titanic

October 14, 2023

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Task-02: Titanic Classification (Data science Intern)

THE MACHINE LEARNING INTERNSHIP.

Make a system which tells whether the peson will be save from sinking. what factors were mostly likely lead to success-socio-economic status, age, gender and more.

[ ]:
```
#Importing All Required Libaries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from warnings import filterwarnings
filterwarnings(action='ignore')
```

[ ]:
```
#Loading Datasets
pd.set_option('display.max_columns',10,'display.width',1000)
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
train.head()
```

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

[5 rows x 12 columns]
```

[ ]:
```
#Display shape
train.shape
```

[ ]:
```
(891, 12)
```

[ ]:
```
test.shape
```

[ ]:
```
(418, 11)
```

[ ]:
```
#Checking for Null values
train.isnull().sum()
```

[ ]:
```
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
```

[ ]:
```
test.isnull().sum()
```

[ ]:
```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

[ ]:
```
#Description of dataset
train.describe(include="all")
```

[ ]:
```
        PassengerId    Survived      Pclass                          Name    Sex  …
Parch  Ticket         Fare     Cabin  Embarked
count    891.000000  891.000000  891.000000                           891    891  …
```

```
891.000000     891  891.000000      204       889
unique          NaN         NaN         NaN                          891     2  …
NaN     681         NaN      147         3
top             NaN         NaN         NaN  Braund, Mr. Owen Harris  male  …
NaN  347082         NaN  B96 B98         S
freq            NaN         NaN         NaN                            1   577  …
NaN       7         NaN        4       644
mean     446.000000    0.383838    2.308642                          NaN   NaN  …
0.381594     NaN   32.204208      NaN       NaN
std      257.353842    0.486592    0.836071                          NaN   NaN  …
0.806057     NaN   49.693429      NaN       NaN
min        1.000000    0.000000    1.000000                          NaN   NaN  …
0.000000     NaN    0.000000      NaN       NaN
25%      223.500000    0.000000    2.000000                          NaN   NaN  …
0.000000     NaN    7.910400      NaN       NaN
50%      446.000000    0.000000    3.000000                          NaN   NaN  …
0.000000     NaN   14.454200      NaN       NaN
75%      668.500000    1.000000    3.000000                          NaN   NaN  …
0.000000     NaN   31.000000      NaN       NaN
max      891.000000    1.000000    3.000000                          NaN   NaN  …
6.000000     NaN  512.329200      NaN       NaN

[11 rows x 12 columns]
```

[ ]:
```
train.groupby('Survived').mean()
```

[ ]:
```
          PassengerId    Pclass        Age     SibSp     Parch       Fare
Survived
0          447.016393  2.531876  30.626179  0.553734  0.329690  22.117887
1          444.368421  1.950292  28.343690  0.473684  0.464912  48.395408
```

[ ]:
```
train.corr()
```

[ ]:
```
             PassengerId  Survived    Pclass       Age     SibSp     Parch
Fare
PassengerId     1.000000 -0.005007 -0.035144  0.036847 -0.057527 -0.001652
0.012658
Survived       -0.005007  1.000000 -0.338481 -0.077221 -0.035322  0.081629
0.257307
Pclass         -0.035144 -0.338481  1.000000 -0.369226  0.083081  0.018443
-0.549500
Age             0.036847 -0.077221 -0.369226  1.000000 -0.308247 -0.189119
0.096067
SibSp          -0.057527 -0.035322  0.083081 -0.308247  1.000000  0.414838
0.159651
Parch          -0.001652  0.081629  0.018443 -0.189119  0.414838  1.000000
0.216225
```

```
Fare            0.012658  0.257307 -0.549500  0.096067  0.159651  0.216225
1.000000
```

[ ]:
```
male_ind = len(train[train['Sex'] == 'male'])
print("No of Males in Titanic:",male_ind)
```

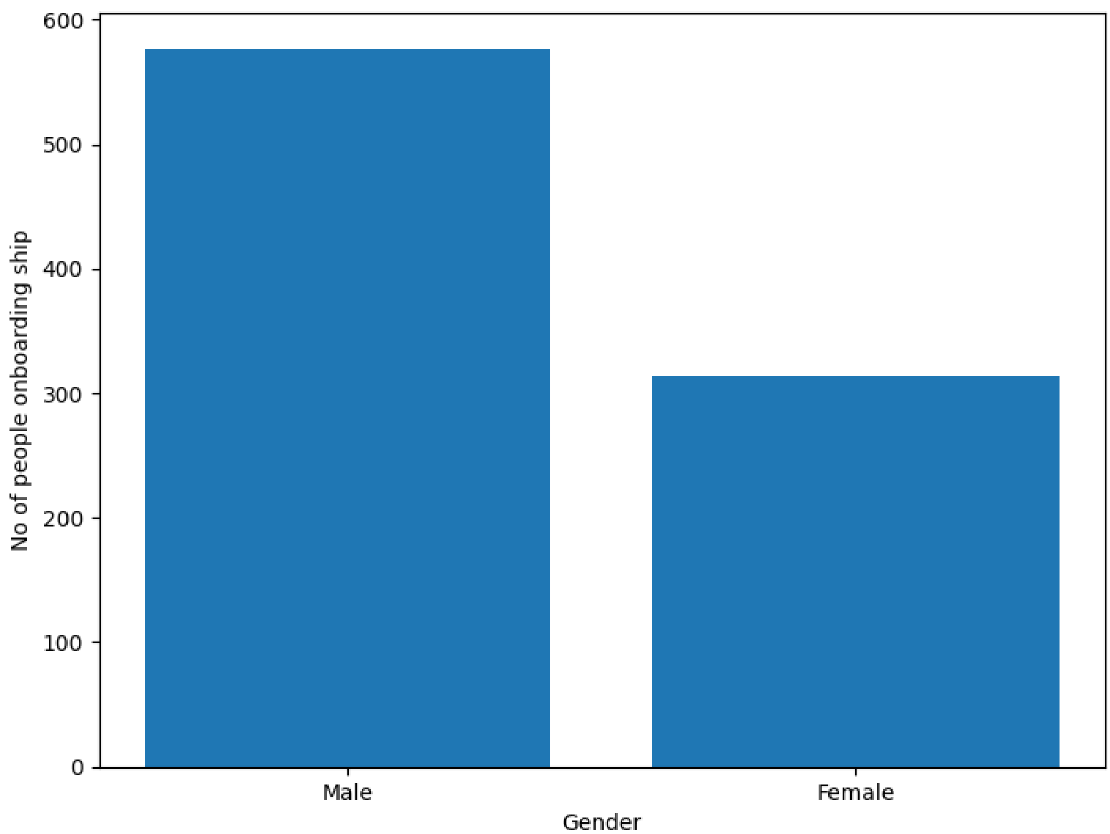
```
No of Males in Titanic: 577
```

[ ]:
```
female_ind = len(train[train['Sex'] == 'female'])
print("No of Females in Titanic:",female_ind)
```

```
No of Females in Titanic: 314
```

2 Plotting

[ ]:
```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
gender = ['Male','Female']
index = [577,314]
ax.bar(gender,index)
plt.xlabel("Gender")
plt.ylabel("No of people onboarding ship")
plt.show()
```



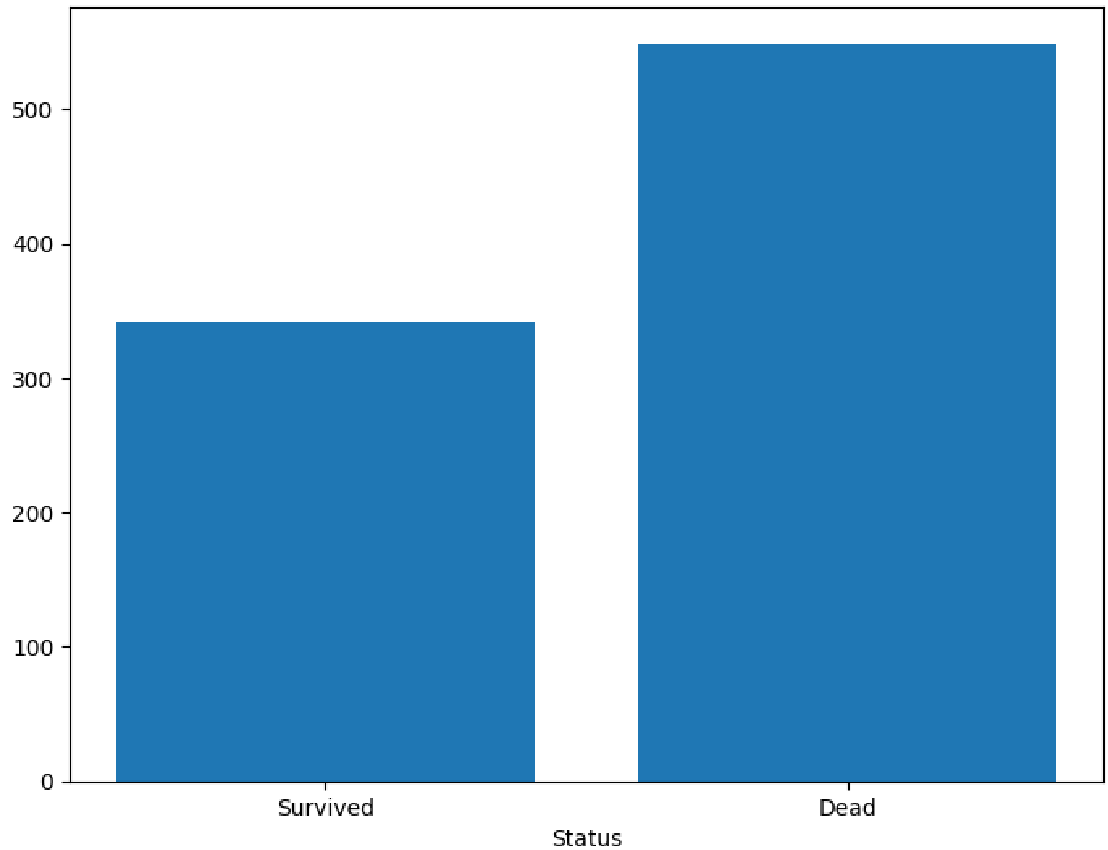
[ ]:
```
alive = len(train[train['Survived'] == 1])
dead = len(train[train['Survived'] == 0])
```

[ ]:
```
train.groupby('Sex')[['Survived']].mean()
```

[ ]:

	Survived
Sex	
female	0.742038
male	0.188908

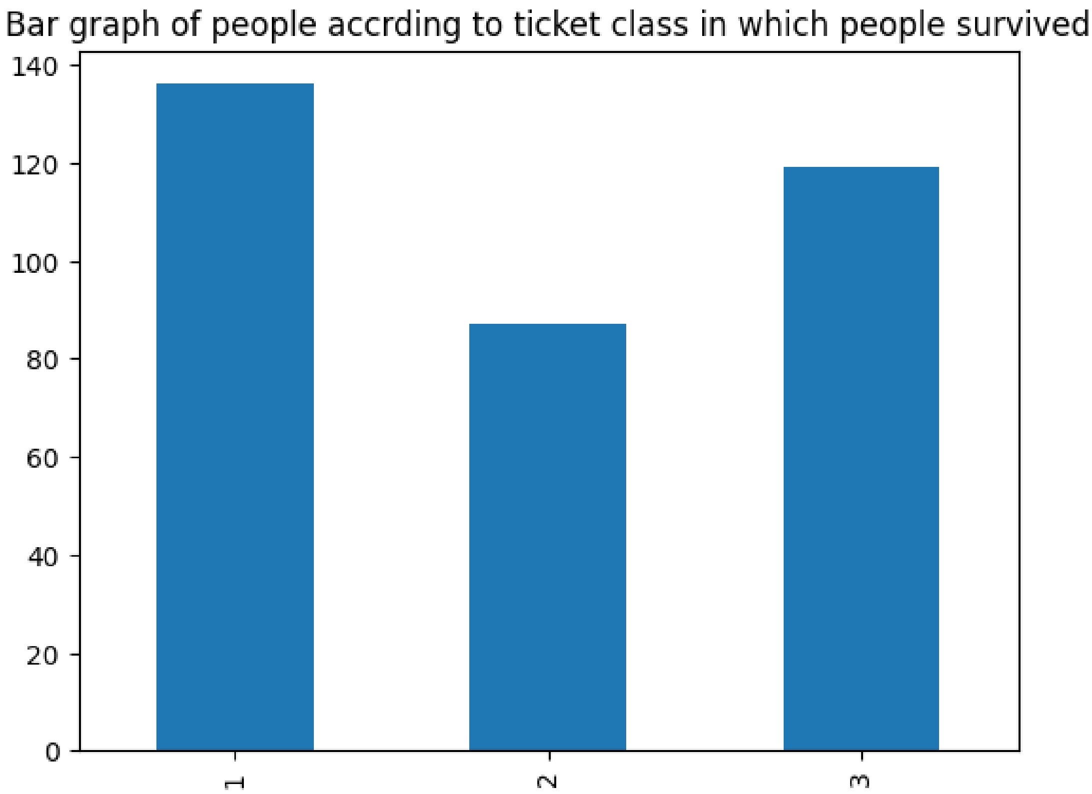
[ ]:
```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
status = ['Survived','Dead']
ind = [alive,dead]
ax.bar(status,ind)
plt.xlabel("Status")
plt.show()
```

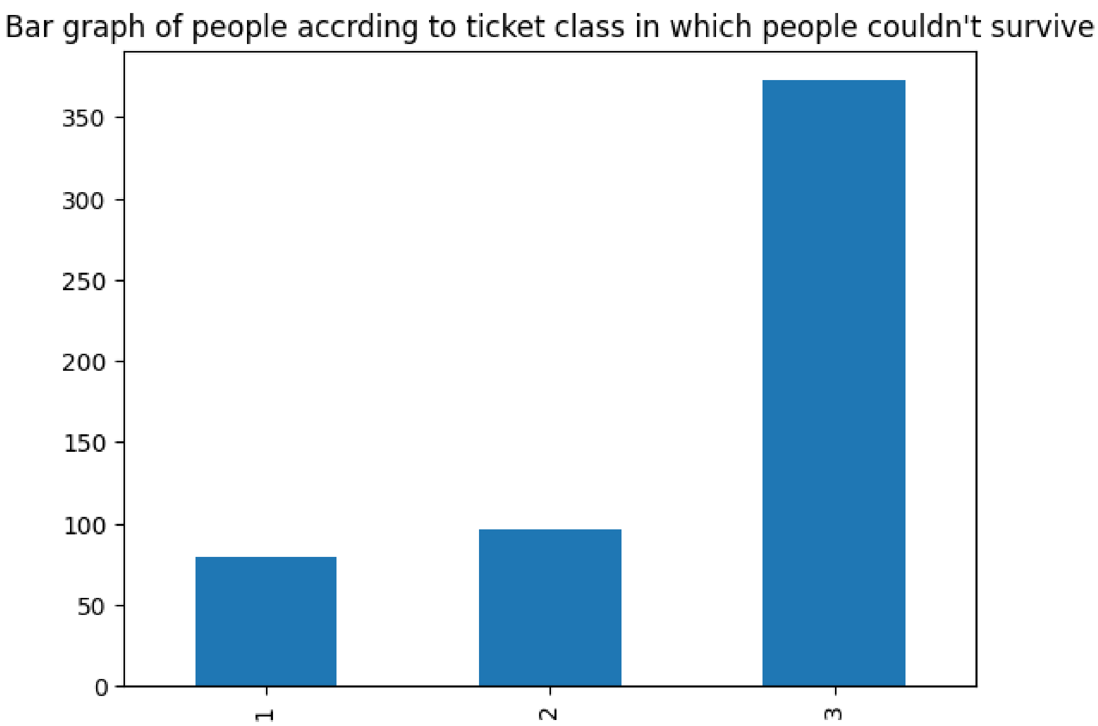


[ ]:
```
plt.figure(1)
train.loc[train['Survived'] == 1, 'Pclass'].value_counts().sort_index().plot.
 ↪bar()
plt.title('Bar graph of people accrding to ticket class in which people␣
 ↪survived')


plt.figure(2)
train.loc[train['Survived'] == 0, 'Pclass'].value_counts().sort_index().plot.
 ↪bar()
plt.title('Bar graph of people accrding to ticket class in which people␣
 ↪couldn\'t survive')
```

[ ]:
```
Text(0.5, 1.0, "Bar graph of people accrding to ticket class in which people
couldn't survive")
```

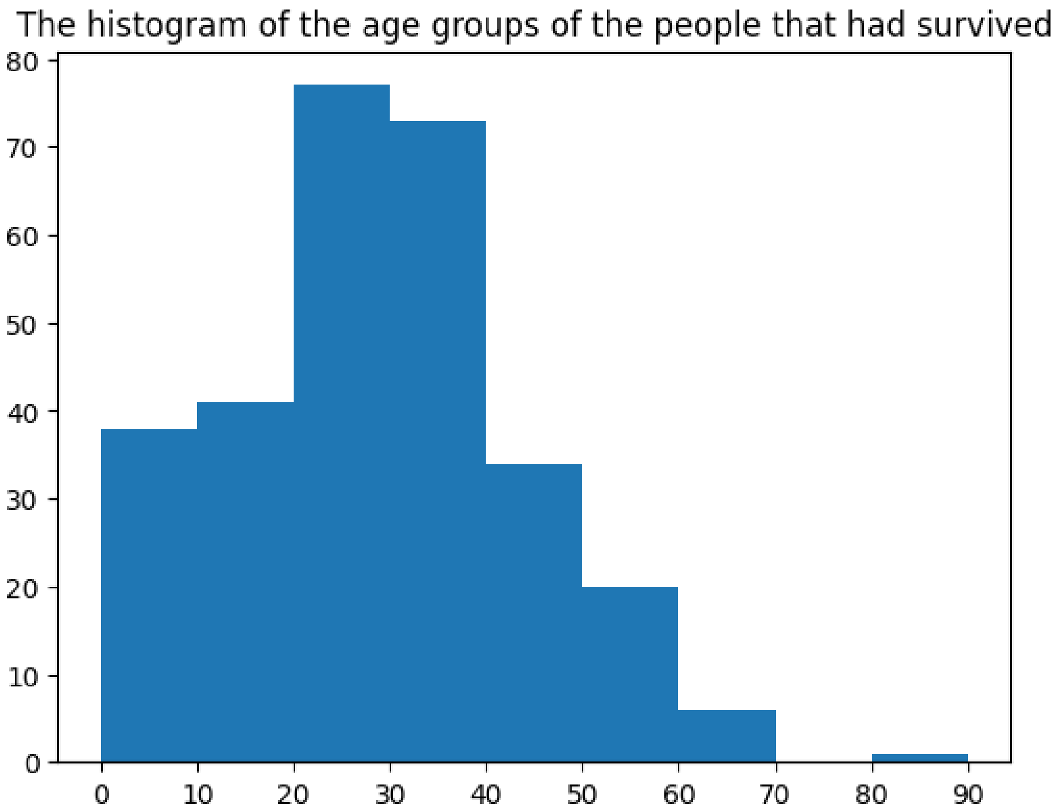

Bar graph of people accrding to ticket class in which people survived
140
120
100
80
60
40
20
0
1
2
3

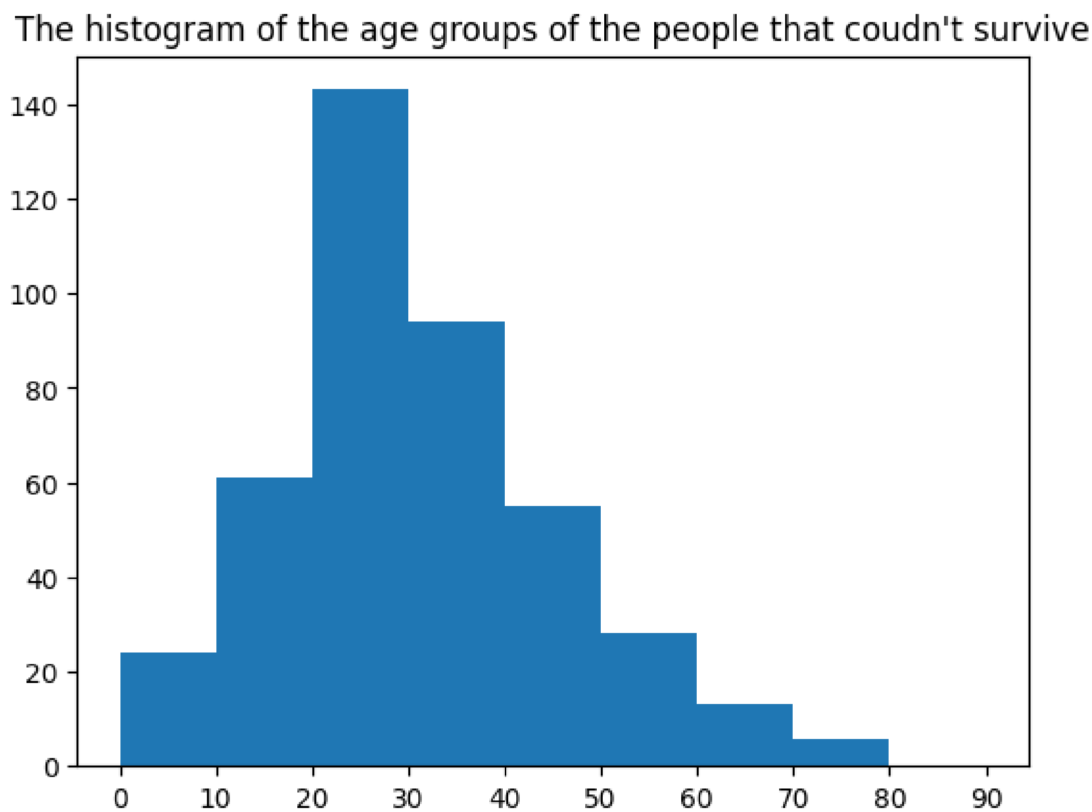

Bar graph of people accrding to ticket class in which people couldn't survive
350
300
250
200
150
100
50
0
1
2
3

[ ]:
```
plt.figure(1)
age  = train.loc[train.Survived == 1, 'Age']
plt.title('The histogram of the age groups of the people that had survived')
plt.hist(age, np.arange(0,100,10))
plt.xticks(np.arange(0,100,10))


plt.figure(2)
age  = train.loc[train.Survived == 0, 'Age']
plt.title('The histogram of the age groups of the people that coudn\'t survive')
plt.hist(age, np.arange(0,100,10))
plt.xticks(np.arange(0,100,10))
```

[ ]:
```
([<matplotlib.axis.XTick at 0x788e6aff14e0>,
  <matplotlib.axis.XTick at 0x788e6aff14b0>,
  <matplotlib.axis.XTick at 0x788e6b00e7a0>,
  <matplotlib.axis.XTick at 0x788e6ae371f0>,
  <matplotlib.axis.XTick at 0x788e6ae37ca0>,
  <matplotlib.axis.XTick at 0x788e6ae36e60>,
  <matplotlib.axis.XTick at 0x788e6ae70b80>,
  <matplotlib.axis.XTick at 0x788e6ae71630>,
  <matplotlib.axis.XTick at 0x788e6ae720e0>,
  <matplotlib.axis.XTick at 0x788e6ae72b90>],
 [Text(0, 0, '0'),
  Text(10, 0, '10'),
  Text(20, 0, '20'),
  Text(30, 0, '30'),
  Text(40, 0, '40'),
  Text(50, 0, '50'),
  Text(60, 0, '60'),
  Text(70, 0, '70'),
  Text(80, 0, '80'),
  Text(90, 0, '90')])
```


The histogram of the age groups of the people that had survived
80
70
60
50
40
30
20
10
0
0
10
20
30
40
50
60
70
80
90




```
[ ]: train[["Pclass", "Survived"]].groupby(['Pclass'], as_index=False).mean().
     ↪sort_values(by='Survived', ascending=False)
```

```
[ ]:    Pclass  Survived
     0       1  0.629630
     1       2  0.472826
     2       3  0.242363
```

```
[ ]: train[["Age", "Survived"]].groupby(['Age'], as_index=False).mean().
     ↪sort_values(by='Age', ascending=True)
```

```
[ ]:       Age  Survived
     0    0.42       1.0
     1    0.67       1.0
     2    0.75       1.0
     3    0.83       1.0
     4    0.92       1.0
     ..     …         …
     83  70.00       0.0
     84  70.50       0.0
     85  71.00       0.0
```

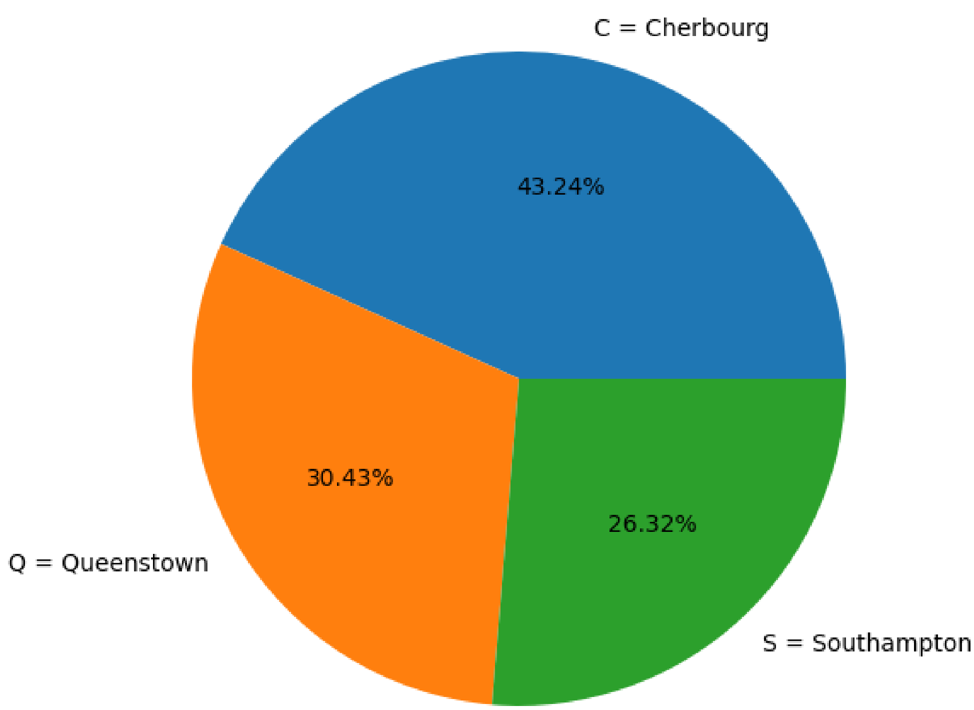
```
86   74.00        0.0
87   80.00        1.0

[88 rows x 2 columns]
```

[ ]:
```
train[["Embarked", "Survived"]].groupby(['Embarked'], as_index=False).mean().
 ↪sort_values(by='Survived', ascending=False)
```

[ ]:
```
  Embarked  Survived
0        C  0.553571
1        Q  0.389610
2        S  0.336957
```

[ ]:
```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.axis('equal')
l = ['C = Cherbourg', 'Q = Queenstown', 'S = Southampton']
s = [0.553571,0.389610,0.336957]
ax.pie(s, labels = l,autopct='%1.2f%%')
plt.show()
```



[ ]:
```
test.describe(include="all")
```

[ ]:
```
         PassengerId      Pclass              Name   Sex         Age  …
Parch     Ticket          Fare           Cabin Embarked
count     418.000000  418.000000              418   418  332.000000  …
418.000000        418  417.000000              91      418
unique           NaN         NaN              418     2         NaN  …
NaN       363         NaN               76        3
top              NaN         NaN  Kelly, Mr. James  male         NaN  …
NaN  PC 17608         NaN  B57 B59 B63 B66        S
freq             NaN         NaN                1   266         NaN  …
NaN         5         NaN                3      270
mean     1100.500000    2.265550              NaN   NaN   30.272590  …
0.392344        NaN   35.627188             NaN      NaN
std       120.810458    0.841838              NaN   NaN   14.181209  …
0.981429        NaN   55.907576             NaN      NaN
min       892.000000    1.000000              NaN   NaN    0.170000  …
0.000000        NaN    0.000000             NaN      NaN
25%       996.250000    1.000000              NaN   NaN   21.000000  …
0.000000        NaN    7.895800             NaN      NaN
50%      1100.500000    3.000000              NaN   NaN   27.000000  …
0.000000        NaN   14.454200             NaN      NaN
75%      1204.750000    3.000000              NaN   NaN   39.000000  …
0.000000        NaN   31.500000             NaN      NaN
max      1309.000000    3.000000              NaN   NaN   76.000000  …
9.000000        NaN  512.329200             NaN      NaN

[11 rows x 11 columns]
```

3 *Feature Selection*

4 training values

[ ]:
```
column_train=['Age','Pclass','SibSp','Parch','Fare','Sex','Embarked']
X=train[column_train]
Y=train['Survived']
```

[ ]:
```
X['Age'].isnull().sum()
X['Pclass'].isnull().sum()
X['SibSp'].isnull().sum()
X['Parch'].isnull().sum()
X['Fare'].isnull().sum()
X['Sex'].isnull().sum()
X['Embarked'].isnull().sum()
```

[ ]:
```
2
```

5 now we have to fill all the missing values

6 age have 177 missing values

7 either we fill missing values with mean or median form existing values

[ ]:
```
X['Age']=X['Age'].fillna(X['Age'].median())
X['Age'].isnull().sum()
```

[ ]: 0

[ ]:
```
X['Embarked'] = train['Embarked'].fillna(method ='pad')
X['Embarked'].isnull().sum()
```

[ ]: 0

8 now we need to convert sex into integer value

[ ]:
```
d={'male':0, 'female':1}
X['Sex']=X['Sex'].apply(lambda x:d[x])
X['Sex'].head()
```

[ ]:
```
0    0
1    1
2    1
3    1
4    0
Name: Sex, dtype: int64
```

[ ]:
```
e={'C':0, 'Q':1 ,'S':2}
X['Embarked']=X['Embarked'].apply(lambda x:e[x])
X['Embarked'].head()
```

[ ]:
```
0    2
1    0
2    2
3    2
4    2
Name: Embarked, dtype: int64
```

9 Training, Testing and Spliting the model

[ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size=0.
↪3,random_state=7)
```

10 Using LogisticRegression

[ ]:
```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
model.fit(X_train,Y_train)
Y_pred = model.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,Y_pred))
```

```
Accuracy Score: 0.7574626865671642
```

11 Confusion Matrix

[ ]:
```
from sklearn.metrics import accuracy_score,confusion_matrix
confusion_mat = confusion_matrix(Y_test,Y_pred)
print(confusion_mat)
```

```
[[130  26]
 [ 39  73]]
```

12 Using Support Vector

[ ]:
```
from sklearn.svm import SVC
model1 = SVC()
model1.fit(X_train,Y_train)

pred_y = model1.predict(X_test)

from sklearn.metrics import accuracy_score
print("Acc=",accuracy_score(Y_test,pred_y))
```

```
Acc= 0.6604477611940298
```

[ ]:
```
from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,classification_report
confusion_mat = confusion_matrix(Y_test,pred_y)
print(confusion_mat)
print(classification_report(Y_test,pred_y))
```

```
[[149   7]
 [ 84  28]]
              precision    recall  f1-score   support

           0       0.64      0.96      0.77       156
           1       0.80      0.25      0.38       112

    accuracy                           0.66       268
   macro avg       0.72      0.60      0.57       268
weighted avg       0.71      0.66      0.61       268
```

13 Using KNN Neighbors

[ ]:
```
from sklearn.neighbors import KNeighborsClassifier
model2 = KNeighborsClassifier(n_neighbors=5)
model2.fit(X_train,Y_train)
y_pred2 = model2.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred2))
```

```
Accuracy Score: 0.6567164179104478
```

[ ]:
```
from sklearn.metrics import␣
 ↪accuracy_score,confusion_matrix,classification_report
confusion_mat = confusion_matrix(Y_test,y_pred2)
print(confusion_mat)
print(classification_report(Y_test,y_pred2))
```

```
[[126  30]
 [ 62  50]]
              precision    recall  f1-score   support

           0       0.67      0.81      0.73       156
           1       0.62      0.45      0.52       112

    accuracy                           0.66       268
   macro avg       0.65      0.63      0.63       268
weighted avg       0.65      0.66      0.64       268
```

14 Using GaussianNB

[ ]:
```
from sklearn.naive_bayes import GaussianNB
model3 = GaussianNB()
model3.fit(X_train,Y_train)
y_pred3 = model3.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred3))
```

```
Accuracy Score: 0.7686567164179104
```

[ ]:
```
from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,classification_report
confusion_mat = confusion_matrix(Y_test,y_pred3)
print(confusion_mat)
print(classification_report(Y_test,y_pred3))
```

```
[[129  27]
 [ 35  77]]
              precision    recall  f1-score   support

           0       0.79      0.83      0.81       156
           1       0.74      0.69      0.71       112

    accuracy                           0.77       268
   macro avg       0.76      0.76      0.76       268
weighted avg       0.77      0.77      0.77       268
```

15 Using Decision Tree

[ ]:
```
from sklearn.tree import DecisionTreeClassifier
model4 = DecisionTreeClassifier(criterion='entropy',random_state=7)
model4.fit(X_train,Y_train)
y_pred4 = model4.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred4))
```

```
Accuracy Score: 0.7425373134328358
```

[ ]:
```
from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,classification_report
confusion_mat = confusion_matrix(Y_test,y_pred4)
print(confusion_mat)
print(classification_report(Y_test,y_pred4))
```

```
[[132  24]
 [ 45  67]]
              precision    recall  f1-score   support

           0       0.75      0.85      0.79       156
           1       0.74      0.60      0.66       112

    accuracy                           0.74       268
   macro avg       0.74      0.72      0.73       268
weighted avg       0.74      0.74      0.74       268
```

[ ]:
```
results = pd.DataFrame({
    'Model': ['Logistic Regression','Support Vector Machines', 'Naive␣
 ↪Bayes','KNN' ,'Decision Tree'],
    'Score': [0.75,0.66,0.76,0.66,0.74]})

result_df = results.sort_values(by='Score', ascending=False)
result_df = result_df.set_index('Score')
result_df.head(9)
```

[ ]:
```
                         Model
Score
0.76               Naive Bayes
0.75       Logistic Regression
0.74             Decision Tree
0.66   Support Vector Machines
0.66                       KNN
```

16 *************** THANK YOU***************