TECH-A-INTERN

LEVEL2 TASK2

TITANIC-SURVIVAL-PREDICTION

Author: Kanishk Karam

==

In [22]:
```
# STEP1: Importing Libaries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [23]:
```
# STEP2: Importing DataSets
train_data = pd.read_csv('./train.csv')
data_test = pd.read_csv('./test.csv')
train_data.head()
```

Out[23]:

	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 [24]:
```
# STEP3: Print summary information
train_data.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]:
```
data_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  418 non-null    int64  
 1   Pclass       418 non-null    int64  
 2   Name         418 non-null    object 
 3   Sex          418 non-null    object 
 4   Age          332 non-null    float64
 5   SibSp        418 non-null    int64  
 6   Parch        418 non-null    int64  
 7   Ticket       418 non-null    object 
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object 
 10  Embarked     418 non-null    object 
dtypes: float64(2), int64(4), object(5)
memory usage: 36.1+ KB
```

In [25]:
```
# STEP4: Display Shape
train_data.shape
```

Out[25]:
```
(891, 12)
```

In [26]:
```
data_test.shape
```

Out[26]:
```
(418, 11)
```

In [27]:
```
# STEP5: Checking null values
train_data.isnull().sum()
```

Out[27]:
```
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 [13]:
```
data_test.isnull().sum()
```

Out[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
```

In [28]:
```
# STEP6: making a discription of datasets
train_data.describe(include="all")
```

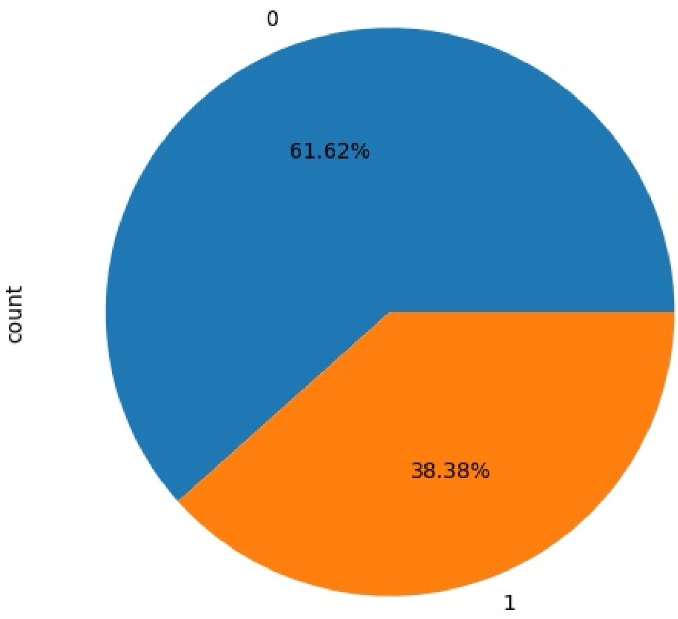
Out[28]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Emb
count	891.000000	891.000000	891.000000	891	891	714.000000	891.000000	891.000000	891	891.000000	204	
unique	NaN	NaN	NaN	891	2	NaN	NaN	NaN	681	NaN	147	
top	NaN	NaN	NaN	Braund, Mr. Owen Harris	male	NaN	NaN	NaN	347082	NaN	B96 B98	
freq	NaN	NaN	NaN	1	577	NaN	NaN	NaN	7	NaN	4	
mean	446.000000	0.383838	2.308642	NaN	NaN	29.699118	0.523008	0.381594	NaN	32.204208	NaN	
std	257.353842	0.486592	0.836071	NaN	NaN	14.526497	1.102743	0.806057	NaN	49.693429	NaN	
min	1.000000	0.000000	1.000000	NaN	NaN	0.420000	0.000000	0.000000	NaN	0.000000	NaN	
25%	223.500000	0.000000	2.000000	NaN	NaN	20.125000	0.000000	0.000000	NaN	7.910400	NaN	
50%	446.000000	0.000000	3.000000	NaN	NaN	28.000000	0.000000	0.000000	NaN	14.454200	NaN	
75%	668.500000	1.000000	3.000000	NaN	NaN	38.000000	1.000000	0.000000	NaN	31.000000	NaN	
max	891.000000	1.000000	3.000000	NaN	NaN	80.000000	8.000000	6.000000	NaN	512.329200	NaN	

In [8]:

```
# STEP7 : let us check the overall survival ratio
fig = plt.figure(figsize=(6,6))
train_data['Survived'].value_counts().plot.pie(autopct = '%1.2f%%')
```

Out[8]: <Axes: ylabel='count'>



In [29]:

```
# checking no.of males
male_ind = len(train_data[train_data['Sex'] == 'male'])
print("No of Males in Titanic:",male_ind)
```

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

In [30]:

```
# checking no.of females
female_ind = len(train_data[train_data['Sex'] == 'female'])
print("No of Females in Titanic:",female_ind)
```

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

In [31]:

```
# checking for missing values
train_data['Embarked'][train_data['Embarked'].isnull()]
train_data['Embarked'][train_data['Embarked'].isnull()] = train_data['Embarked'].dropna().mode().values
```

```
C:\Users\kanis\AppData\Local\Temp\ipykernel_14612\1307233320.py:3: FutureWarning: ChainedAssignmentError: behavi
our will change in pandas 3.0!
You are setting values through chained assignment. Currently this works in certain cases, but when using Copy-on
-Write (which will become the default behaviour in pandas 3.0) this will never work to update the original DataF
rame or Series, because the intermediate object on which we are setting values will behave as a copy.
A typical example is when you are setting values in a column of a DataFrame, like:

df["col"][row_indexer] = value

Use `df.loc[row_indexer, "col"] = values` instead, to perform the assignment in a single step and ensure this ke
eps updating the original `df`.

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#retu
rning-a-view-versus-a-copy

  train_data['Embarked'][train_data['Embarked'].isnull()] = train_data['Embarked'].dropna().mode().values
C:\Users\kanis\AppData\Local\Temp\ipykernel_14612\1307233320.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#retu
rning-a-view-versus-a-copy
  train_data['Embarked'][train_data['Embarked'].isnull()] = train_data['Embarked'].dropna().mode().values
```

PROCSSING MISSING DATA/VALUES

When analyzing the data, it is important to note whether there are missing values in it.

Some machine learning algorithms can handle missing values, such as neural networks, and some cannot. For missing values, there are several general ways to handle them.

*If the dataset is large but has few missing values, the rows with missing values can be deleted.

*If the attribute is not very important relative to the learning, you can assign a mean or plurality to the missing values. For example, if the attribute Embarked (there are three embarkation locations) has two missing values, you can use the plural to assign the value

In [32]:
```python
train_data['Cabin'] = train_data['Cabin'].fillna('U0')
```

*For nominal attributes, you can assign a value that represents the absence, such as 'U0'. Because the absence itself may also represent some implicit information. For example, the missing property Cabin may mean that there is no cabin.

In [33]:
```python
# STEP8 : adding libraries to find age and survived pepople
from sklearn.ensemble import RandomForestRegressor

age_df = train_data[['Age','Survived','Fare', 'Parch', 'SibSp', 'Pclass']]
age_df_notnull = age_df.loc[(train_data['Age'].notnull())]
age_df_isnull = age_df.loc[(train_data['Age'].isnull())]
X = age_df_notnull.values[:,1:]
Y = age_df_notnull.values[:,0]
# use RandomForestRegression to train data
RFR = RandomForestRegressor(n_estimators=1000,n_jobs=-1)
RFR.fit(X,Y)
predictAges = RFR.predict(age_df_isnull.values[:,1:])
train_data.loc[train_data['Age'].isnull(), ['Age']]= predictAges
```

*regression Random Forest to predict the values of missing attributes. Since Age is a fairly important feature in this dataset (as can be seen by first analyzing Age), it is very important to ensure a certain accuracy in filling in the missing values, which can also have a large impact on the results. In general, entries with complete data are used as the training set for the model as a way to predict missing values. For this current data, either random forest can be used to predict or linear regression can be used to predict. Here the random forest prediction model is used, and the numerical attributes in the dataset are selected as features (because sklearn's model can only handle numerical attributes, so only numerical features are selected here first, but in practical applications non-numerical features need to be converted to numerical features)

In [34]:
```python
# STEP9: checking complementary data
train_data.info()
```

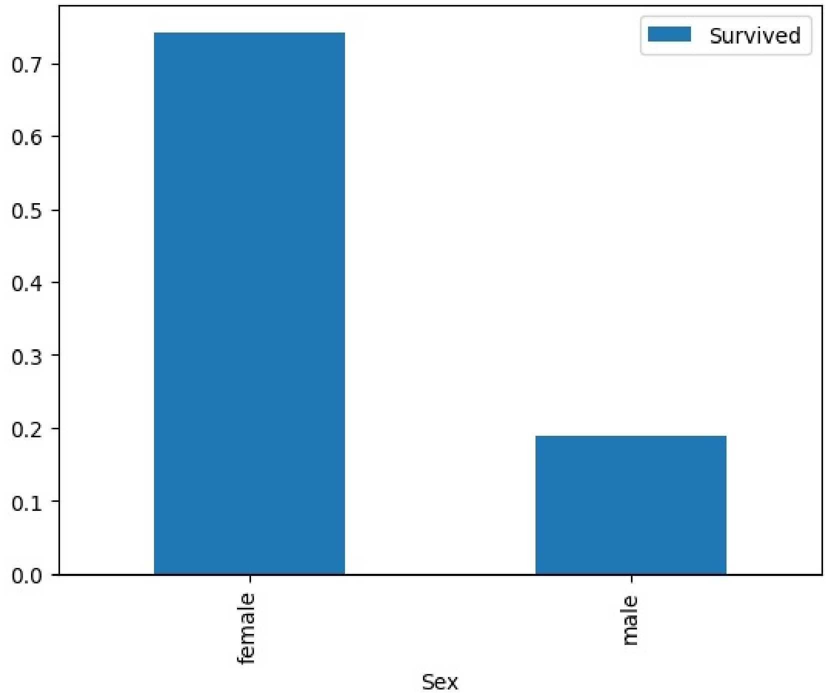
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null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

In [16]:
```
train_data.groupby(['Sex','Survived'])['Survived'].count()
```

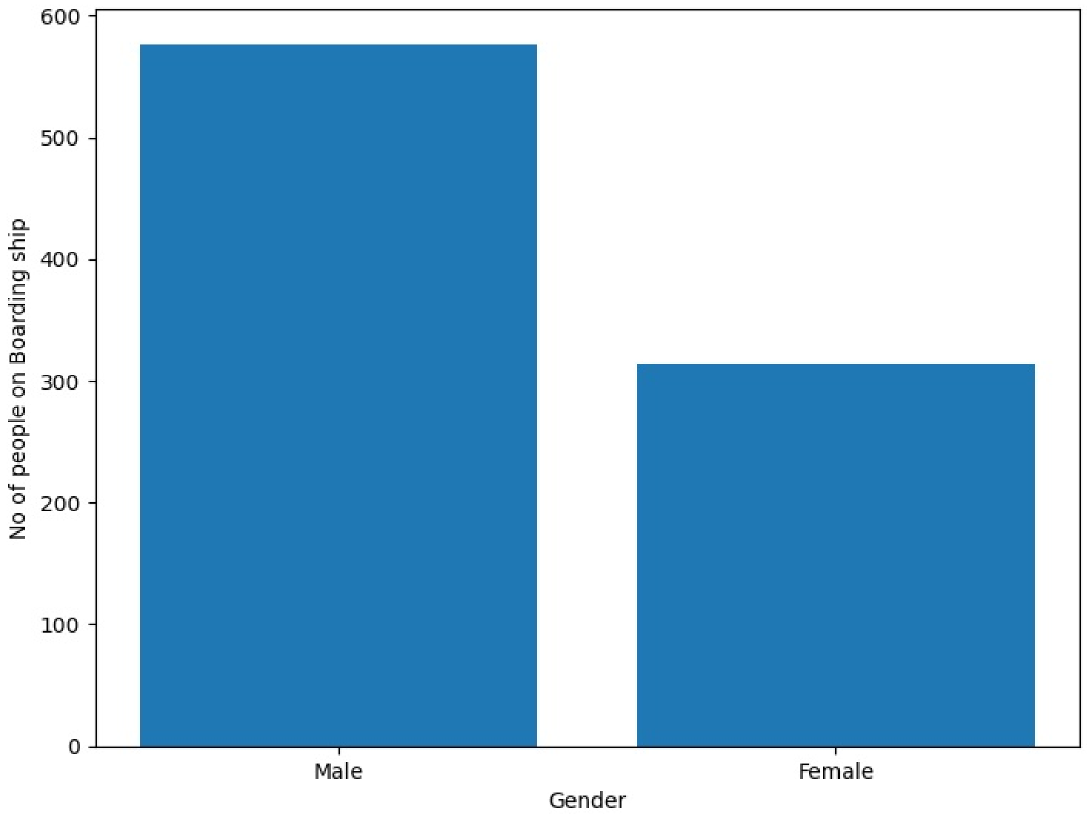
Out[16]:
```
Sex     Survived
female  0            81
        1           233
male    0           468
        1           109
Name: Survived, dtype: int64
```

In [35]:
```
# making a barplot
survived_by_sex = train_data[['Sex','Survived']].groupby('Sex').mean()
type(survived_by_sex)
survived_by_sex.plot.bar()
```

Out[35]:
```
<Axes: xlabel='Sex'>
```



In [36]:
```
#Plotting the no.of people on boarding in ship
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 on Boarding ship")
plt.show()
```



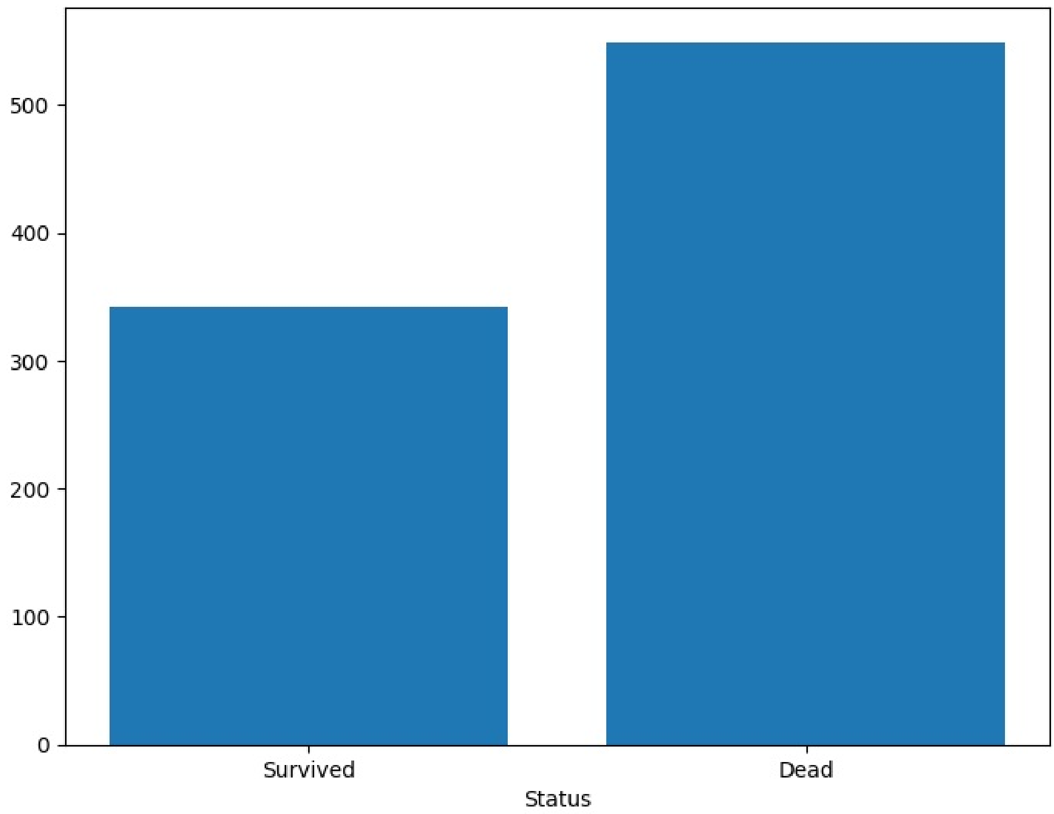
In [38]:
```
# STEP10: checking alives and dead
alive = len(train_data[train_data['Survived'] == 1])
dead = len(train_data[train_data['Survived'] == 0])
```

In [39]:
```
train_data.groupby('Sex')[['Survived']].mean()
```

Out[39]:

Sex	Survived
female	0.742038
male	0.188908

In [40]:
```
# ploting alive and dead
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()
```

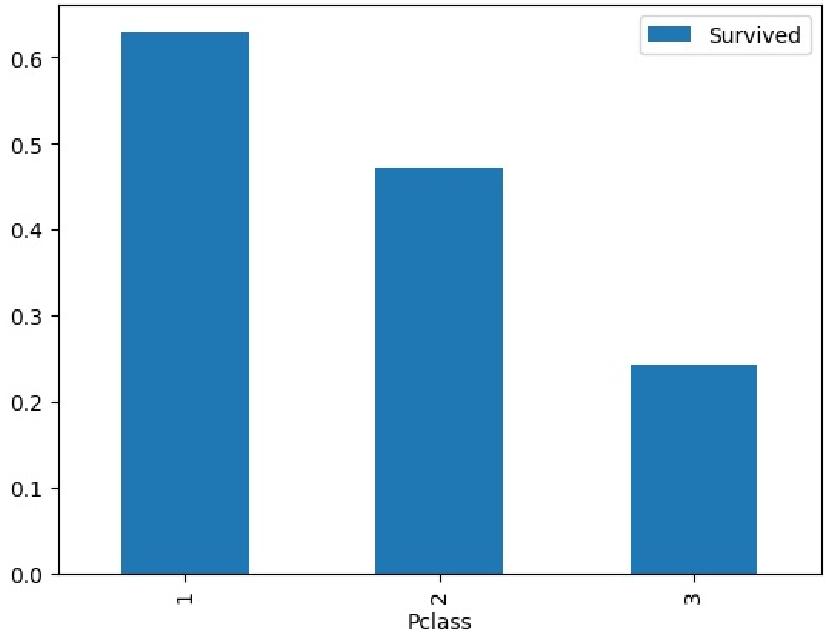


In [41]:
```
# STEP11: relationship between cabin class and survival or not Pclass
train_data.groupby(['Pclass','Survived'])['Pclass'].count()
```

Out[41]:
```
Pclass  Survived
1       0            80
        1           136
2       0            97
        1            87
3       0           372
        1           119
Name: Pclass, dtype: int64
```

In [42]:
```
train_data[['Pclass','Survived']].groupby(['Pclass']).mean().plot.bar()
```

Out[42]: <Axes: xlabel='Pclass'>

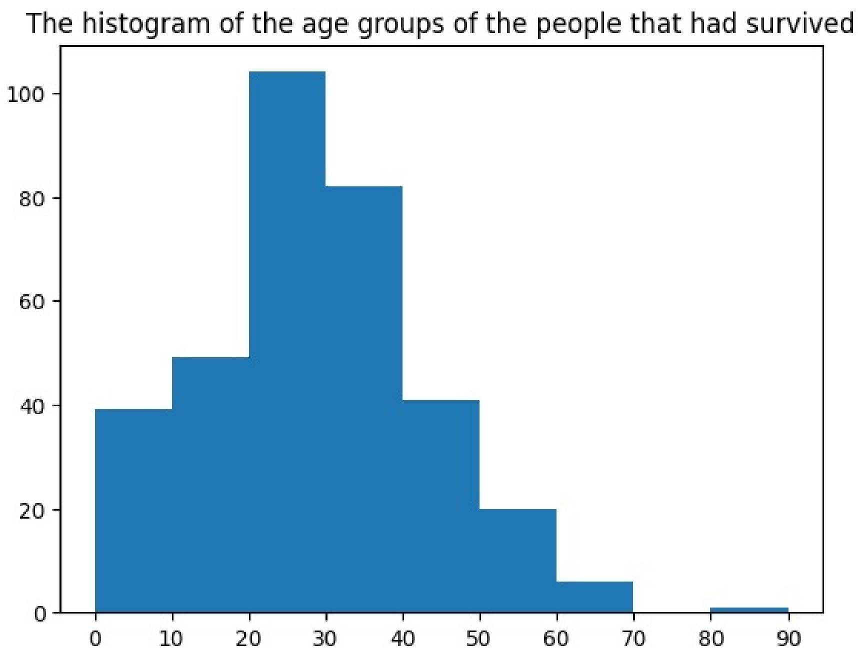


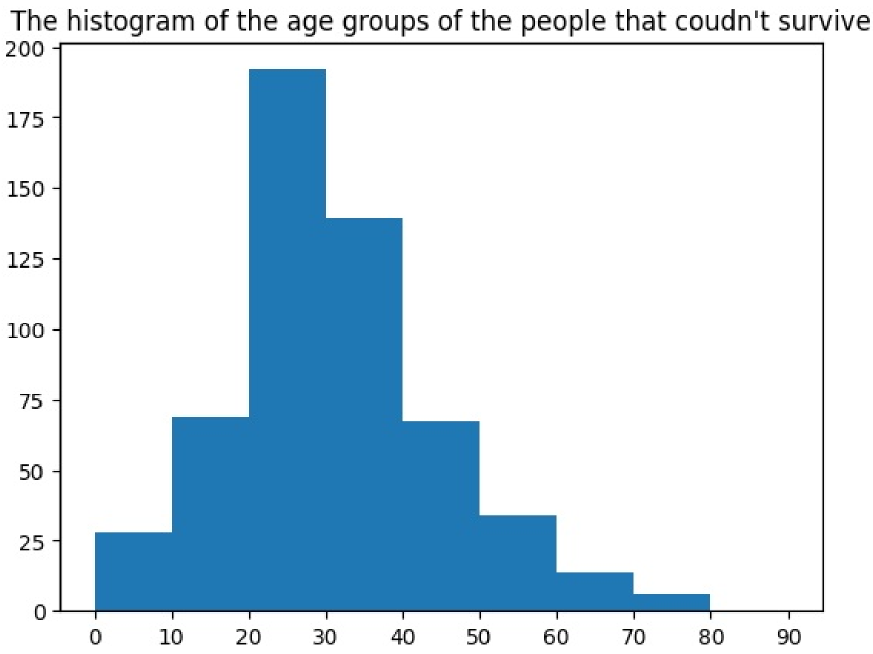
In [43]:
```
train_data.groupby(['Sex', 'Pclass', 'Survived'])['Survived'].count()
```

Out[43]:
```
Sex     Pclass  Survived
female  1       0             3
                1            91
        2       0             6
                1            70
        3       0            72
                1            72
male    1       0            77
                1            45
        2       0            91
                1            17
        3       0           300
                1            47
Name: Survived, dtype: int64
```

In [44]:
```
plt.figure(1)
age  = train_data.loc[train_data.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_data.loc[train_data.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[44]:
```
([<matplotlib.axis.XTick at 0x2766ea13410>,
  <matplotlib.axis.XTick at 0x2766ea2cec0>,
  <matplotlib.axis.XTick at 0x2766e9c07d0>,
  <matplotlib.axis.XTick at 0x2766ea2fad0>,
  <matplotlib.axis.XTick at 0x2766ea5dc40>,
  <matplotlib.axis.XTick at 0x2766ea5e540>,
  <matplotlib.axis.XTick at 0x2766ea5eea0>,
  <matplotlib.axis.XTick at 0x2766ea5f710>,
  <matplotlib.axis.XTick at 0x2766ea5fe30>,
  <matplotlib.axis.XTick at 0x2766ea5eb40>],
 [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')])
```

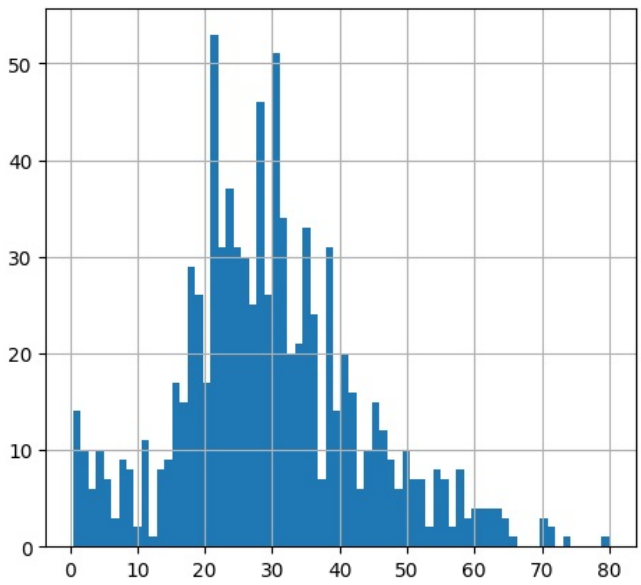


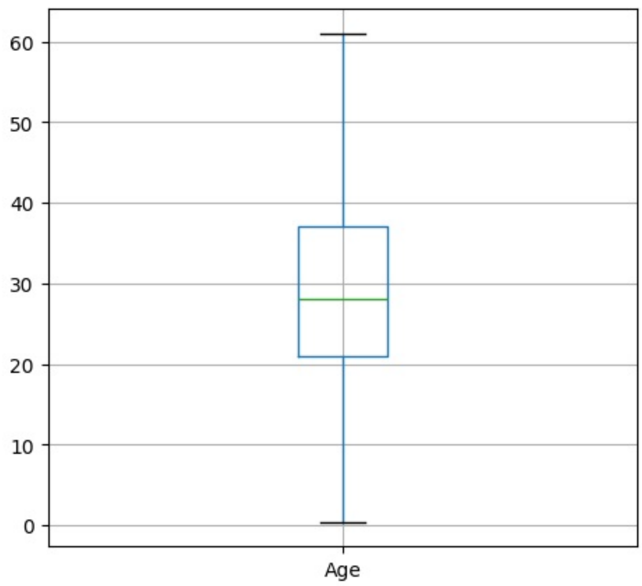


Analysis of the overall age distribution.

```
In [45]: plt.figure(figsize=(12,5))
         plt.subplot(121)
         train_data['Age'].hist(bins=70)

         plt.subplot(122)
         train_data.boxplot(column='Age', showfliers=False)
```

Out[45]: <Axes: >





Distribution of survival and non-survival at different ages.

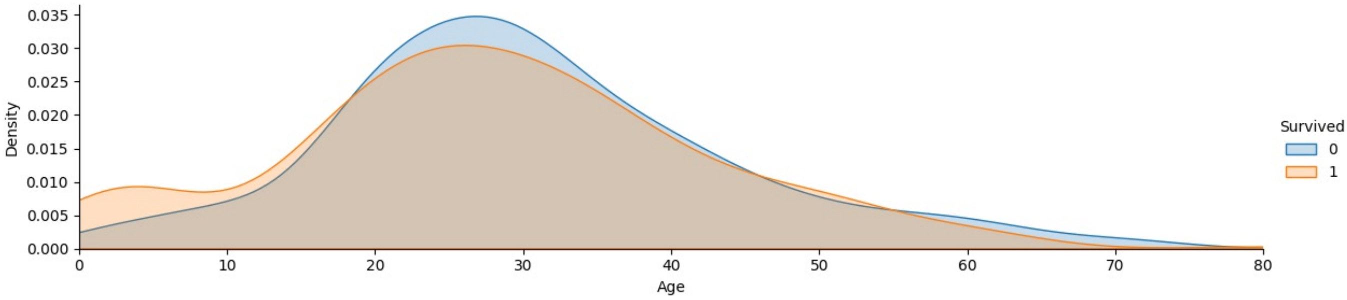
The relationship between age and survival

```
In [52]: import seaborn as sns
```

```
In [53]: facet = sns.FacetGrid(train_data,hue='Survived',aspect=4)
         facet.map(sns.kdeplot, 'Age', shade=True)
         facet.set(xlim=(0, train_data['Age'].max()))
         facet.add_legend()
```

```
C:\Users\kanis\AppData\Local\Programs\Python\Python312\Lib\site-packages\seaborn\axisgrid.py:854: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  func(*plot_args, **plot_kwargs)
C:\Users\kanis\AppData\Local\Programs\Python\Python312\Lib\site-packages\seaborn\axisgrid.py:854: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  func(*plot_args, **plot_kwargs)
```

Out[53]: <seaborn.axisgrid.FacetGrid at 0x2766f63af30>



In [54]:
```
train_data[["SibSp", "Survived"]].groupby(['SibSp'], as_index=False).mean().sort_values(by='Survived', ascending
```

Out[54]:

	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 [55]:
```
train_data[["Pclass", "Survived"]].groupby(['Pclass'], as_index=False).mean().sort_values(by='Survived', ascend
```

Out[55]:

	Pclass	Survived
0	1	0.629630
1	2	0.472826
2	3	0.242363

In [56]:
```
train_data[["Age", "Survived"]].groupby(['Age'], as_index=False).mean().sort_values(by='Age', ascending=True)
```

Out[56]:

	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
...	...	...
171	70.00	0.0
172	70.50	0.0
173	71.00	0.0
174	74.00	0.0
175	80.00	1.0

176 rows × 2 columns

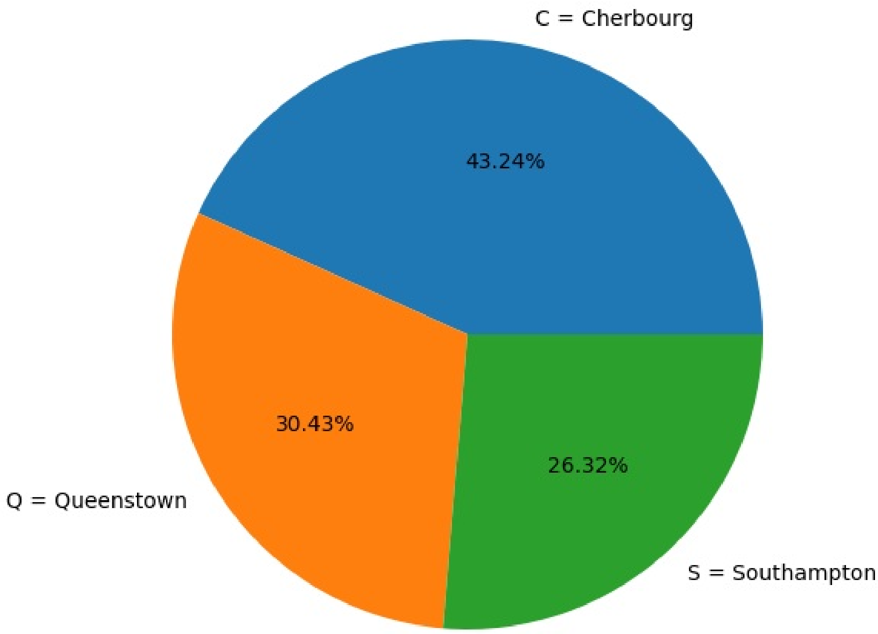
In [57]:
```
train_data[["Embarked", "Survived"]].groupby(['Embarked'], as_index=False).mean().sort_values(by='Survived', as
```

Out[57]:

	Embarked	Survived
0	C	0.553571
1	Q	0.389610
2	S	0.339009

In [58]:

```
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 [ ]: