PRODIGY_DS_02

September 20, 2024

1 TASK 2

Perform data cleaning and exploratory data analysis (EDA) on a dataset of your choice, such as the Titanic dataset from Kaggle. Explore the relationships between variables and identify patterns and trends in the data.

[3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from warnings import filterwarnings
filterwarnings(action='ignore')
```

[5]:
```
pd.set_option('display.max_columns',10,'display.width',1000)
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
train.head()
```

[5]:
```
   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]
```

[7]:
```
train.shape
```

[7]: (891, 12)

[9]:
```
test.shape
```

[9]: (418, 11)

[11]:
```
#Checking for Null values
train.isnull().sum()
```

[11]:
```
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
```

[13]:
```
test.isnull().sum()
```

[13]:
```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

[17]:
```
#Description of data set
train.describe(include="all")
```

[17]:
```
        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]
```

[93]:
```
numeric_columns = train.select_dtypes(include=[np.number])
mean_values = numeric_columns.groupby(train['Survived']).mean()
print(mean_values)
```

```
          PassengerId  Survived    Pclass        Age     SibSp     Parch
Fare
Survived
0          447.016393       0.0  2.531876  30.626179  0.553734  0.329690
22.117887
1          444.368421       1.0  1.950292  28.343690  0.473684  0.464912
48.395408
```

[91]:
```
correlation_matrix = train.corr(numeric_only=True)
print(correlation_matrix)
```

```
             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
```

[25]:
```
male_ind = len(train[train['Sex'] == 'male'])
print("No of Males in Titanic:",male_ind)
```

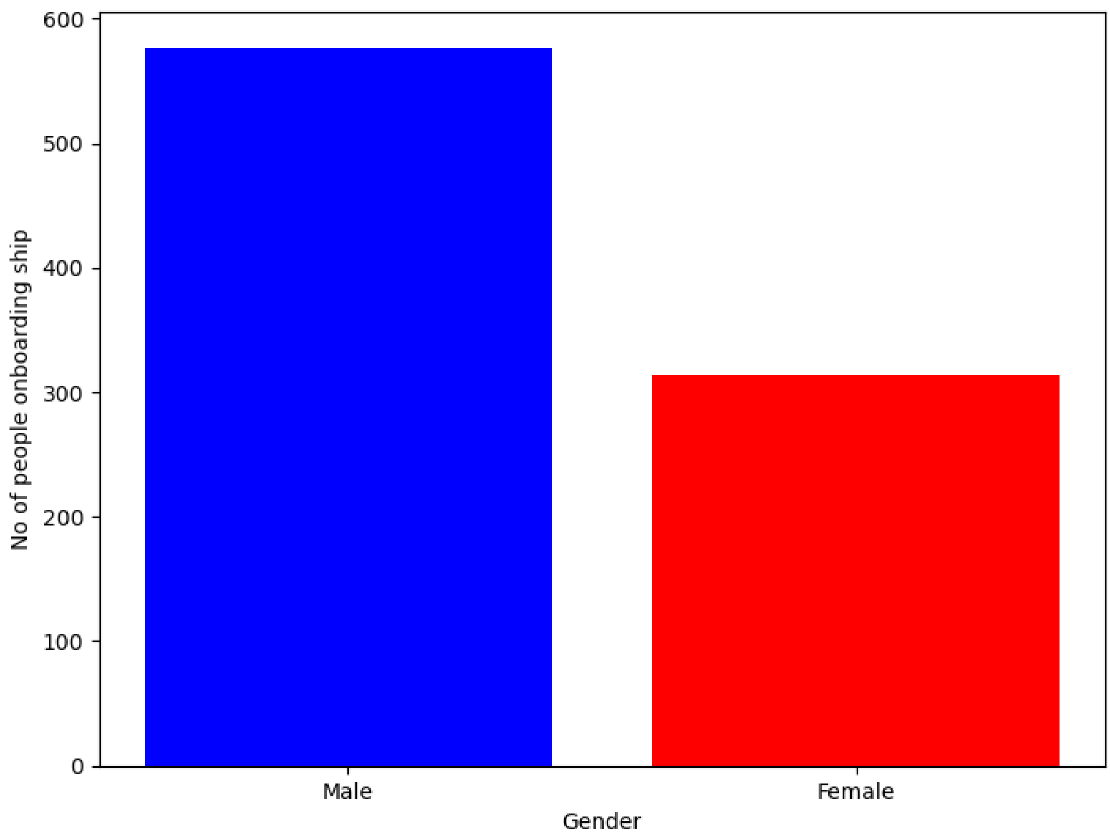
```
No of Males in Titanic: 577
```

[27]:
```
female_ind = len(train[train['Sex'] == 'female'])
print("No of Females in Titanic:",female_ind)
```

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

[31]:
```
import matplotlib.pyplot as plt

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



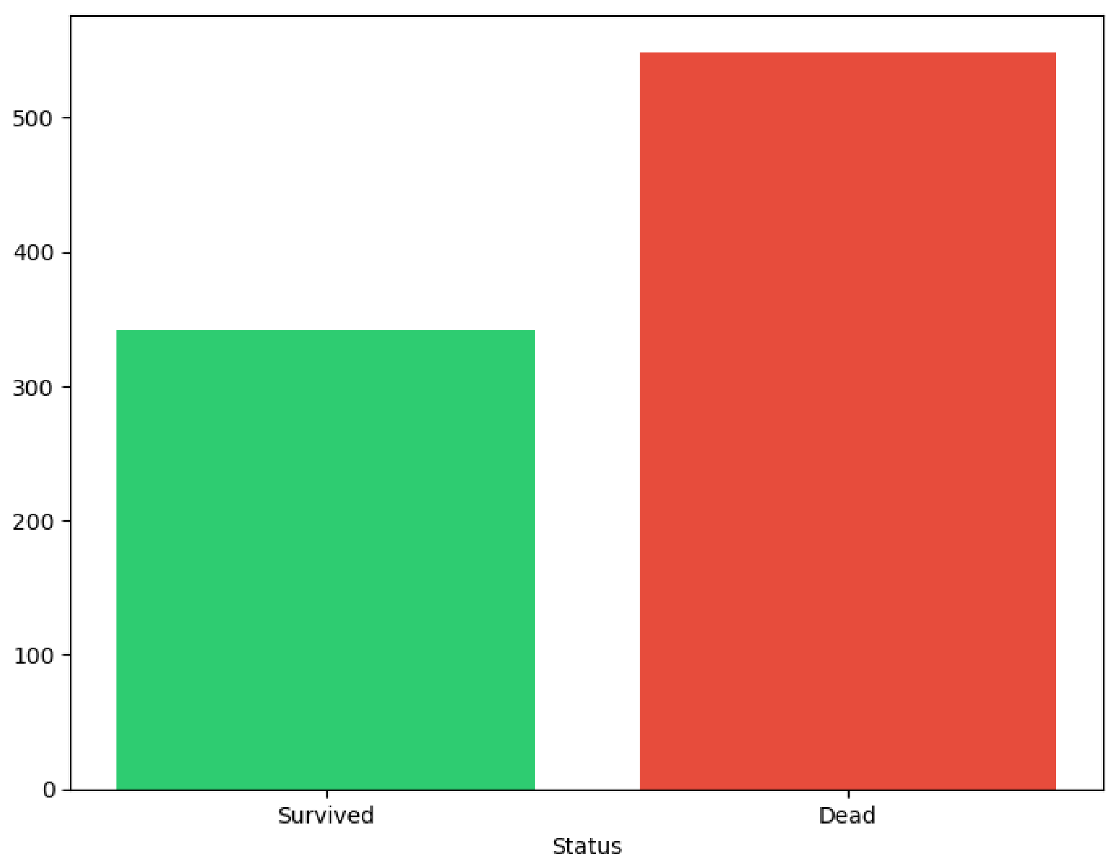
[33]:
```
alive = len(train[train['Survived'] == 1])
dead = len(train[train['Survived'] == 0])
```

[35]:
```
train.groupby('Sex')[['Survived']].mean()
```

[35]:

	Survived
Sex	
female	0.742038
male	0.188908

[37]:
```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
status = ['Survived','Dead']
ind = [alive,dead]
ax.bar(status,ind, color=['#2ecc71', '#e74c3c'])
plt.xlabel("Status")
plt.show()
```

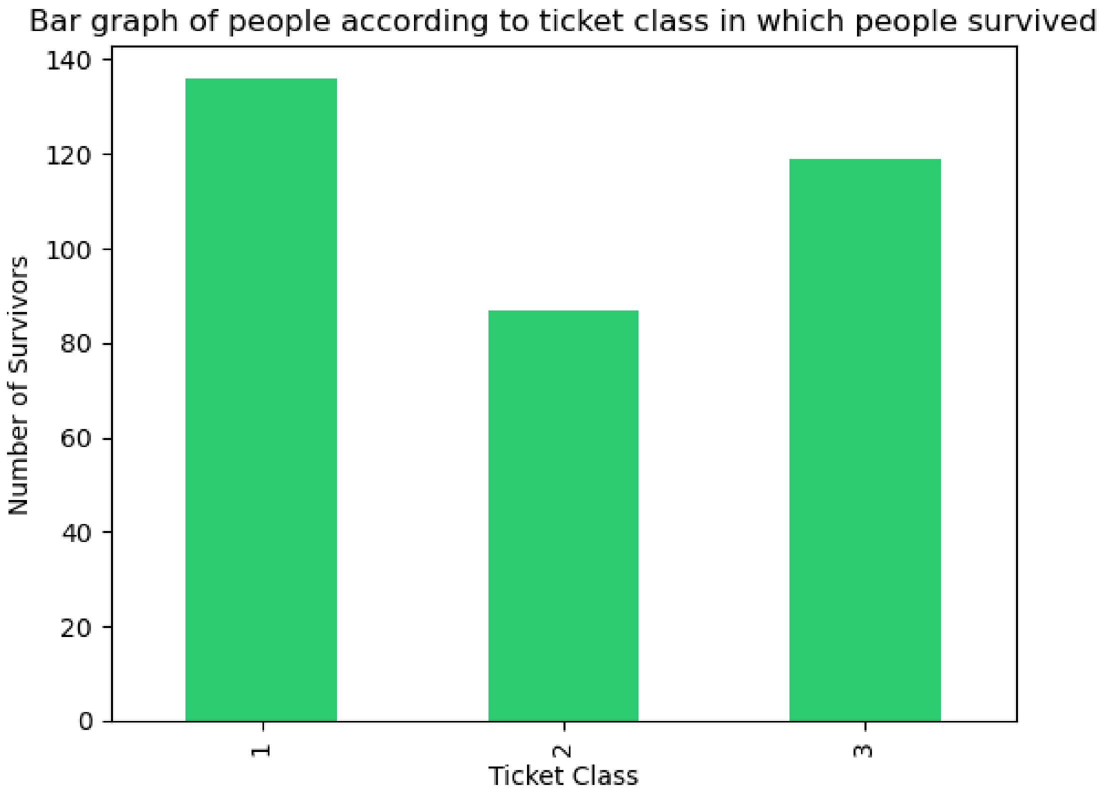


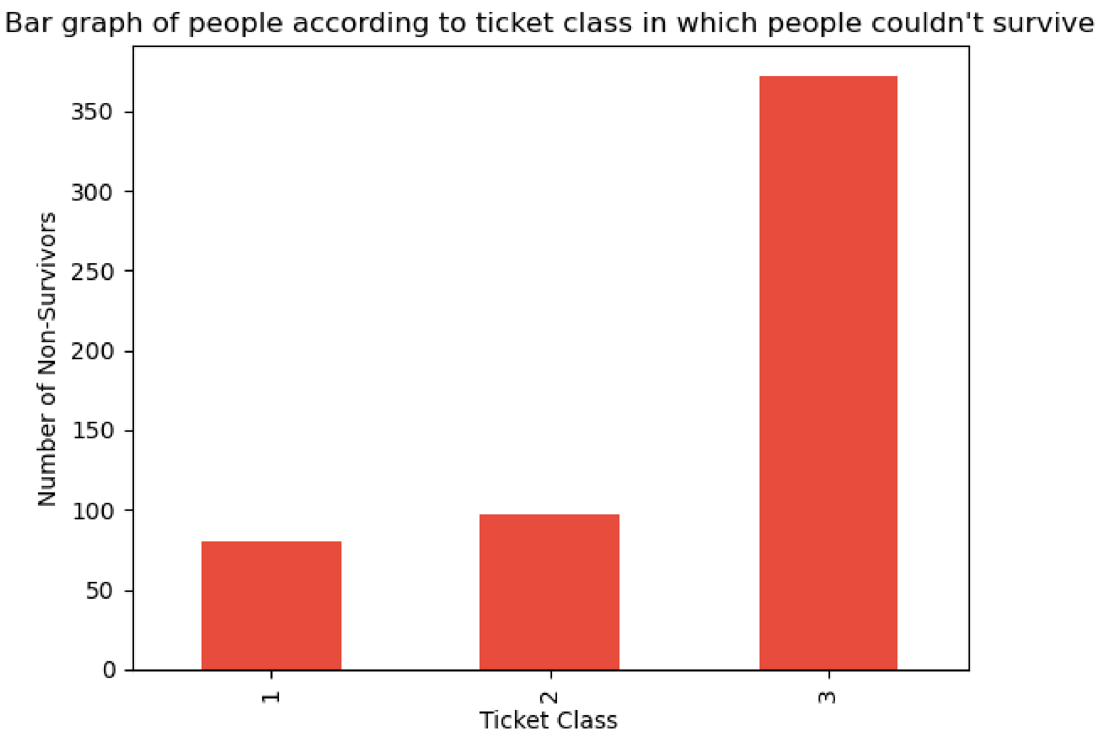
[39]:

```
plt.figure(1)
train.loc[train['Survived'] == 1, 'Pclass'].value_counts().sort_index().plot.
 ↪bar(color='#2ecc71')
plt.title('Bar graph of people according to ticket class in which people␣
 ↪survived')
plt.xlabel('Ticket Class')
plt.ylabel('Number of Survivors')

plt.figure(2)
train.loc[train['Survived'] == 0, 'Pclass'].value_counts().sort_index().plot.
 ↪bar(color='#e74c3c')
plt.title('Bar graph of people according to ticket class in which people␣
 ↪couldn\'t survive')
plt.xlabel('Ticket Class')
plt.ylabel('Number of Non-Survivors')

plt.show()
```

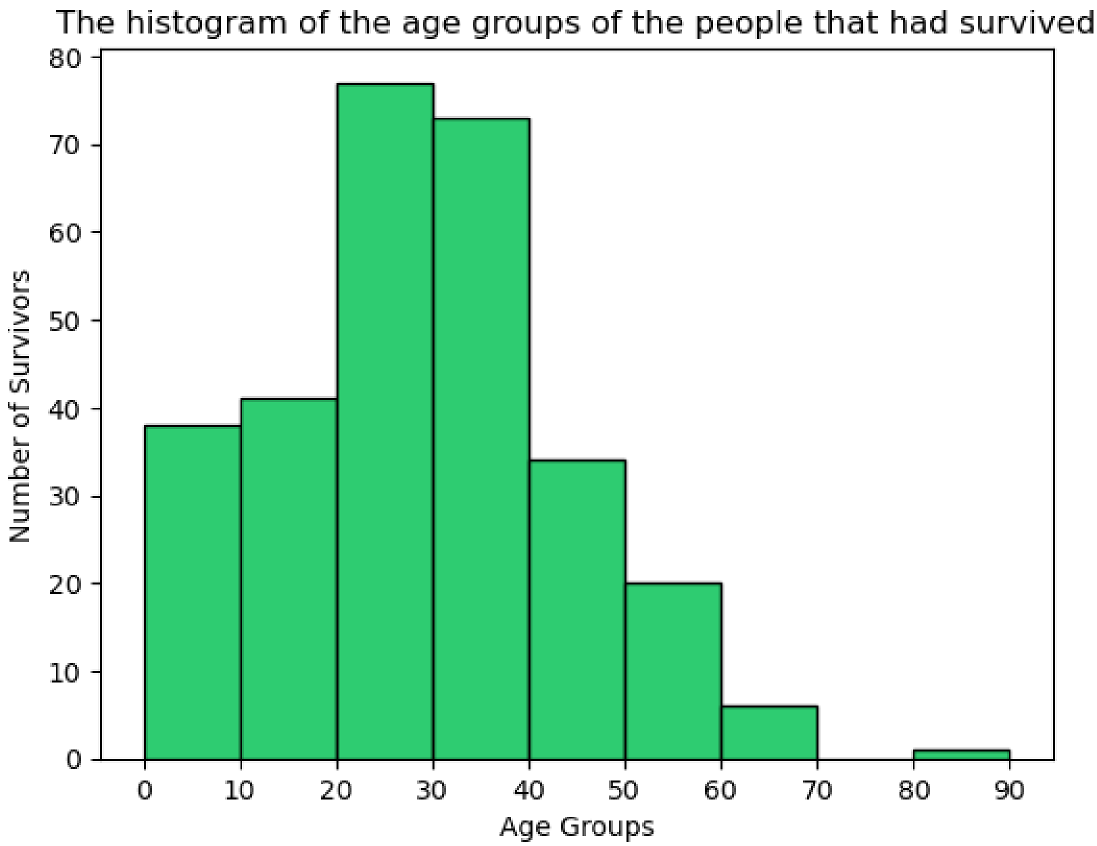


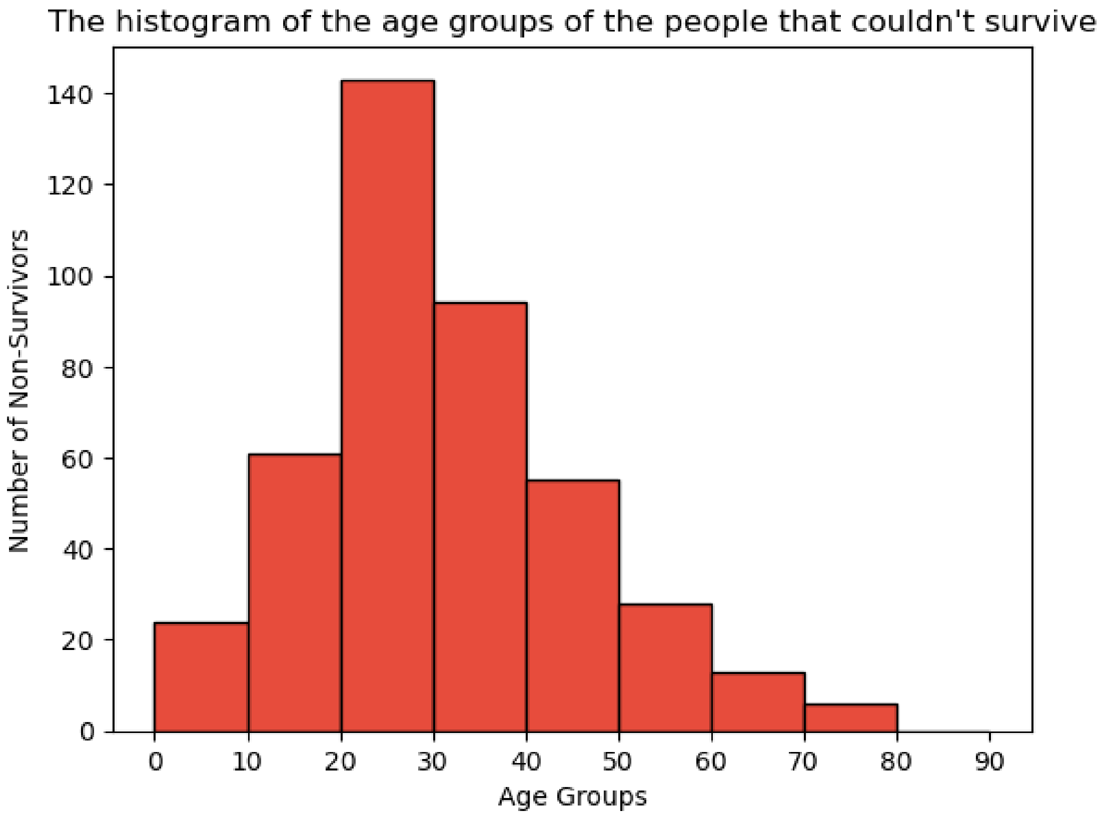


[49]:
```
plt.figure(1)
age_survived = train.loc[train.Survived == 1, 'Age']
plt.title('The histogram of the age groups of the people that had survived')
plt.hist(age_survived, bins=np.arange(0, 100, 10), color='#2ecc71',␣
 ↪edgecolor='black')
plt.xticks(np.arange(0, 100, 10))
plt.xlabel('Age Groups')
plt.ylabel('Number of Survivors')

plt.figure(2)
age_not_survived = train.loc[train.Survived == 0, 'Age']
plt.title('The histogram of the age groups of the people that couldn\'t␣
 ↪survive')
plt.hist(age_not_survived, bins=np.arange(0, 100, 10), color='#e74c3c',␣
 ↪edgecolor='black')
plt.xticks(np.arange(0, 100, 10))
plt.xlabel('Age Groups')
plt.ylabel('Number of Non-Survivors')

plt.show()
```


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



[41]:
```
train[["SibSp", "Survived"]].groupby(['SibSp'], as_index=False).mean().
    ↪sort_values(by='Survived', ascending=False)
```

[41]:

	SibSp	Survived
1	1	0.535885
2	2	0.464286
0	0	0.345395
3	3	0.250000
4	4	0.166667
5	5	0.000000
6	8	0.000000

[43]:
```
train[["Pclass", "Survived"]].groupby(['Pclass'], as_index=False).mean().
    ↪sort_values(by='Survived', ascending=False)
```

[43]:

	Pclass	Survived
0	1	0.629630
1	2	0.472826
2	3	0.242363

[45]:
```
train[["Age", "Survived"]].groupby(['Age'], as_index=False).mean().
↪sort_values(by='Age', ascending=True)
```

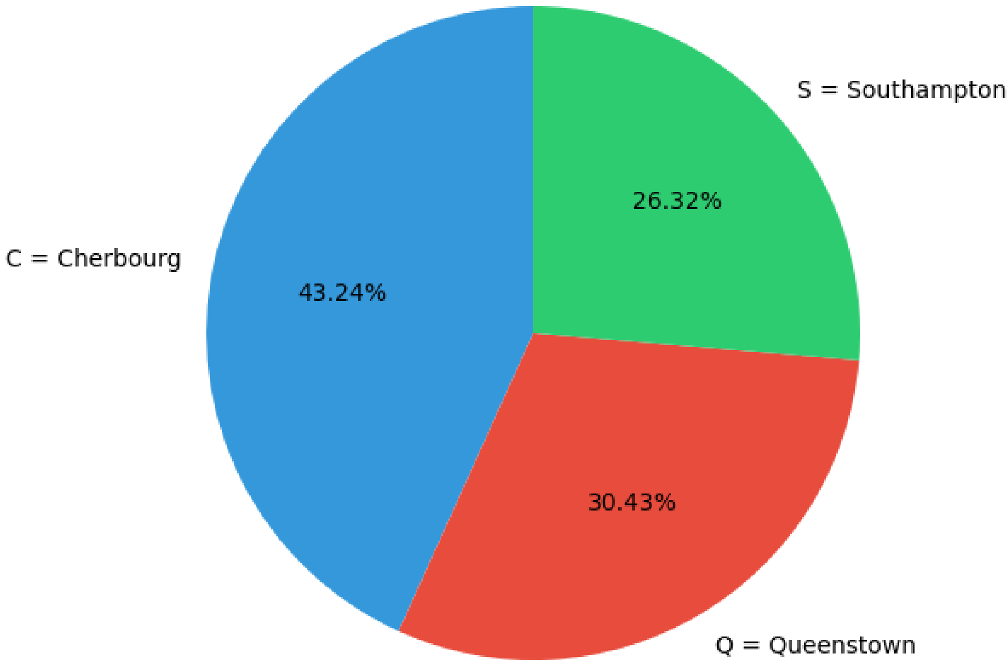
[45]:
```
      Age  Survived
0    0.42       1.0
1    0.67       1.0
2    0.75       1.0
3    0.83       1.0
4    0.92       1.0
..    …        …
83  70.00       0.0
84  70.50       0.0
85  71.00       0.0
86  74.00       0.0
87  80.00       1.0

[88 rows x 2 columns]
```

[47]:
```
train[["Embarked", "Survived"]].groupby(['Embarked'], as_index=False).mean().
↪sort_values(by='Survived', ascending=False)
```

[47]:
```
  Embarked  Survived
0        C  0.553571
1        Q  0.389610
2        S  0.336957
```

[63]:
```
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%%', colors=['#3498db', '#e74c3c',␣
↪'#2ecc71'], startangle=90)
plt.show()
```



[51]:
```
test.describe(include="all")
```

[51]:
```
        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]
```

[53]:
```
train = train.drop(['Ticket'], axis = 1)
test = test.drop(['Ticket'], axis = 1)
```

[55]:
```
train = train.drop(['Cabin'], axis = 1)
test = test.drop(['Cabin'], axis = 1)
```

[89]:
```
if 'Name' in train.columns:
    train = train.drop(['Name'], axis=1)

if 'Name' in test.columns:
    test = test.drop(['Name'], axis=1)
```

[65]:
```
#Feature Selection
column_train=['Age','Pclass','SibSp','Parch','Fare','Sex','Embarked']
#training values
X=train[column_train]
#target value
Y=train['Survived']
```

[67]:
```
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()
```

[67]: 2

[69]:
```
X['Age']=X['Age'].fillna(X['Age'].median())
X['Age'].isnull().sum()
```

[69]: 0

[71]:
```
X['Embarked'] = train['Embarked'].fillna(method ='pad')
X['Embarked'].isnull().sum()
```

[71]: 0

[73]:
```
d={'male':0, 'female':1}
X['Sex']=X['Sex'].apply(lambda x:d[x])
X['Sex'].head()
```

[73]:
```
0    0
1    1
2    1
3    1
4    0
Name: Sex, dtype: int64
```

[75]:
```
e={'C':0, 'Q':1 ,'S':2}
X['Embarked']=X['Embarked'].apply(lambda x:e[x])
X['Embarked'].head()
```

[75]:
```
0    2
1    0
2    2
3    2
4    2
Name: Embarked, dtype: int64
```

[77]:
```
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)
```

[79]:
```
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
```

[81]:
```
from sklearn.metrics import accuracy_score,confusion_matrix
confusion_mat = confusion_matrix(Y_test,Y_pred)
print(confusion_mat)
```

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

[83]:
```
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
```

[85]:
```
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
```

[87]:
```
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
```

[40]:
```
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))
```

```
[[127  29]
 [ 62  50]]
              precision    recall  f1-score   support

           0       0.67      0.81      0.74       156
           1       0.63      0.45      0.52       112
```

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

[41]:
```
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
```

[42]:
```
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
```

[43]:
```
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
```

[44]:
```
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
```

[45]:
```
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)
```

[45]:
```
                         Model
Score
0.76               Naive Bayes
0.75       Logistic Regression
0.74             Decision Tree
0.66   Support Vector Machines
0.66                       KNN
```