titanic-survival-prediction

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PROJECT TOPIC : Perform data cleaning and exploratary data analysis (EDA) on a Dataset of your choice, such as the Titanic dataset from Kaggle. Explore the Relationship between variables and identify patterns and trends in the data.

PROJECT NAME : TITANIC SURVIVAL PREDICTION

#importing all the libraries

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

#Loading Dataset

[ ]:
```
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]
```

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

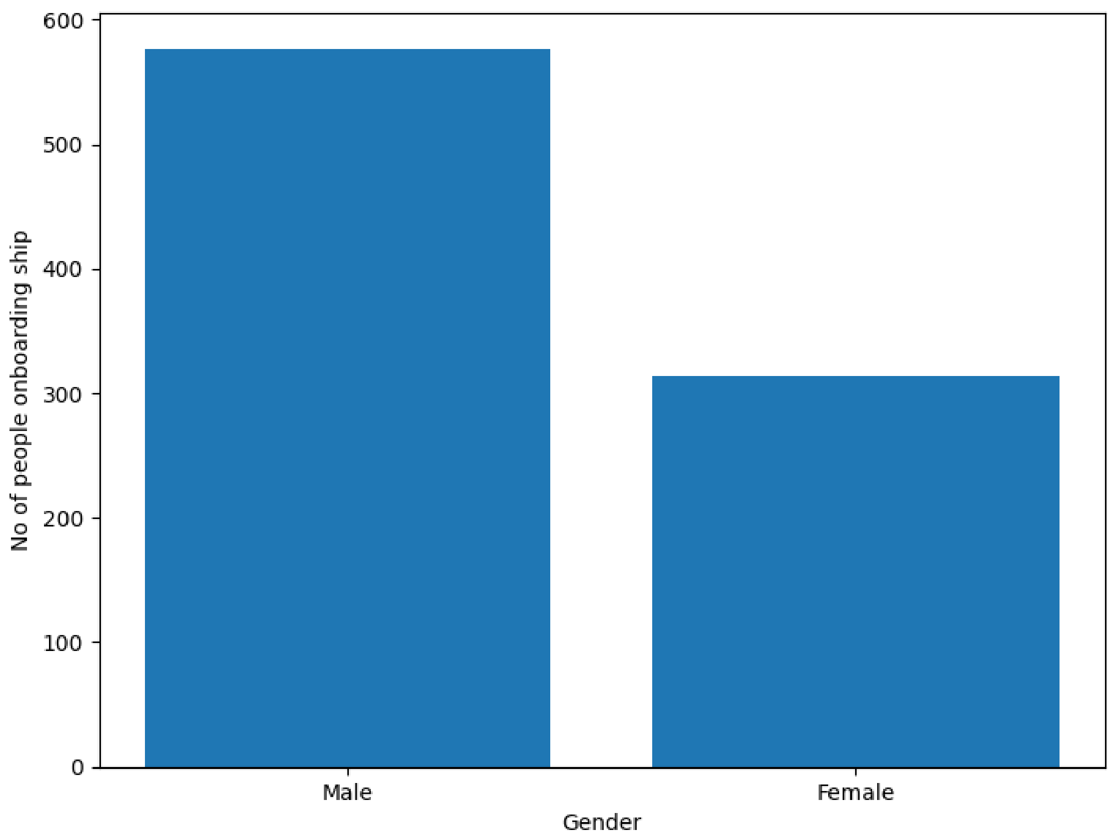
```
No of Males in Titanic: 577
```

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

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

#Gender 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()
```

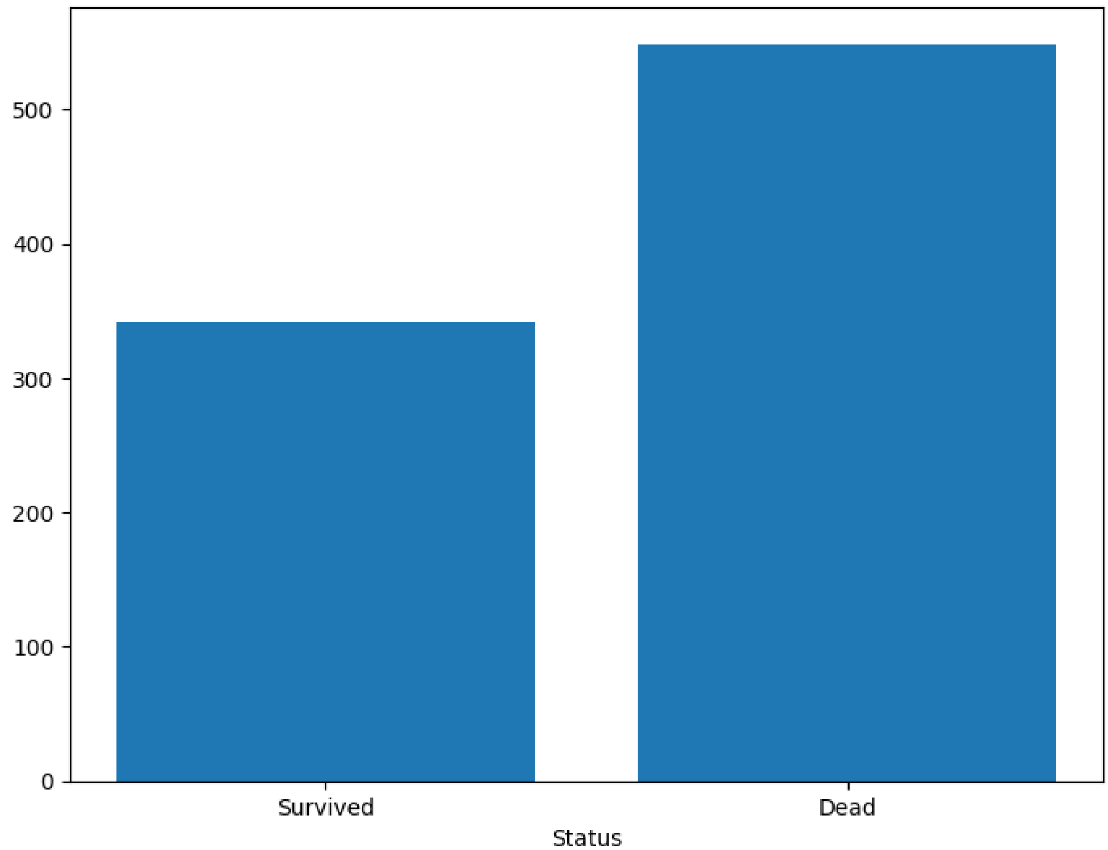


[ ]:
```
alive = len(train[train['Survived'] == 1])
dead = len(train[train['Survived'] == 0])
```

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

[ ]:
```
        Survived
Sex
female  0.742038
male    0.188908
```

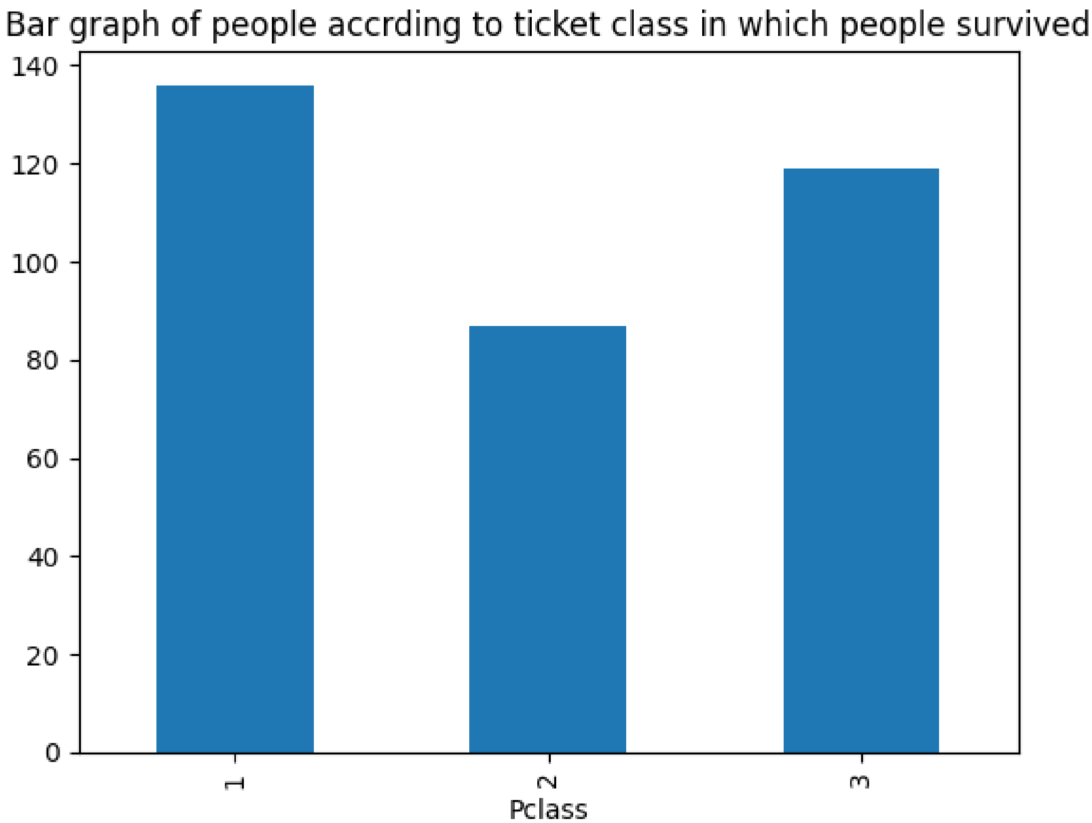
[ ]:
```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
status = ['Survived','Dead']
ind = [alive,dead]
ax.bar(status,ind)
plt.xlabel("Status")
plt.show()
```

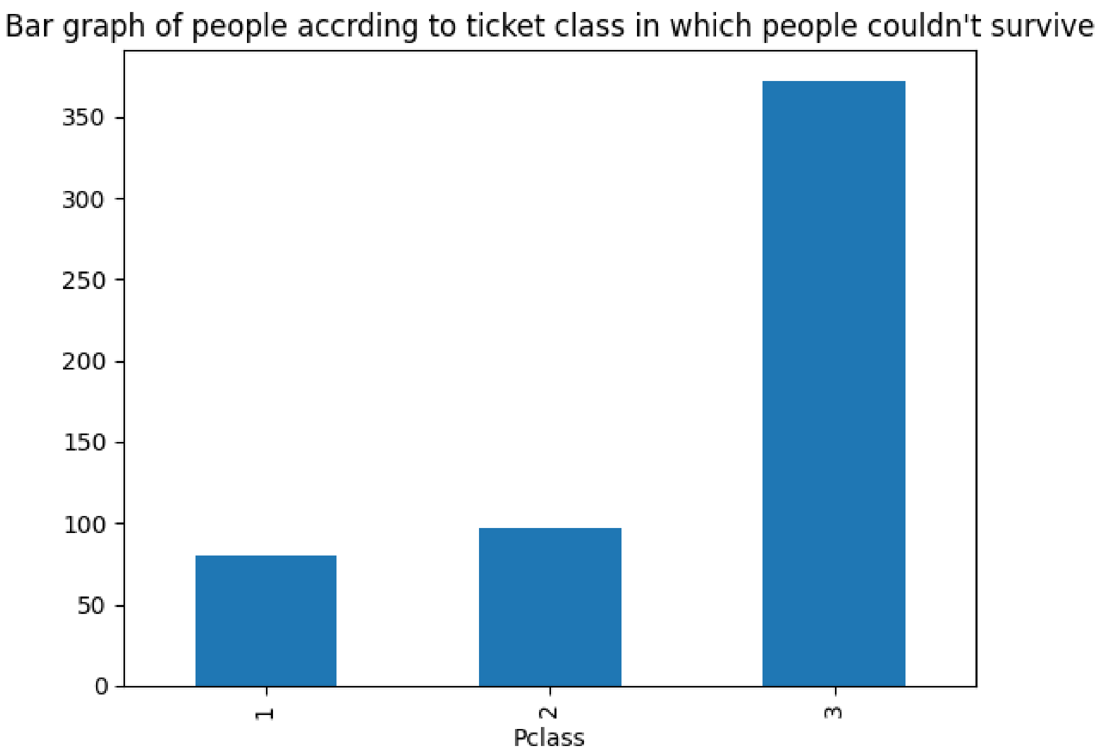


[ ]:
```
plt.figure(1)
train.loc[train['Survived'] == 1, 'Pclass'].value_counts().sort_index().plot.
  ↪bar()
plt.title('Bar graph of people accrding to ticket class in which people␣
  ↪survived')


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
Pclass

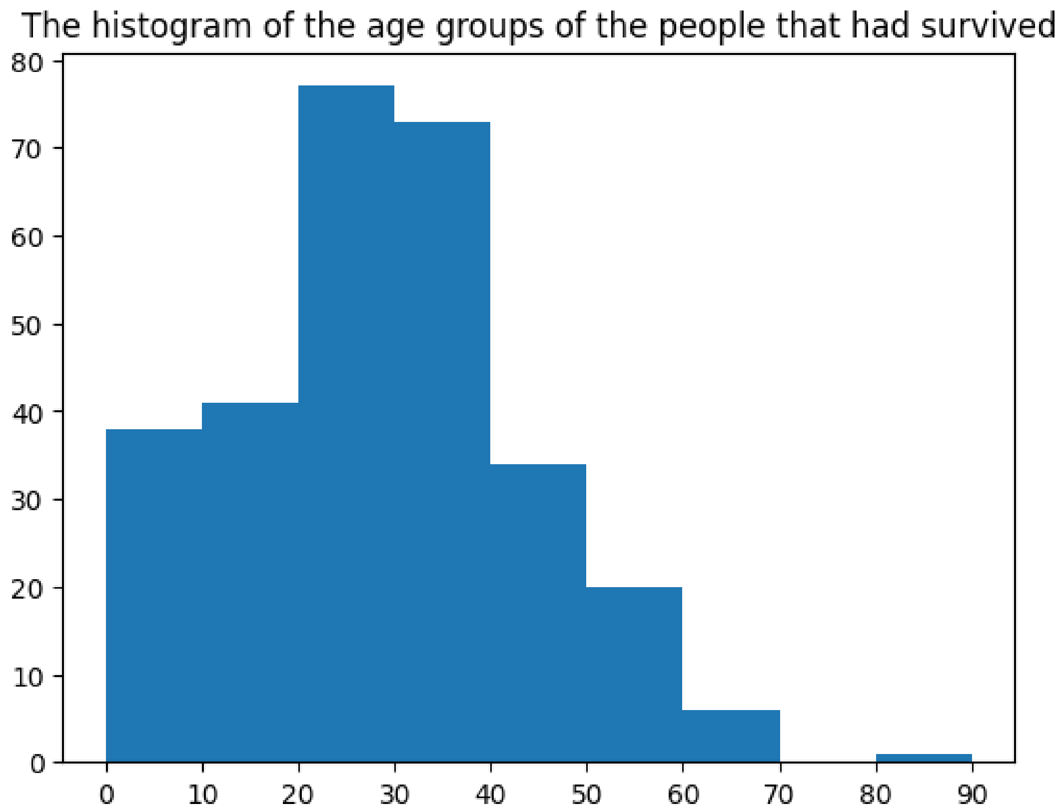


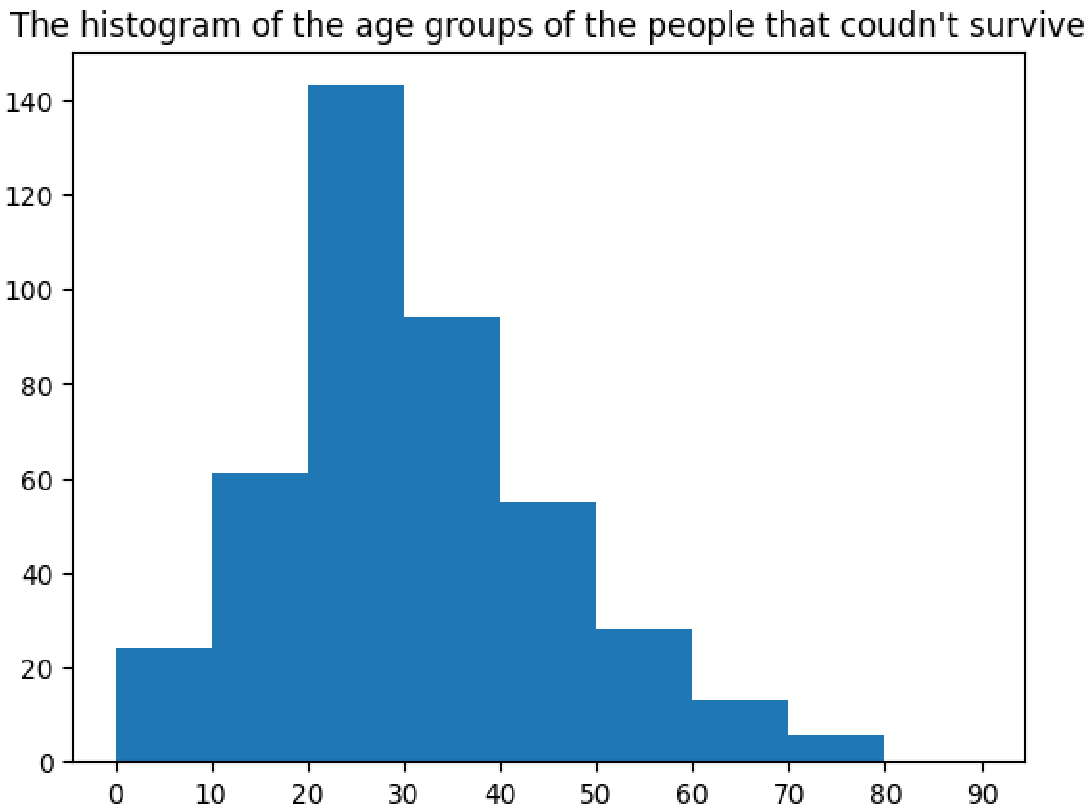

```
[ ]: plt.figure(1)
     age  = train.loc[train.Survived == 1, 'Age']
     plt.title('The histogram of the age groups of the people that had survived')
     plt.hist(age, np.arange(0,100,10))
     plt.xticks(np.arange(0,100,10))


     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 0x7adbd65c7070>,
       <matplotlib.axis.XTick at 0x7adbd65c7040>,
       <matplotlib.axis.XTick at 0x7adbd65c6f50>,
       <matplotlib.axis.XTick at 0x7adbd63efbe0>,
       <matplotlib.axis.XTick at 0x7adbd642c6d0>,
       <matplotlib.axis.XTick at 0x7adbd642d180>,
       <matplotlib.axis.XTick at 0x7adbd642c220>,
       <matplotlib.axis.XTick at 0x7adbd642de70>,
       <matplotlib.axis.XTick at 0x7adbd642e920>,
       <matplotlib.axis.XTick at 0x7adbd642f3d0>],
```

```
[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')])
```






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

```
[ ]:    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
```

```
[ ]: 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)
```

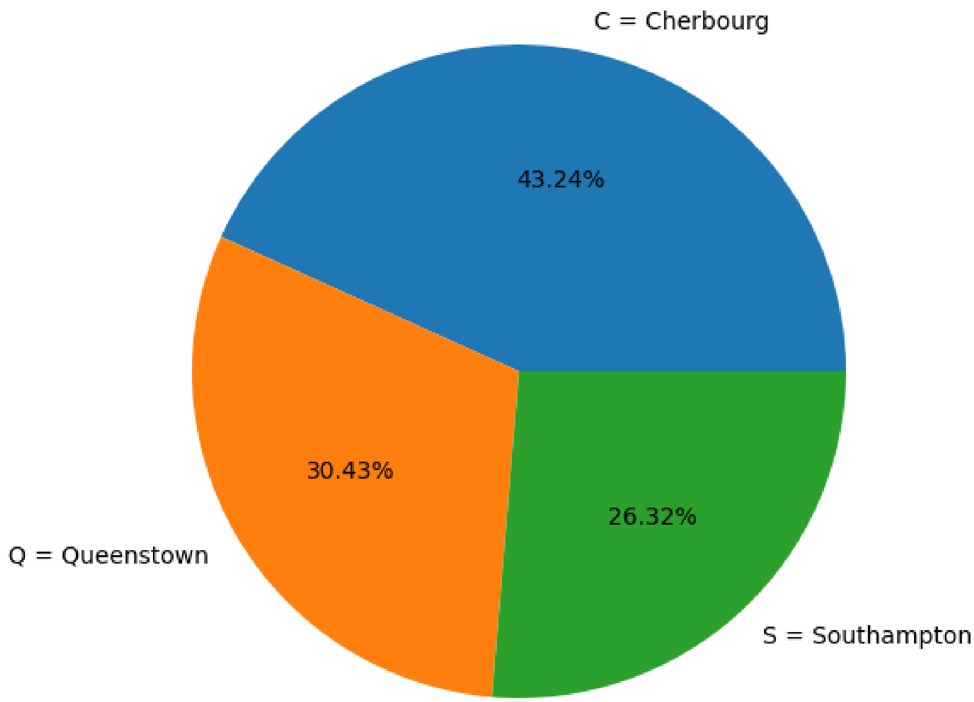
[ ]:
```
      Age  Survived
0    0.42       1.0
1    0.67       1.0
2    0.75       1.0
3    0.83       1.0
4    0.92       1.0
..    …        …
83  70.00       0.0
84  70.50       0.0
85  71.00       0.0
86  74.00       0.0
87  80.00       1.0

[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]
```

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

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

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

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

[ ]:
```
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

[ ]:
```
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
```

[ ]:
```
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)
```

[ ]:
```
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
```

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

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

[ ]:
```
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
```

[ ]:
```python
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
```

[ ]:
```python
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
```

[ ]:
```python
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
```

```
[ ]: 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
```

```
[ ]: 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
```