y.shape
```

Out[24]:

```
(889,)
```

In [25]:

```
#use x and y variable to split the training data into train and test set
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.20,random_state=101)
```

In [26]:

```
x_train.shape
x_train
```

Out[26]:

```
     Pclass   Age  SibSp  Parch      Fare  male  Q  S
307       1  17.0      1      0  108.9000     0  0  0
229       3  24.0      3      1   25.4667     0  0  1
 82       3  24.0      0      0    7.7875     0  1  0
353       3  25.0      1      0   17.8000     1  0  1
707       1  42.0      0      0   26.2875     1  0  1
...     ...   ...    ...    ...       ...   ... ... ...
576       2  34.0      0      0   13.0000     0  0  1
840       3  20.0      0      0    7.9250     1  0  1
338       3  45.0      0      0    8.0500     1  0  1
524       3  24.0      0      0    7.2292     1  0  0
865       2  42.0      0      0   13.0000     0  0  1

711 rows × 8 columns
```

In [27]:

```
y_train
```

Out[27]:

```
307    1
229    0
82     1
353    0
707    1
      ..
576    1
840    0
338    1
524    0
865    1
Name: Survived, Length: 711, dtype: int64
```

In [28]:

```
x_test.shape
x_test
```

Out[28]:

	Pclass	Age	SibSp	Parch	Fare	male	Q	S
511	3	24.0	0	0	8.0500	1	0	1
613	3	24.0	0	0	7.7500	1	1	0
615	2	24.0	1	2	65.0000	0	0	1
337	1	41.0	0	0	134.5000	0	0	0
718	3	24.0	0	0	15.5000	1	1	0
...	...	...	...	...	...	...	...	...
155	1	51.0	0	1	61.3792	1	0	0
450	2	36.0	1	2	27.7500	1	0	1
756	3	28.0	0	0	7.7958	1	0	1
187	1	45.0	0	0	26.5500	1	0	1
180	3	24.0	8	2	69.5500	0	0	1

178 rows × 8 columns

In [29]:

```
y_test
```

Out[29]:

```
511    0
613    0
615    1
337    1
718    0
      ..
155    0
450    0
756    0
187    1
180    0
Name: Survived, Length: 178, dtype: int64
```

LOGISTIC REGRESSION

Model Training

In [30]:

```
#fit
# import model
from sklearn.linear_model import LogisticRegression
ireg=LogisticRegression()
# pass training data to model
ireg.fit(x_train,y_train)
```

Out[30]:

```
▾ LogisticRegression

LogisticRegression()
```

Model Testing

Class prediction

In [31]:

```
#predict
y_predict_ireg=ireg.predict(x_test)
print(y_predict_ireg)
y_predict_ireg.shape
```

```
[0 0 1 1 0 0 0 0 0 1 1 1 0 1 0 0 1 1 1 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1
 0 0 0 1 0 0 1 1 0 1 1 0 0 0 1 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 0 0 1 1
 0 1 0 0 0 0 0 0 0 0 0 1 0 1 0 1 1 1 0 0 0 1 1 0 0 1 0 1 0 0 1 0 1 0 0 0 0
 0 1 1 0 1 0 0 1 1 0 0 0 0 0 0 1 0 1 1 0 0 1 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0
 0 1 0 1 1 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0]
```

Out[31]:

```
(178,)
```

In [32]:

```
probabilities = ireg.predict_proba(x_test)[:, 1]
print(probabilities.shape)
print(probabilities)
```

```
(178,)
[0.109253   0.17773178 0.74823182 0.92026066 0.17923442 0.04189799
 0.11564511 0.23012612 0.07881639 0.67516479 0.78824821 0.94479684
 0.10923316 0.57766638 0.10943974 0.12263706 0.91633419 0.84251929
 0.54118197 0.10003649 0.10933185 0.08695044 0.42380718 0.34707463
 0.04222597 0.43918353 0.60045413 0.58878005 0.0929513  0.29927329
 0.09264006 0.25338225 0.01225878 0.10605718 0.10918171 0.1104076
 0.75615953 0.06367026 0.122465   0.13442274 0.53043283 0.13742608
 0.1191466  0.92765522 0.61210721 0.12698455 0.61567376 0.86568878
 0.10291069 0.26675351 0.48912444 0.79795881 0.16935772 0.12292071
 0.10912438 0.07196006 0.42748848 0.08624919 0.07430792 0.91084004
 0.67516479 0.9342894  0.88905049 0.08654536 0.13952978 0.04975333
 0.11568205 0.43216119 0.05801084 0.14302875 0.33799147 0.13596739
 0.61964136 0.88739382 0.11184746 0.72909713 0.08107326 0.13596739
 0.10373381 0.29707041 0.29917306 0.37634534 0.45073918 0.12263706
 0.28121186 0.65842528 0.07119817 0.87047924 0.0989935  0.88734228
 0.55674718 0.52694311 0.08623616 0.0722172  0.29480303 0.92359897
 0.69021029 0.3355044  0.13607098 0.77168882 0.11564511 0.87963572
 0.17773178 0.14429419 0.61344592 0.10921762 0.94864459 0.38447325
 0.27683014 0.41913199 0.06293228 0.42239949 0.85521533 0.78435729
 0.10923316 0.90494556 0.1299251  0.14666842 0.77711242 0.81406789
 0.47251129 0.1337268  0.1001278  0.16454344 0.11916741 0.23392748
 0.69029527 0.4710366  0.86321887 0.65020872 0.22954095 0.30248085
 0.90447884 0.5687659  0.06980651 0.07362874 0.08397234 0.17755952
 0.53034015 0.1376967  0.07188541 0.12266492 0.25139208 0.1144939
 0.42135498 0.578893   0.11923798 0.32474649 0.31620415 0.83282132
 0.10921762 0.76156431 0.6353817  0.80365766 0.14938478 0.28449429
 0.49208212 0.06007666 0.85805943 0.326199   0.17757723 0.10923316
 0.0838508  0.4694775  0.09731344 0.38865081 0.23538235 0.06770784
 0.22335517 0.2397733  0.72912868 0.24032413 0.82539082 0.35183358
 0.13297171 0.09711566 0.35432179 0.13386825]
```

In [33]:

```
for i in range(len(y_test)):
  print(round(probabilities[i], 3)," --> ", y_predict_ireg[i])
```

```
0.109  -->  0
0.178  -->  0
0.748  -->  1
0.92  -->  1
0.179  -->  0
0.042  -->  0
0.116  -->  0
0.23  -->  0
0.079  -->  0
0.675  -->  1
0.788  -->  1
0.945  -->  1
0.109  -->  0
0.578  -->  1
0.109  -->  0
0.123  -->  0
0.916  -->  1
0.843  -->  1
0.541  -->  1
```

In [34]:

```
# Score It
from sklearn.metrics import classification_report, accuracy_score

print('Classification Model')
# Accuracy
print('--'*30)
logreg_accuracy = round(accuracy_score(y_test, y_predict_ireg) * 100,2)
print('Accuracy', logreg_accuracy,'%')
```

```
Classification Model
------------------------------------------------------------
Accuracy 82.02 %
```