Titanic Survival Prediction

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Using Machine learning algorithm on the famous Titanic Disaster Dataset for Predicting the survival of the passenger

In [53]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

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

In [4]:
```
pd.set_option('display.max_columns',10,'display.width',1000)
train = pd.read_csv(r"E:\Pg Studies\Intership\Bharath intren\train.csv")
test = pd.read_csv(r"E:\Pg Studies\Intership\Bharath intren\test.csv")
```

In [5]:
```
train.head()
```

Out[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 × 12 columns

In [55]:
```
#Display shape
train.shape
```

Out[55]:
```
(891, 9)
```

In [7]:
```python
test.shape
```
Out[7]:
```
(418, 11)
```
In [8]:
```python
#Checking for Null values
train.isnull().sum()
```
Out[8]:
```
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
```
In [9]:
```python
test.isnull().sum()
```
Out[9]:
```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```
In [10]:
```python
#Description of dataset
train.describe(include="all")
```

Out[10]:

	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 × 12 columns

In [11]:
```
train.groupby('Survived').mean()
```

Out[11]:

	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

In [12]:
```
train.corr()
```

Out[12]:

	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

In [13]:

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

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

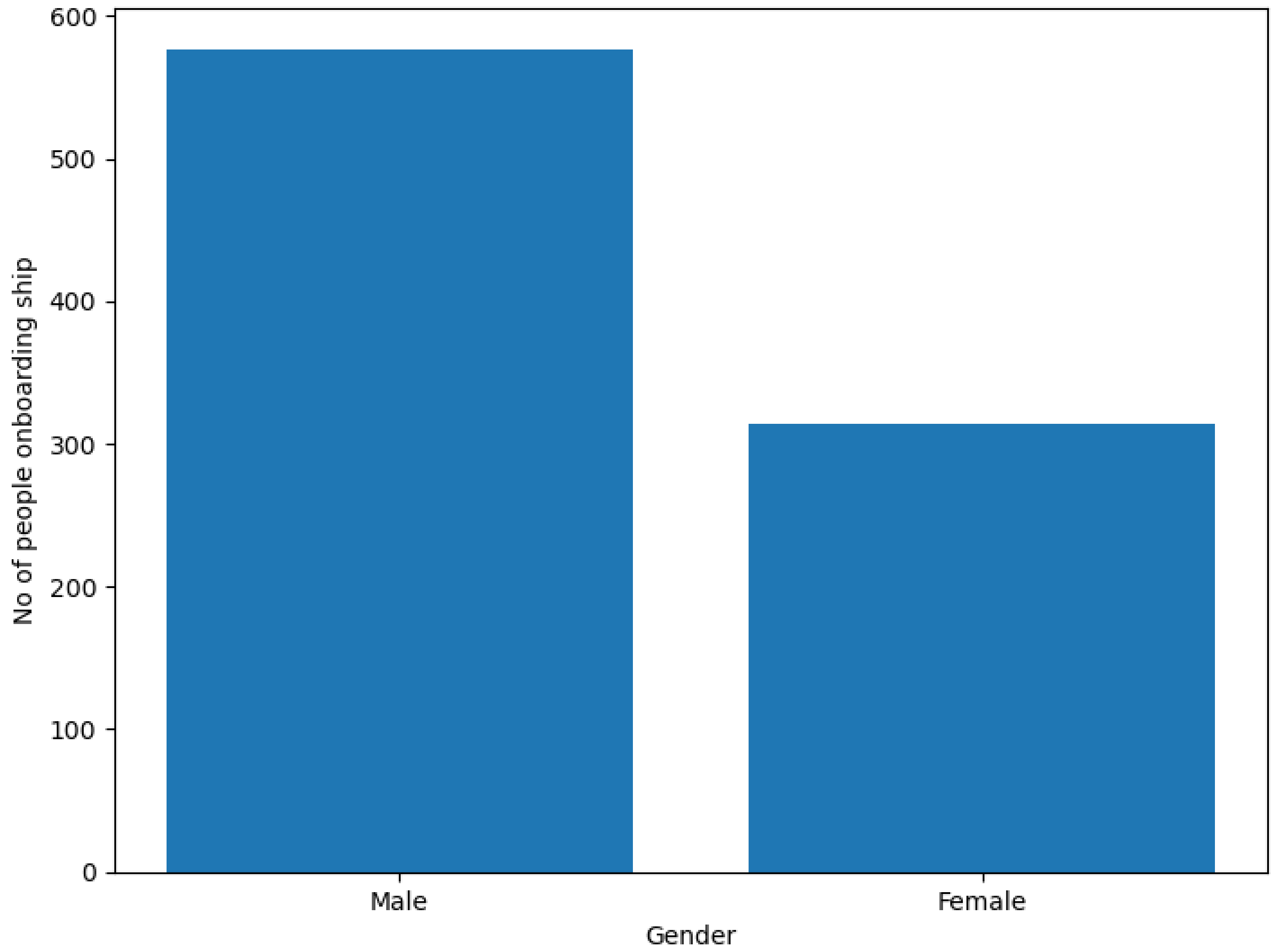
In [14]:

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

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

In [17]:

```
#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()
```



In [18]:
```
alive = len(train[train['Survived'] == 1])
dead = len(train[train['Survived'] == 0])
```

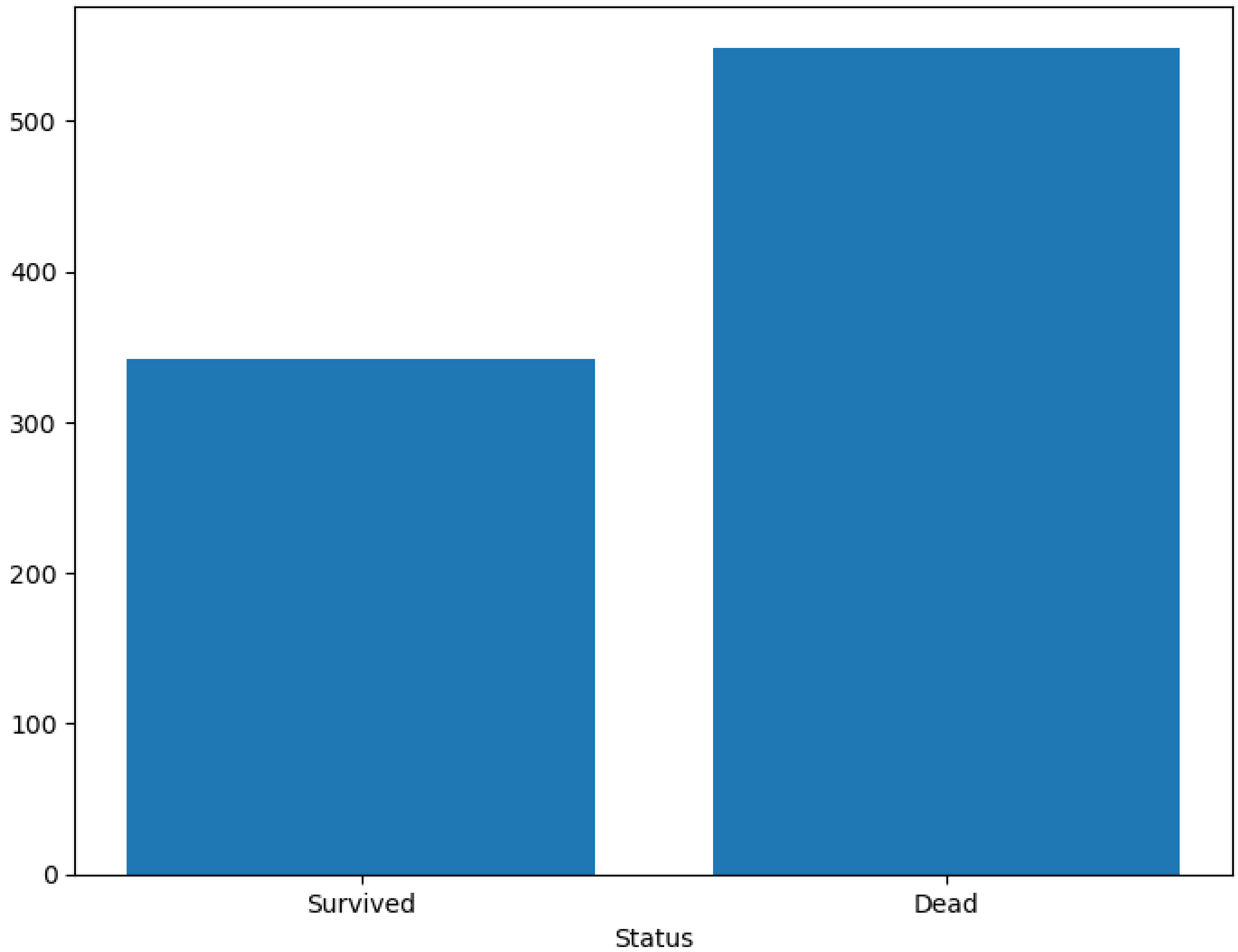
In [19]:
```
train.groupby('Sex')[['Survived']].mean()
```

Out[19]:

	Survived
Sex	
female	0.742038
male	0.188908

In [20]:

```
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()
```

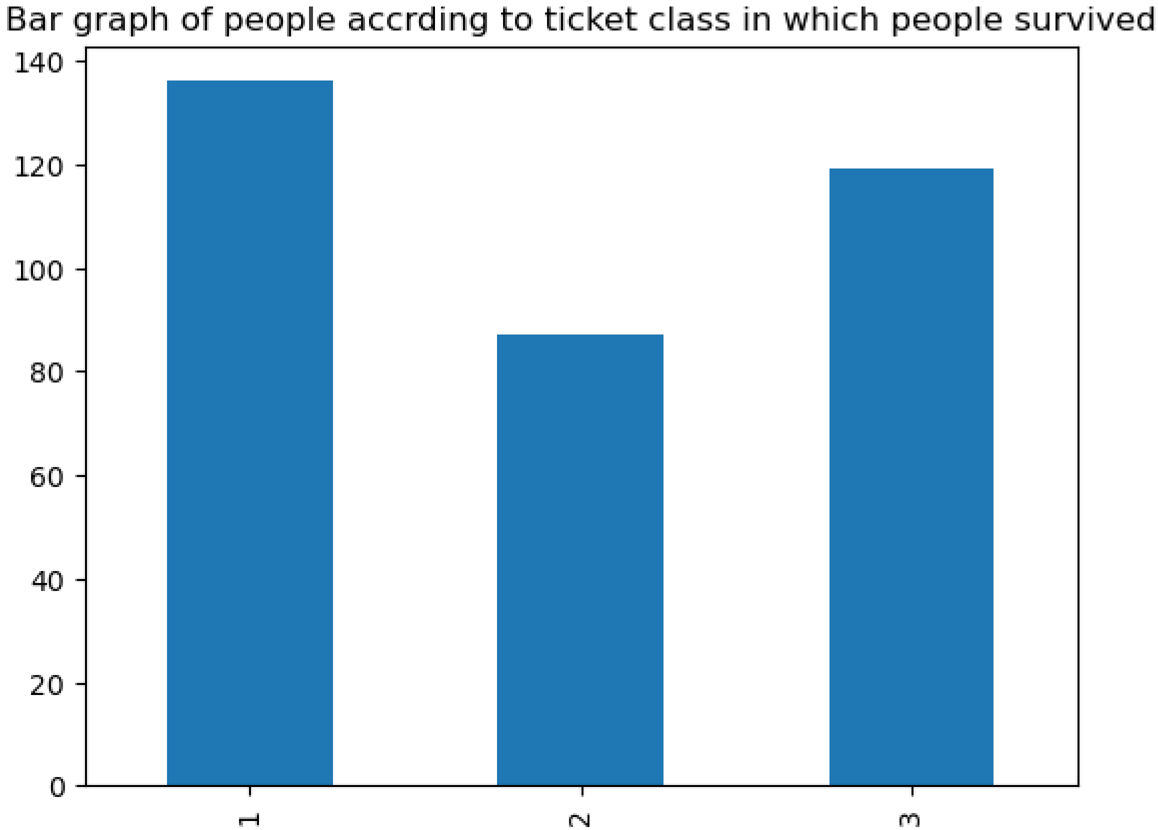


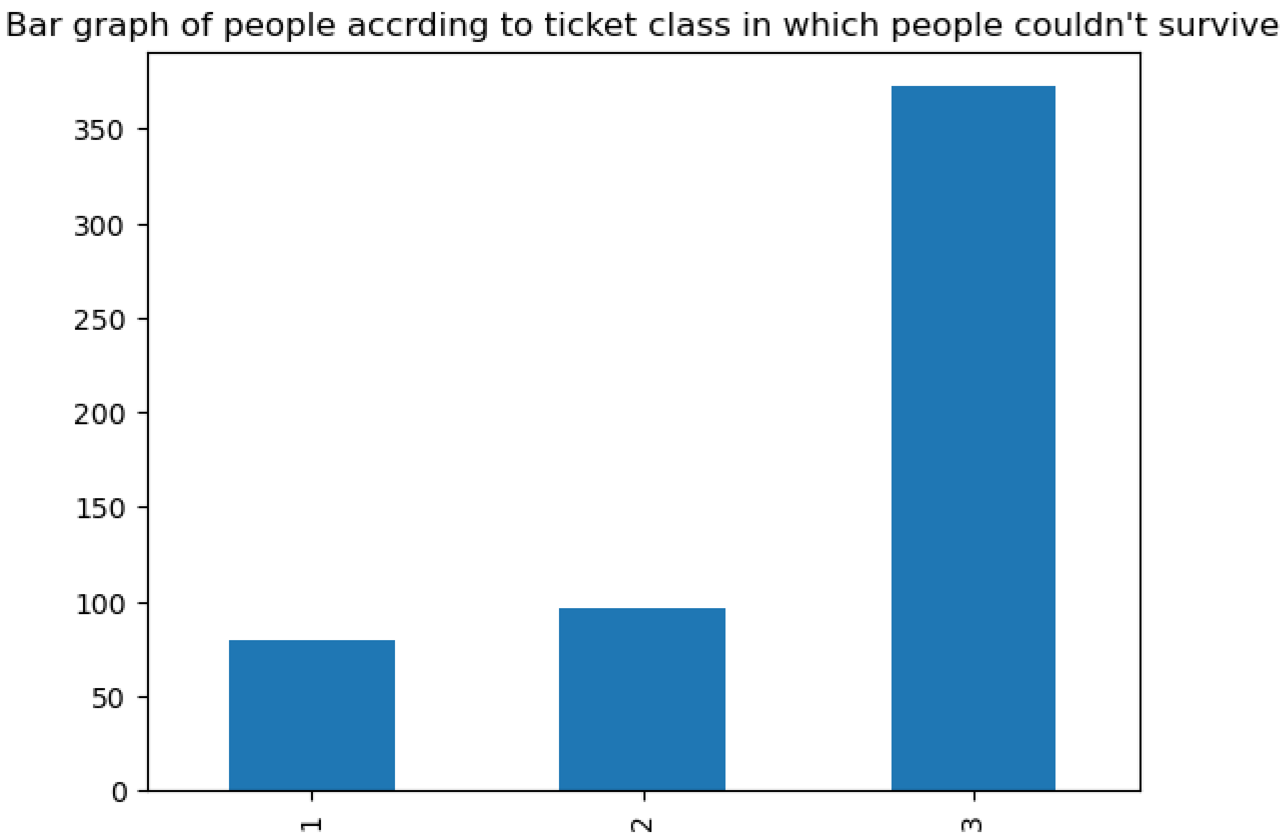
In [21]:

```
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')
```

Out[21]: Text(0.5, 1.0, "Bar graph of people accrding to ticket class in which people couldn't survive")



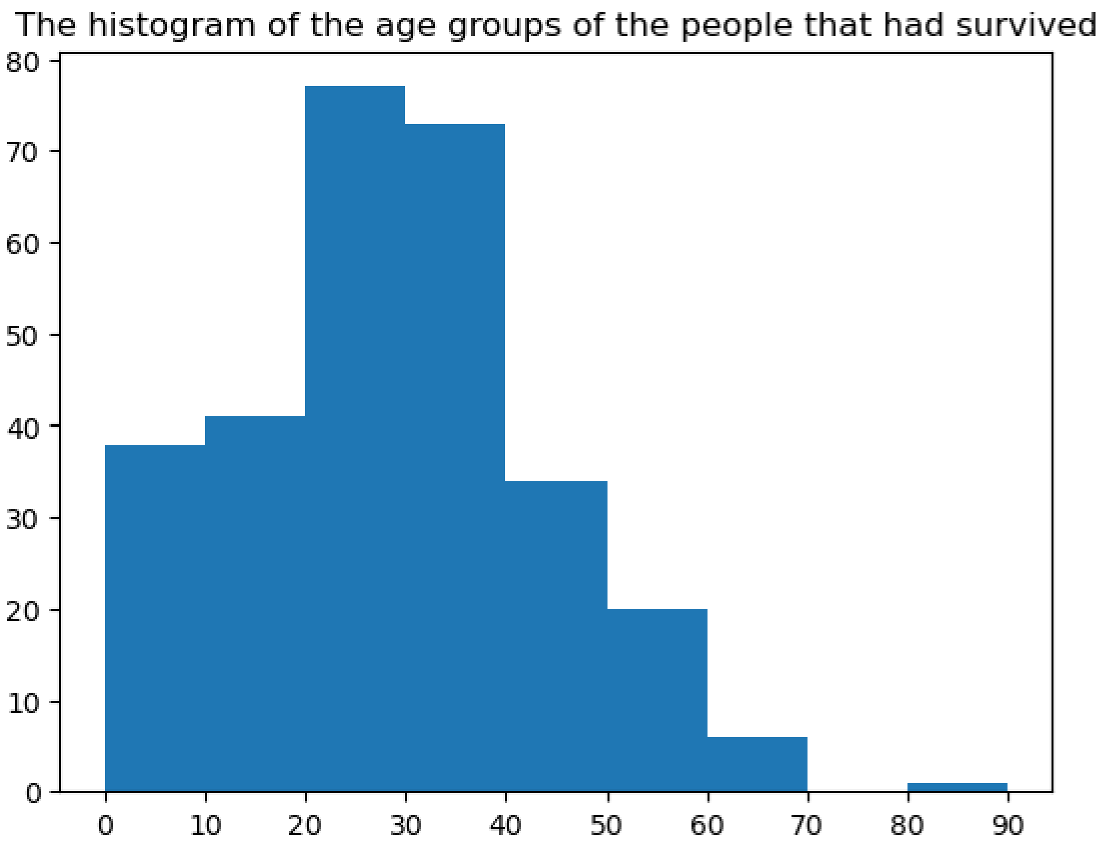


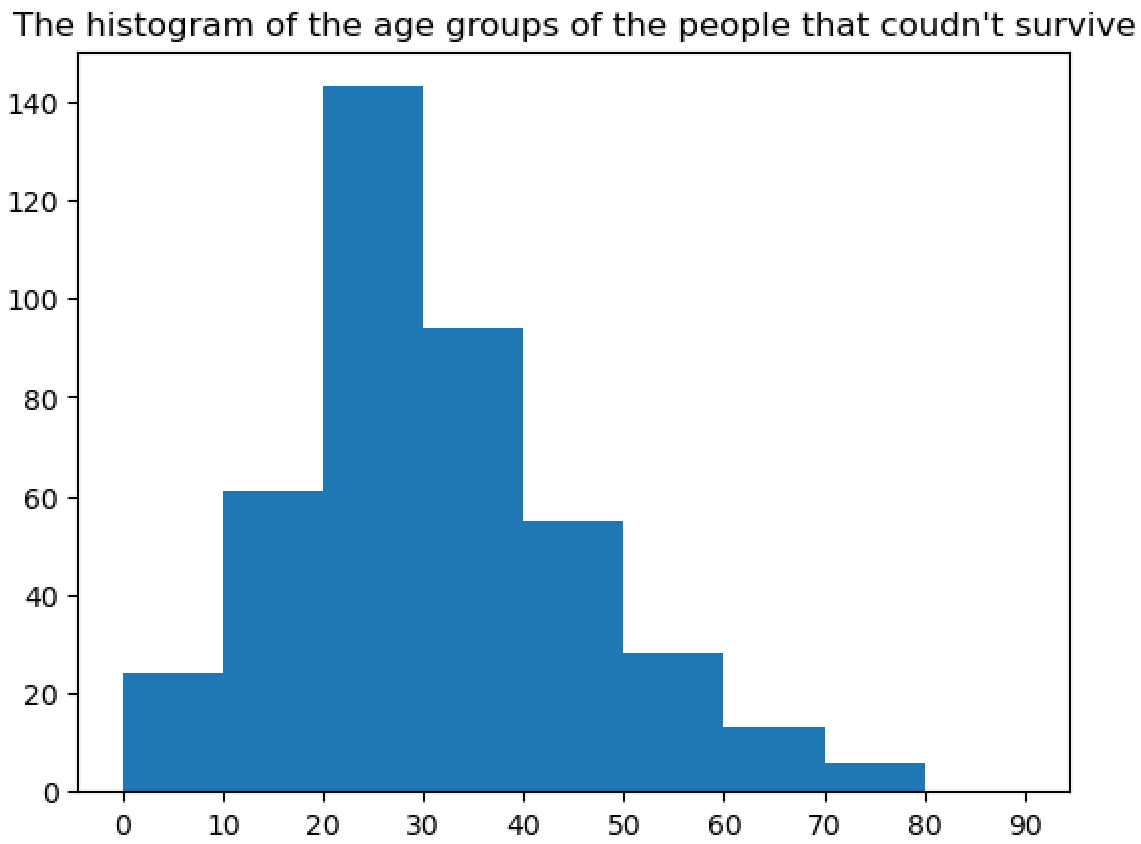
In [22]:

```
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))
```

Out[22]:
```
([<matplotlib.axis.XTick at 0x1619e714130>,
  <matplotlib.axis.XTick at 0x1619e714040>,
  <matplotlib.axis.XTick at 0x1619e71b790>,
  <matplotlib.axis.XTick at 0x1619e761550>,
  <matplotlib.axis.XTick at 0x1619e761ca0>,
  <matplotlib.axis.XTick at 0x1619e768430>,
  <matplotlib.axis.XTick at 0x1619e768b80>,
  <matplotlib.axis.XTick at 0x1619e768910>,
  <matplotlib.axis.XTick at 0x1619e761610>,
  <matplotlib.axis.XTick at 0x1619e76f670>],
 [Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, '')])
```


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



In [23]:
```
train[["SibSp", "Survived"]].groupby(['SibSp'], as_index=False).mean().sort_values(by='Survived', ascending=False)
```

Out[23]:

	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

In [24]:

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

Out[24]:

	Pclass	Survived
0	1	0.629630
1	2	0.472826
2	3	0.242363

In [25]:

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

Out[25]:

	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

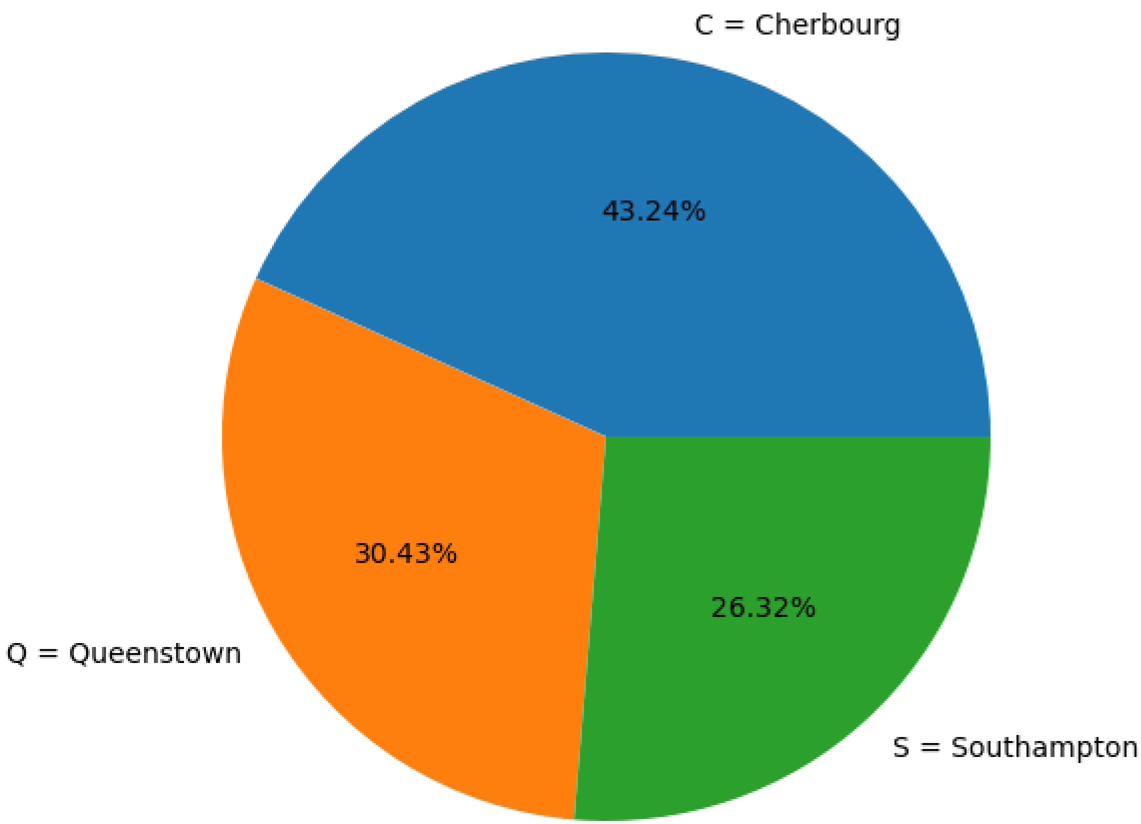
88 rows × 2 columns

In [26]:
```
train[["Embarked", "Survived"]].groupby(['Embarked'], as_index=False).mean().sort_values(by='Survived', ascending=False)
```

Out[26]:

	Embarked	Survived
0	C	0.553571
1	Q	0.389610
2	S	0.336957

In [27]:
```
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()
```



In [28]:
```
test.describe(include="all")
```

Out[28]:

	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 × 11 columns

In [29]:

```
#Droping Useless Columns
train = train.drop(['Ticket'], axis = 1)
test = test.drop(['Ticket'], axis = 1)
```

In [30]:

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

In [31]:

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

Feature Selection

In [32]:

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

```
#target value
Y=train['Survived']
```

In [33]:
```
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()
```

Out[33]:
```
2
```

In [34]:
```
#now we have to fill all the missing values
#age have 177  missing values
#either we fill missing values with mean or median form existing values
X['Age']=X['Age'].fillna(X['Age'].median())
X['Age'].isnull().sum()
```

Out[34]:
```
0
```

In [35]:
```
X['Embarked'] = train['Embarked'].fillna(method ='pad')
X['Embarked'].isnull().sum()
```

Out[35]:
```
0
```

In [36]:
```
#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()
```

Out[36]:
```
0    0
1    1
2    1
3    1
4    0
Name: Sex, dtype: int64
```

In [37]:
```
e={'C':0, 'Q':1 ,'S':2}
X['Embarked']=X['Embarked'].apply(lambda x:e[x])
X['Embarked'].head()
```

Out[37]:
```
0    2
1    0
2    2
3    2
4    2
Name: Embarked, dtype: int64
```

Training Testing and Spliting the model

In [38]:
```
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)
```

Using LogisticRegression

Logistic Regression is a statistical method commonly employed for binary classification tasks, where the outcome to be predicted falls into one of two categories. It's an extension of linear regression but utilizes the logistic function (also known as the sigmoid function) to constrain the output to a value between 0 and 1, representing the probability of the positive class. This probability is then compared to a threshold (typically 0.5) to make the final classification decision.

In [39]:
```
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
```

In [40]:
```
#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]]
```

Using Support Vector

Support Vector Machines (SVMs) are a class of supervised learning algorithms widely used for classification and regression tasks. At their core, SVMs aim to find the optimal hyperplane that best separates the data points belonging to different classes in the feature space. This hyperplane is chosen to maximize the margin, which is the distance between the hyperplane and the nearest data points from each class. By maximizing the margin, SVMs aim to achieve a robust decision boundary that generalizes well to unseen data.

In [41]:
```
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
```

In [42]:
```
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
```

Using KNN Neighbors

K-Nearest Neighbors (KNN) is a simple yet effective algorithm used for both classification and regression tasks in machine learning. Its approach is straightforward: given a new, unseen data point, KNN identifies its k nearest neighbors from the training dataset based on a chosen distance metric. The class or value of the new data point is then determined by a majority vote (in classification) or averaging (in regression) the values of its k nearest neighbors.

In [43]:
```
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: 0.6604477611940298
```

In [47]:
```
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
```

Using GaussianNB

Gaussian Naive Bayes (GaussianNB) is a variant of the Naive Bayes algorithm, a probabilistic classifier widely used in machine learning for its simplicity and effectiveness. GaussianNB is specifically tailored for data with continuous features that are assumed to follow a Gaussian (normal) distribution.

In [48]:
```
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
```

In [49]:
```
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
```

Using Decision Tree

Decision Tree is a widely-used algorithm in machine learning known for its simplicity, interpretability, and effectiveness in both classification and regression tasks. Conceptually, it resembles a flowchart where decisions are made based on the values of input features. Here's a closer look at its components and functionality:

In [50]:
```
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
```

In [51]:
```
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
```

In [52]:
```
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)
```

Out[52]:

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

Conclusion

The Naive Bayes classifier achieved the highest accuracy score of 0.76, followed closely by Logistic Regression with a score of 0.75. This suggests that both Naive Bayes and Logistic Regression models are effective for predicting survival on the Titanic dataset.

The Decision Tree model performed slightly lower with an accuracy score of 0.74. While still competitive, it didn't surpass the performance of Naive Bayes and Logistic Regression.

Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) models lagged behind with accuracy scores of 0.66 each. These models demonstrated relatively weaker performance compared to Naive Bayes, Logistic Regression, and Decision Tree.

In conclusion, based on the accuracy scores, we can prioritize the Naive Bayes and Logistic Regression models for predicting survival on the Titanic dataset due to their higher accuracy. However, it's essential to consider other factors such as model interpretability, computational complexity, and potential overfitting when selecting the final model for deployment. Further exploration and fine-tuning may be necessary to improve the model's performance and robustness.