EDA_Titanicdataset

July 24, 2024

0.1 Exploratory Data Analysis on the Titanic Data Set

Data Description The Titanic dataset is a widely used dataset for machine learning and data analysis, containing information about the passengers of the RMS Titanic, which sank on its maiden voyage in 1912. The dataset includes various attributes for each passenger, such as:

PassengerId: Unique identifier for each passenger.

Survived: Survival status (0 = No, 1 = Yes).

Pclass: Ticket class (1 = First, 2 = Second, 3 = Third).

Name: Name of the passenger.

Sex: Gender of the passenger.

Age: Age of the passenger.

SibSp: Number of siblings or spouses aboard the Titanic.

Parch: Number of parents or children aboard the Titanic.

Ticket: Ticket number.

Fare: Passenger fare.

Cabin: Cabin number.

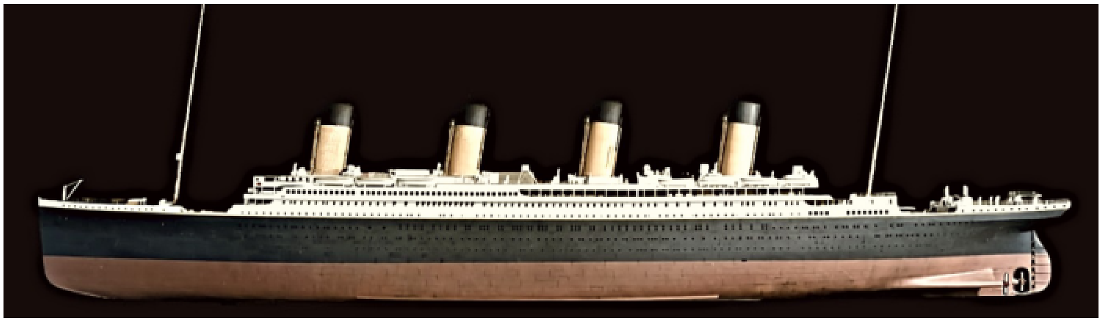
Embarked: Port of embarkation (C = Cherbourg, Q = Queenstown, S = Southampton).

This dataset is commonly used for binary classification tasks, such as predicting survival, and for exploring patterns and relationships within the data, such as the impact of socio-economic status, gender, and age on survival rates.

Importing necessary Libraries

[226]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.image as mpimg


img = mpimg.imread('Titanic_Portside_Diagram.jpg')
plt.imshow(img)
```

```
plt.axis('off')
plt.show()

%matplotlib inline
sns.set_style(style="darkgrid")
plt.rcParams['figure.figsize']=[9.0, 6.0]
```



0.1.1 Loading and Previewing the dataset

[7]:
```
train_df = pd.read_csv("train.csv", index_col=['PassengerId'])
df=train_df
train_df.head()
```

[7]:
```
             Survived  Pclass  \
PassengerId
1                   0       3
2                   1       1
3                   1       3
4                   1       1
5                   0       3

                                                          Name     Sex   Age  \
PassengerId
1                                      Braund, Mr. Owen Harris    male  22.0
2            Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0
3                                       Heikkinen, Miss. Laina  female  26.0
4                 Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
5                                     Allen, Mr. William Henry    male  35.0

             SibSp  Parch            Ticket     Fare Cabin Embarked
PassengerId
1                1      0         A/5 21171   7.2500   NaN        S
2                1      0          PC 17599  71.2833   C85        C
3                0      0  STON/O2. 3101282   7.9250   NaN        S
```

```
4                1      0            113803   53.1000   C123         S
5                0      0            373450    8.0500    NaN         S
```

[454]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 891 entries, 1 to 891
Data columns (total 11 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Survived  891 non-null    int64
 1   Pclass    891 non-null    int64
 2   Name      891 non-null    object
 3   Sex       891 non-null    object
 4   Age       714 non-null    float64
 5   SibSp     891 non-null    int64
 6   Parch     891 non-null    int64
 7   Ticket    891 non-null    object
 8   Fare      891 non-null    float64
 9   Cabin     204 non-null    object
 10  Embarked  889 non-null    object
dtypes: float64(2), int64(4), object(5)
memory usage: 83.5+ KB
```

[ ]:

0.1.2 Fixing Missing Data

[10]:
```
mean_ages = train_df.groupby(['Sex', 'Pclass'])['Age'].mean()
display(mean_ages)
```

```
Sex     Pclass
female  1         34.611765
        2         28.722973
        3         21.750000
male    1         41.281386
        2         30.740707
        3         26.507589
Name: Age, dtype: float64
```

[59]:
```
def replace_nan_age(row):
   if pd.isnull(row['Age']):
     return mean_ages[row['Sex'], row['Pclass']]
   else:
    return row['Age']
train_df['Age'] = train_df.apply(replace_nan_age, axis=1)
train_df.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        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

[393]:
```
train_df.describe()
```

[393]:

	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

Total Passengers On Board

[107]:
```
total = len(train_df)
print(total)
```

```
891
```

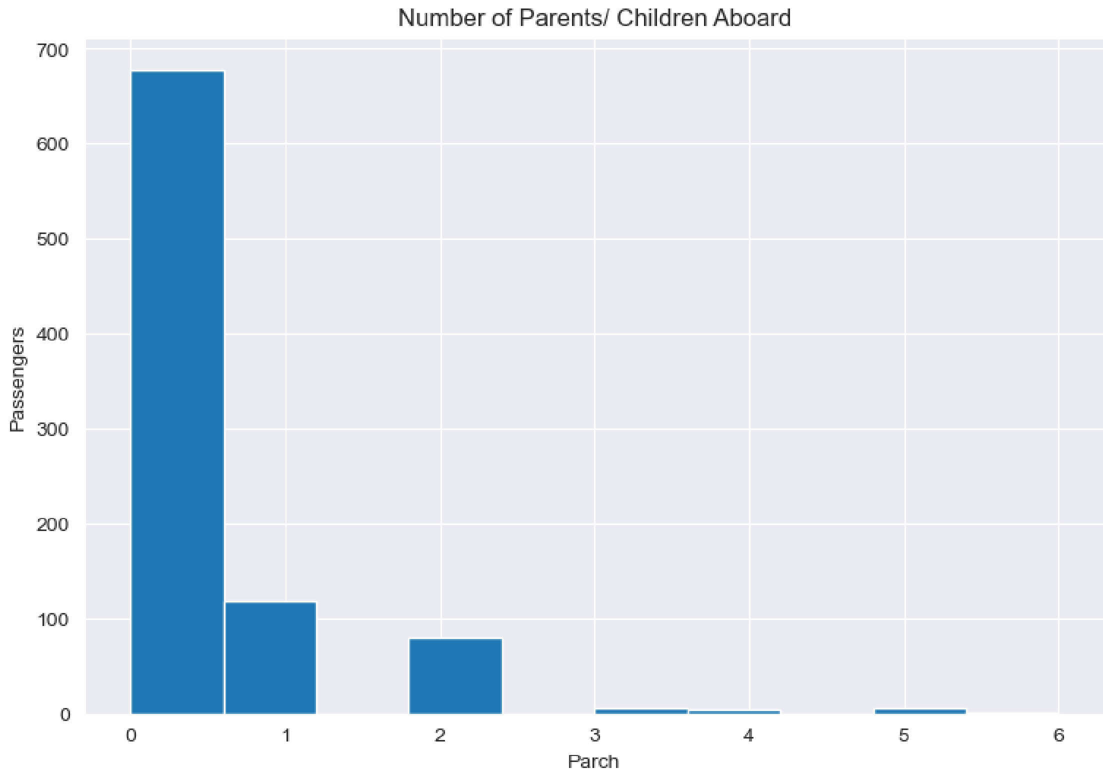
Number of Survivors

[114]:
```
survived = (train_df.Survived == 1).sum()
print(survived)
```

```
342
```

[12]:
```
train_df.Parch.hist()
plt.xlabel('Parch')
plt.ylabel('Passengers')
plt.title('Number of Parents/ Children Aboard')
```

```
plt.show()
```

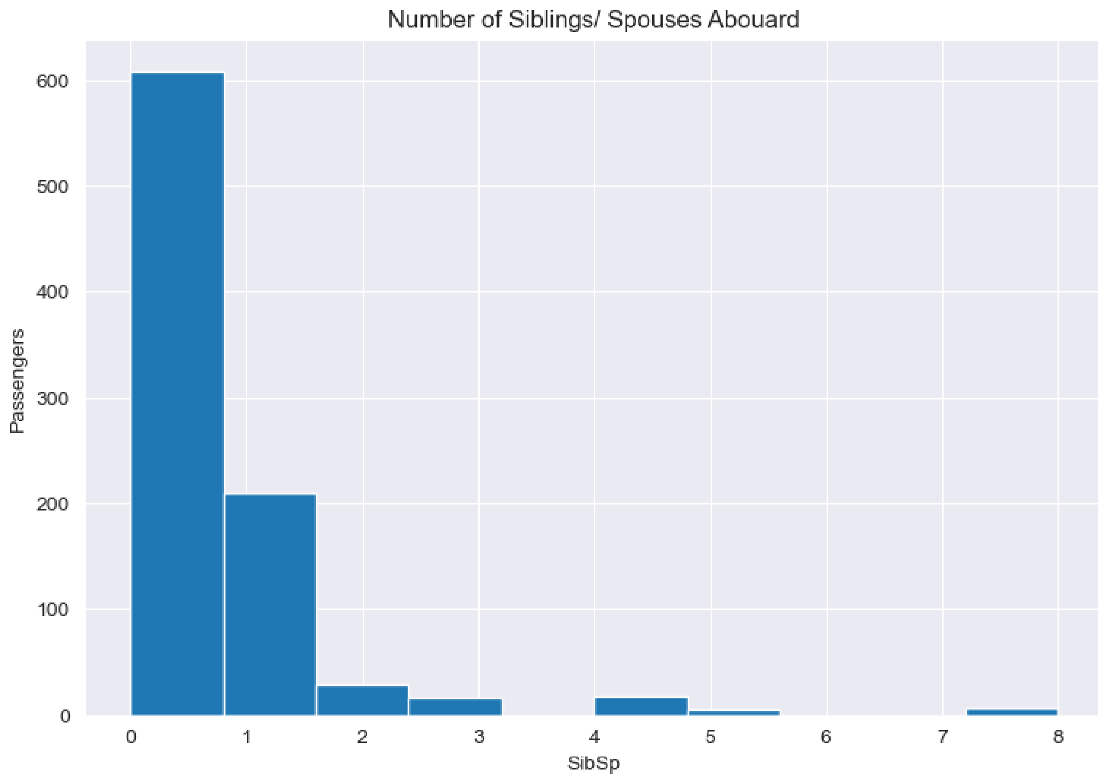


[ ]:

```

```

[14]:

```
train_df.SibSp.hist()
plt.xlabel('SibSp')
plt.ylabel('Passengers')
plt.title('Number of Siblings/ Spouses Abouard')
plt.show()
```



From the train dataset of the titanic above, we notice; - Oldest passenger: 80 years old

- Youngest passenger: Approximately 5 months old
- Average age of passengers: 29-32 (with missing ages)
- Mean survival rate: 38.38%
- Maximum fare charged: $512.33
- Maximum number of siblings/spouses: 8
- Maximum number of parents/children: 6

1 QUESTIONS

1. Did the passenger class make any difference to his survival?
2. Which gender had more survivors?
3. Person traveling with others have more survival possibilities?
4. Which age group had a better chance of survival?
5. What was male and female survival per class and age?

1.0.1 1. Did the passenger class make any difference to his survival?

[16]:
```
survived_plass_df=train_df[['Survived', 'Pclass']]
survived_plass_df.head()


survived_by_pclass= survived_plass_df.groupby(['Pclass']).sum()
total_by_pclass=survived_plass_df.groupby(['Pclass']).count()

total_by_pclass.rename(columns={'Survived': 'Total'}, inplace=True)


survived_total_by_pclass = pd.merge(survived_by_pclass, total_by_pclass,␣
 ↪left_index=True, right_index=True)
 #Merge by index
survived_total_by_pclass
```

[16]:

Pclass	Survived	Total
1	136	216
2	87	184
3	119	491

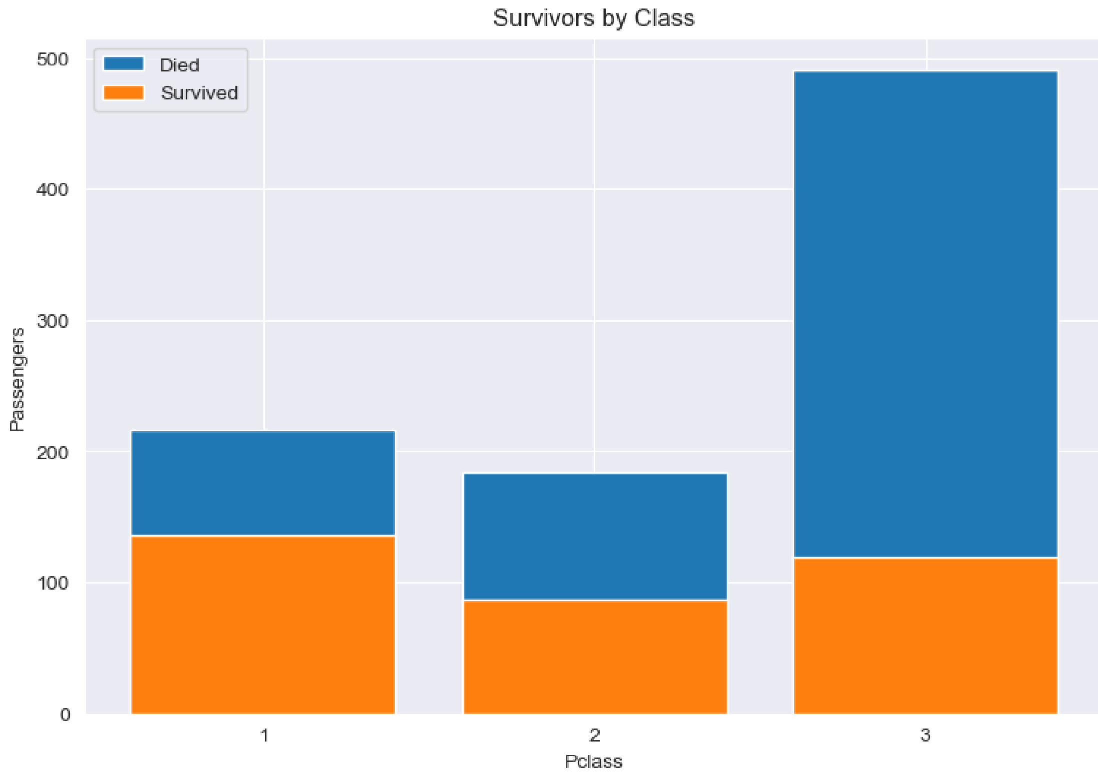
[18]:
```
percent_survived=(survived_total_by_pclass['Survived']/
 ↪survived_total_by_pclass['Total']) * 100
survived_total_by_pclass['Percentage']=percent_survived

survived_total_by_pclass
```

[18]:

Pclass	Survived	Total	Percentage
1	136	216	62.962963
2	87	184	47.282609
3	119	491	24.236253

[403]:
```
x=survived_total_by_pclass.index.values
ht=survived_total_by_pclass.Total
hs=survived_total_by_pclass.Survived

pht=plt.bar(x, ht)
phs=plt.bar(x, hs)

plt.xticks(x, x)
plt.xlabel('Pclass')
plt.ylabel('Passengers')
plt.title('Survivors by Class')

plt.legend([pht,phs],['Died', 'Survived'])
```

[403]: <matplotlib.legend.Legend at 0x1f05e49aff0>



1.0.2 Conclusion

As can be seen from the visualization and the dataframe table above, First Class passengers had the highest survival rate, followed by the Second Class passengers with Third Class having the least passenger survival rate. A large number of passengers were travelling in Third Class(491), but only 22.24% survived.

2.Which gender had more survivors?

[20]:
```
group_by_sex=train_df.groupby('Sex')

survived_by_sex=group_by_sex['Survived'].sum()
survived_by_sex.name='Survived'
display(survived_by_sex)

Total_by_sex=group_by_sex['Survived'].size()
Total_by_sex.name= 'Total'
display(Total_by_sex)


survived_total_by_sex=pd.concat([survived_by_sex, Total_by_sex], axis=1)
```

```
survived_total_by_sex
```

```
Sex
female    233
male      109
Name: Survived, dtype: int64
```

```
Sex
female    314
male      577
Name: Total, dtype: int64
```

[20]:

Sex	Survived	Total
female	233	314
male	109	577

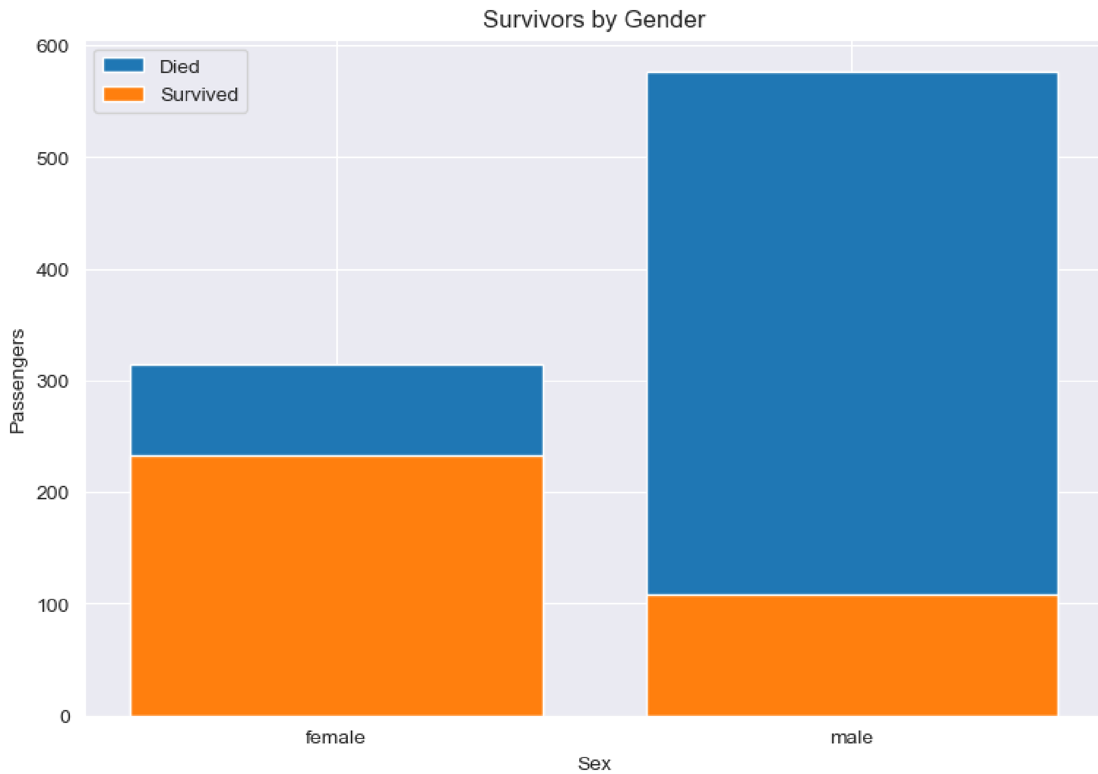
[407]:
```
percent_survived= (survived_total_by_sex['Survived']/
 ↪survived_total_by_sex['Total']) *100
survived_total_by_sex['Percentage']=percent_survived

survived_total_by_sex
```

[407]:

Sex	Survived	Total	Percentage
female	233	314	74.203822
male	109	577	18.890815

[22]:
```
x=range(len(survived_total_by_sex.index.values))
ht=survived_total_by_sex.Total
hs=survived_total_by_sex.Survived

pht=plt.bar(x, ht)
phs=plt.bar(x, hs)

plt.xticks(x, survived_total_by_sex.index.values)
plt.xlabel('Sex')
plt.ylabel('Passengers')
plt.title('Survivors by Gender')

plt.legend([pht,phs],['Died', 'Survived'])
```

[22]: <matplotlib.legend.Legend at 0x2e0f337dd90>



1.0.3 Conclusion

Based on the visualization and survival percentages from the dataframe above, it is evident that females had a significantly higher survival rate. The survival rate for females was 74.3%, while for males it was 18.9%, making the female survival rate approximately four times higher than that of males. It can be concluded that females were given preference in rescue operations, and males must have sacrificed themselves to let the females survive.

1.1 3. Person traveling with others have more survival possibilities?

[24]:
```
is_not_alone=(train_df.SibSp + train_df.Parch)>=1
passengers_not_alone=train_df[is_not_alone]

is_alone=(train_df.SibSp + train_df.Parch)==0
passengers_alone=train_df[is_alone]

print('Not alone-describe')
display(passengers_not_alone.describe())
print('Alone-describe')
display(passengers_alone.describe())
```

```
Not alone-describe
```

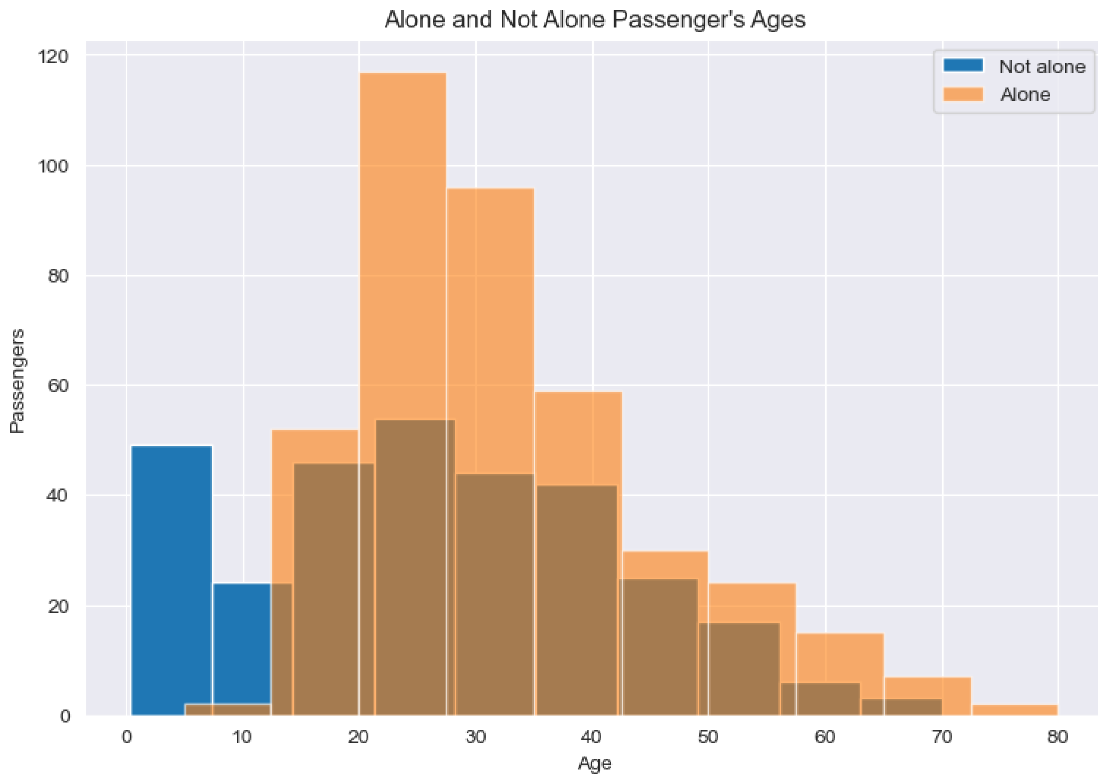
	Survived	Pclass	Age	SibSp	Parch	Fare
count	354.000000	354.000000	310.000000	354.000000	354.000000	354.000000
mean	0.505650	2.169492	26.413452	1.316384	0.960452	48.832275
std	0.500676	0.864520	15.834923	1.420774	1.039512	55.307615
min	0.000000	1.000000	0.420000	0.000000	0.000000	6.495800
25%	0.000000	1.000000	16.000000	1.000000	0.000000	18.000000
50%	1.000000	2.000000	26.000000	1.000000	1.000000	27.750000
75%	1.000000	3.000000	37.000000	1.000000	2.000000	59.044800
max	1.000000	3.000000	70.000000	8.000000	6.000000	512.329200

Alone-describe

	Survived	Pclass	Age	SibSp	Parch	Fare
count	537.000000	537.000000	404.000000	537.0	537.0	537.000000
mean	0.303538	2.400372	32.220297	0.0	0.0	21.242689
std	0.460214	0.804511	12.899871	0.0	0.0	42.223510
min	0.000000	1.000000	5.000000	0.0	0.0	0.000000
25%	0.000000	2.000000	22.000000	0.0	0.0	7.775000
50%	0.000000	3.000000	29.500000	0.0	0.0	8.137500
75%	1.000000	3.000000	39.000000	0.0	0.0	15.000000
max	1.000000	3.000000	80.000000	0.0	0.0	512.329200

[272]:
```
passengers_not_alone.Age.hist(label='Not alone')
passengers_alone.Age.hist(label='Alone', alpha=0.6)

plt.xlabel('Age')
plt.ylabel('Passengers')
plt.title('Alone and Not Alone Passenger\'s Ages')
plt.legend(loc='best')
```

[272]: <matplotlib.legend.Legend at 0x1f05891d3d0>



From the above distribution, we can see that

- Those in the age range of 0-10, that is kids, were not alone- which makes sense
- There however is one old kid age 5 who is alone
- There was an 80-year-old person also who was alone
- 537 passengers were alone, whereas 345 were in company
- Except for age group 0-10, for all other age groups, those traveling alone outnumbered those traveling in company

Reviewing their Survival

[26]:
```
notalone=np.where((train_df.SibSp + train_df.Parch)>=1, 'Not Alone', 'Alone')
loneliness_summary = train_df.groupby(notalone, as_index=False)['Survived'].
  ↪agg(["sum", "size"])

loneliness_summary.rename(columns={'sum': 'Survived', 'size': 'Total'},␣
  ↪inplace=True)

(loneliness_summary)
```

[26]:
```
         index  Survived  Total
0        Alone       163    537
1    Not Alone       179    354
```

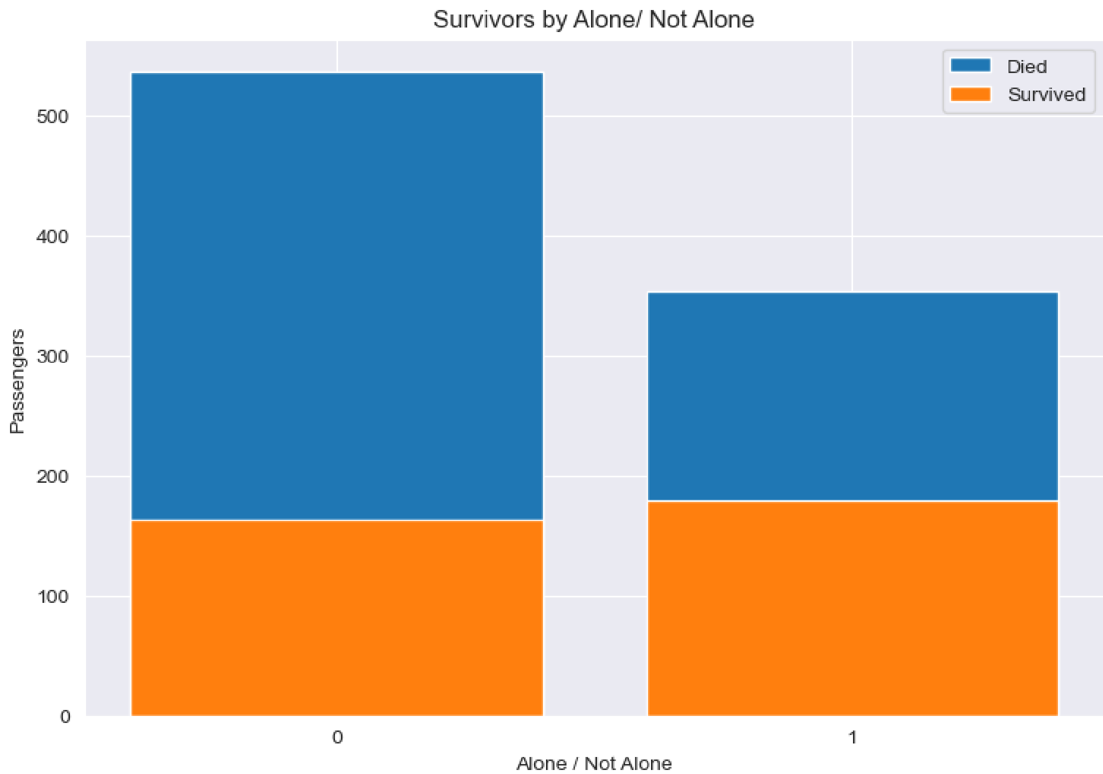
[458]:
```
loneliness_summary['Percent survived'] = (loneliness_summary.Survived/
 ↪loneliness_summary.Total)*100

loneliness_summary
```

[458]:
```
         index  Survived  Total  Percent survived
0        Alone       163    537         30.353818
1    Not Alone       179    354         50.564972
```

Visualizing

[28]:
```
x = range(len(loneliness_summary.index.values))
ht = loneliness_summary.Total
hs =loneliness_summary.Survived

pht=plt.bar(x, ht)
phs=plt.bar(x, hs)

plt.xticks(x, loneliness_summary.index.values)
plt.xlabel('Alone / Not Alone')
plt.ylabel('Passengers')
plt.title('Survivors by Alone/ Not Alone')

plt.legend([pht,phs],['Died', 'Survived'])
```

[28]:
```
<matplotlib.legend.Legend at 0x2e0f3117b30>
```



1.1.1 Conclusion

The visualization clearly indicates that people with company had a higher survival rate.

1.2 4. Which age group had a better chance of survival?

[30]:
```
male_ages = train_df[train_df.Sex == 'male']['Age']
male_ages.describe()
```

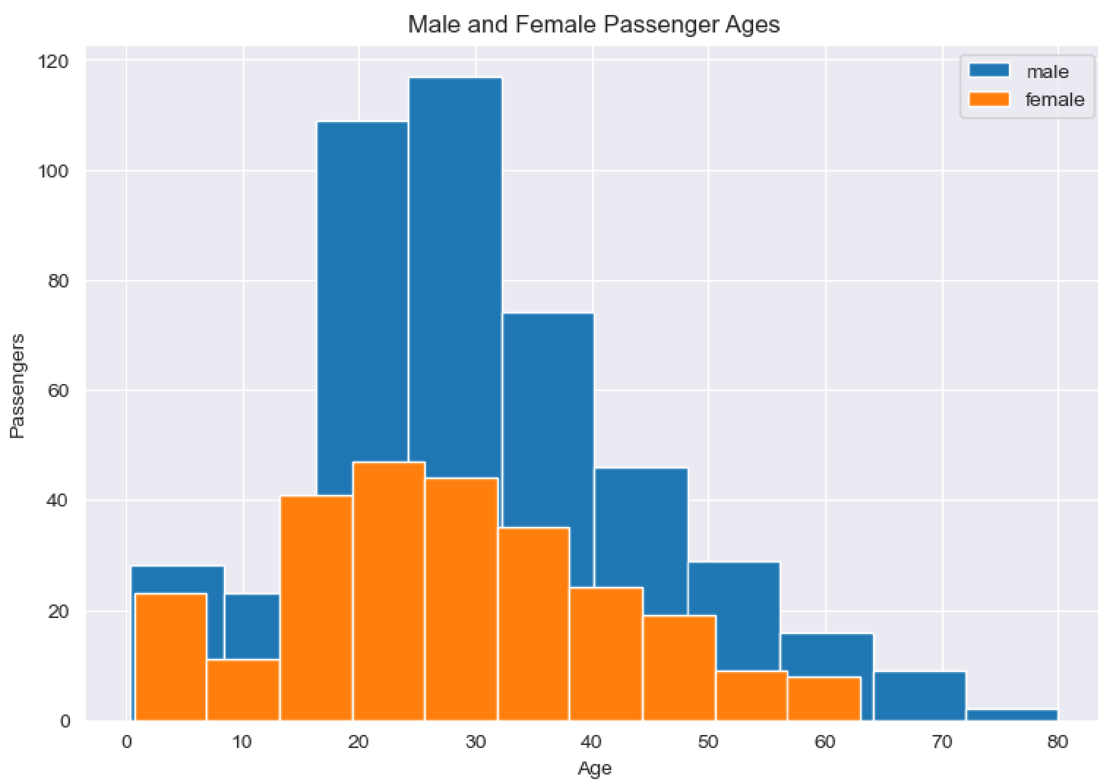
[30]:
```
count    453.000000
mean      30.726645
std       14.678201
min        0.420000
25%       21.000000
50%       29.000000
75%       39.000000
max       80.000000
Name: Age, dtype: float64
```

[32]:
```
female_ages = train_df[train_df.Sex == 'female']['Age']
female_ages.describe()
```

[32]:
```
count    261.000000
mean      27.915709
std       14.110146
min        0.750000
25%       18.000000
50%       27.000000
75%       37.000000
max       63.000000
Name: Age, dtype: float64
```

[320]:
```python
male_ages.hist(label='male')
female_ages.hist(label='female')

plt.xlabel('Age')
plt.ylabel('Passengers')
plt.title('Male and Female Passenger Ages')
plt.legend(loc='best')
```

[320]:
```
<matplotlib.legend.Legend at 0x1f05b6c8b60>
```



From the above distribution, we can see that

1. For every age group the number of females was less than the number of males

2. The age of the oldest woman is 60

1.2.1 Survival Analysis By Age Group

[54]:
```
def age_group(age):
    if age >= 80:
        return '80-89'
    if age >= 70:
        return '70-79'
    if age >= 60:
        return '60-69'
    if age >= 50:
        return '50-59'
    if age >= 40:
        return '40-49'
    if age >= 30:
        return '30-39'
    if age >= 20:
        return '20-29'
    if age >= 10:
        return '10-19'
    if age >= 0:
        return '0-9'

train_df['AgeGroup'] = train_df['Age'].apply(age_group)
train_df.head()
```

[54]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked AgeGroup
0      0         A/5 21171   7.2500   NaN        S    20-29
1      0          PC 17599  71.2833   C85        C    30-39
2      0  STON/O2. 3101282   7.9250   NaN        S    20-29
3      0            113803  53.1000  C123        S    30-39
4      0            373450   8.0500   NaN        S    30-39
```

[ ]:

```

```

[87]:

```
age_group_summary = train_df.groupby(['AgeGroup'], as_index=True)['Survived'].
 ↪agg(['sum', 'size'])
age_group_summary = age_group_summary.rename(columns={'sum': 'Survived', 'size':
 ↪ 'Total'})

age_group_summary
```

[87]:

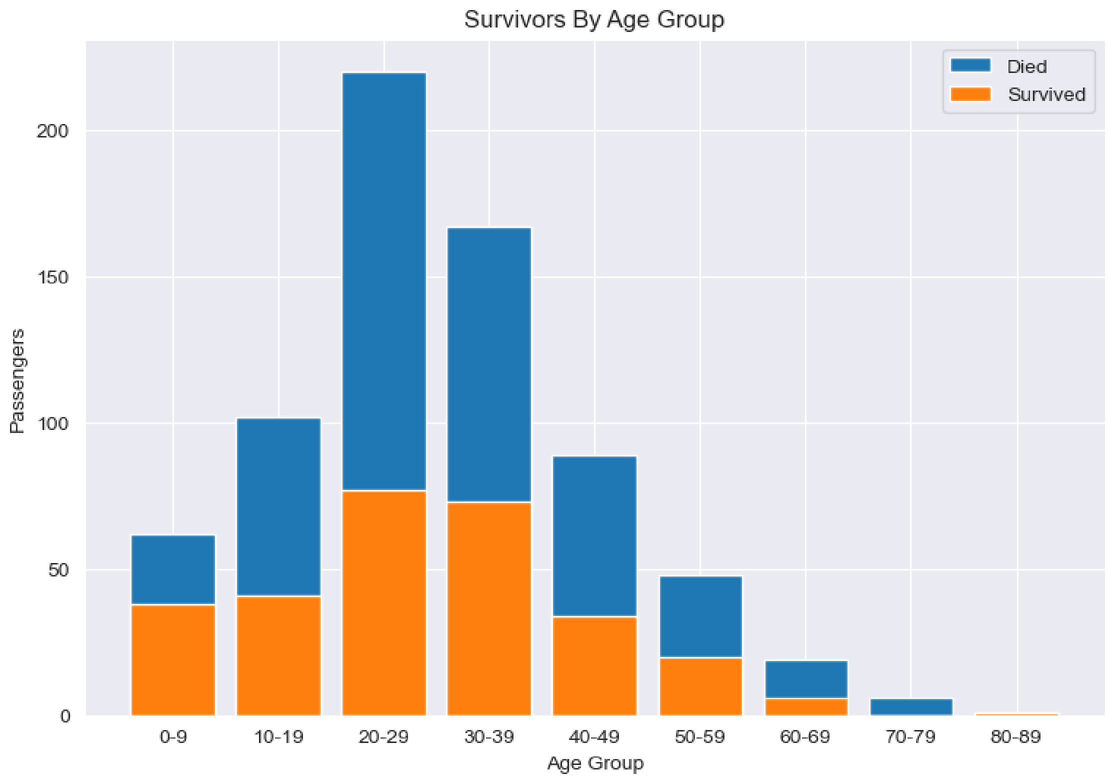
AgeGroup	Survived	Total
0-9	38	62
10-19	41	102
20-29	77	220
30-39	73	167
40-49	34	89
50-59	20	48
60-69	6	19
70-79	0	6
80-89	1	1

[89]:

```
x = range(len(age_group_summary.index.values))
ht = age_group_summary.Total
hs = age_group_summary.Survived

pht=plt.bar(x, ht)
phs=plt.bar(x, hs)

plt.xticks(x, age_group_summary.index.values)
plt.xlabel('Age Group')
plt.ylabel('Passengers')
plt.title('Survivors By Age Group')

plt.legend([pht,phs],['Died', 'Survived'])
```

[89]:

```
<matplotlib.legend.Legend at 0x2e0f31754c0>
```



[176]:
```
age_group_summary['SurvivedPercent'] = (age_group_summary['Survived'] /␣
↪age_group_summary['Total']) * 100
age_group_summary['DiedPercent'] = ((age_group_summary['Total'] -␣
↪age_group_summary['Survived']) / age_group_summary['Total']) * 100

age_group_summary
```

[176]:

AgeGroup	Survived	Total	SurvivedPercent	DiedPercent
0-9	38	62	61.290323	38.709677
10-19	41	102	40.196078	59.803922
20-29	77	220	35.000000	65.000000
30-39	73	167	43.712575	56.287425
40-49	34	89	38.202247	61.797753
50-59	20	48	41.666667	58.333333
60-69	6	19	31.578947	68.421053
70-79	0	6	0.000000	100.000000
80-89	1	1	100.000000	0.000000

Based on the visualization and percentages, it's clear that the majority of survivors were between the ages of 20 and 29. Interestingly, the survival rate for the 0-9 age group is the highest at 61.29%. Additionally, we noticed that females had a better survival rate, so it's important to consider both male and female survival rates for a comprehensive view.

[100]:
```
sex_agegroup_summary= train_df.groupby(['Sex', 'AgeGroup'],␣
    ↪as_index=False)['Survived'].mean()
sex_agegroup_summary
```

[100]:

	Sex	AgeGroup	Survived
0	female	0-9	0.633333
1	female	10-19	0.755556
2	female	20-29	0.722222
3	female	30-39	0.833333
4	female	40-49	0.687500
5	female	50-59	0.888889
6	female	60-69	1.000000
7	male	0-9	0.593750
8	male	10-19	0.122807
9	male	20-29	0.168919
10	male	30-39	0.214953
11	male	40-49	0.210526
12	male	50-59	0.133333
13	male	60-69	0.133333
14	male	70-79	0.000000
15	male	80-89	1.000000

[102]:
```
male_agegroup_summary =␣
    ↪sex_agegroup_summary[sex_agegroup_summary['Sex']=='male']
sex_agegroup_summary
```

[102]:

	Sex	AgeGroup	Survived
0	female	0-9	0.633333
1	female	10-19	0.755556
2	female	20-29	0.722222
3	female	30-39	0.833333
4	female	40-49	0.687500
5	female	50-59	0.888889
6	female	60-69	1.000000
7	male	0-9	0.593750
8	male	10-19	0.122807
9	male	20-29	0.168919
10	male	30-39	0.214953
11	male	40-49	0.210526
12	male	50-59	0.133333
13	male	60-69	0.133333
14	male	70-79	0.000000
15	male	80-89	1.000000

[48]:
```
train_df = pd.read_csv("train.csv", index_col=False)
```

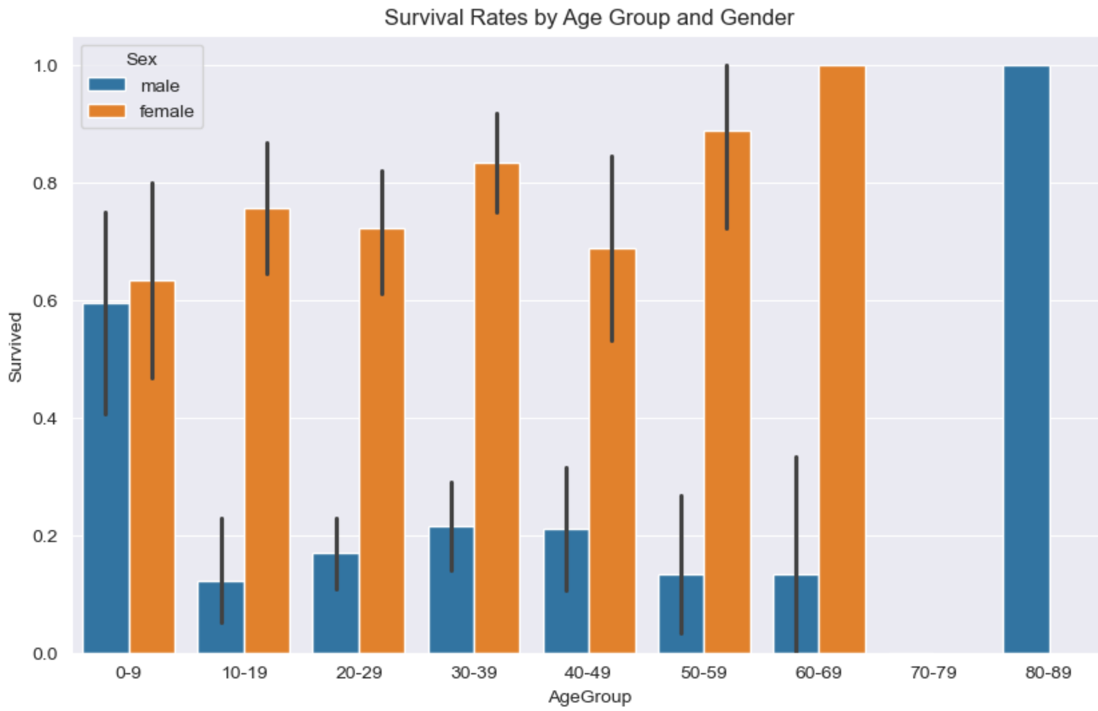
[64]:
```
female_agegroup_summary = ␣
↪sex_agegroup_summary[sex_agegroup_summary['Sex']=='female']
sex_agegroup_summary
```

[64]:
```
       Sex AgeGroup  Survived
0   female      0-9  0.633333
1   female    10-19  0.755556
2   female    20-29  0.722222
3   female    30-39  0.833333
4   female    40-49  0.687500
5   female    50-59  0.888889
6   female    60-69  1.000000
7     male      0-9  0.593750
8     male    10-19  0.122807
9     male    20-29  0.168919
10    male    30-39  0.214953
11    male    40-49  0.210526
12    male    50-59  0.133333
13    male    60-69  0.133333
14    male    70-79  0.000000
15    male    80-89  1.000000
```

[72]:
```
age_group = train_df.AgeGroup.unique()
age_group = [age for age in age_group if pd.notna(age)]
age_labels = sorted(age_group)
print(age_labels)
```

```
['0-9', '10-19', '20-29', '30-39', '40-49', '50-59', '60-69', '70-79', '80-89']
```

[104]:
```
plt.figure(figsize=(10, 6))
ax = sns.barplot(x='AgeGroup', y='Survived', data=train_df, hue='Sex',␣
↪order=age_labels)

plt.title("Survival Rates by Age Group and Gender")
plt.show()
```



Conclusion Based on the proportions and visualizations, it is evident that female and children received priority in rescue operations by male passengers.

Both male and female children in the 0-9 age group had a very high rate of survival.

1.3 5.What was male and female survival per class and age?

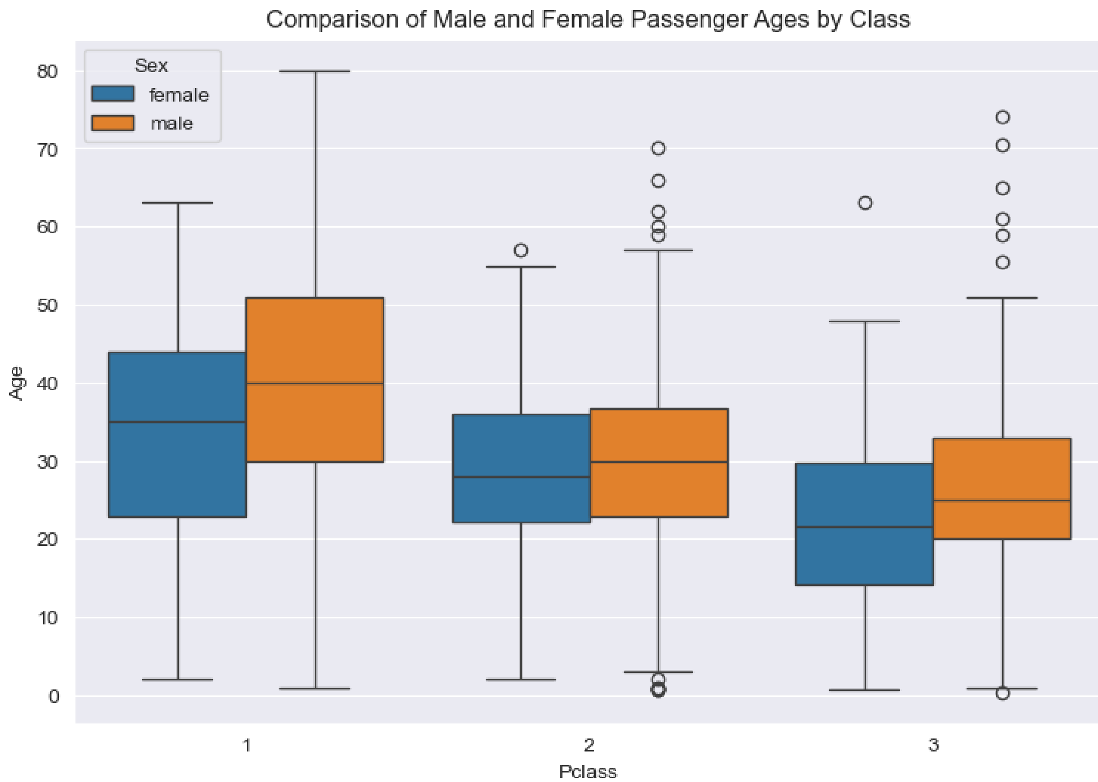
Male and Female Per Pclass

[130]:
```
sns.swarmplot(x='Pclass', y='Age', data=train_df, hue='Sex', dodge=True)

plt.title("Male and Female Passenger Ages by Class")
plt.show()
```

Looking at the data, we can see that there were more passengers in third class compared to first and second class. Specifically, there was a large number of male passengers, with the majority being between the ages of 18 and 32.

[174]:
```
sns.boxplot(x='Pclass', y='Age', data=train_df, hue='Sex').
 ↪set_title("Comparison of Male and Female Passenger Ages by Class")
```

[174]:
```
Text(0.5, 1.0, 'Comparison of Male and Female Passenger Ages by Class')
```



Based on the data, it's clear that the average age of male and female passengers in the 3rd class was lower than that of males and females in the 2nd and 1st class.

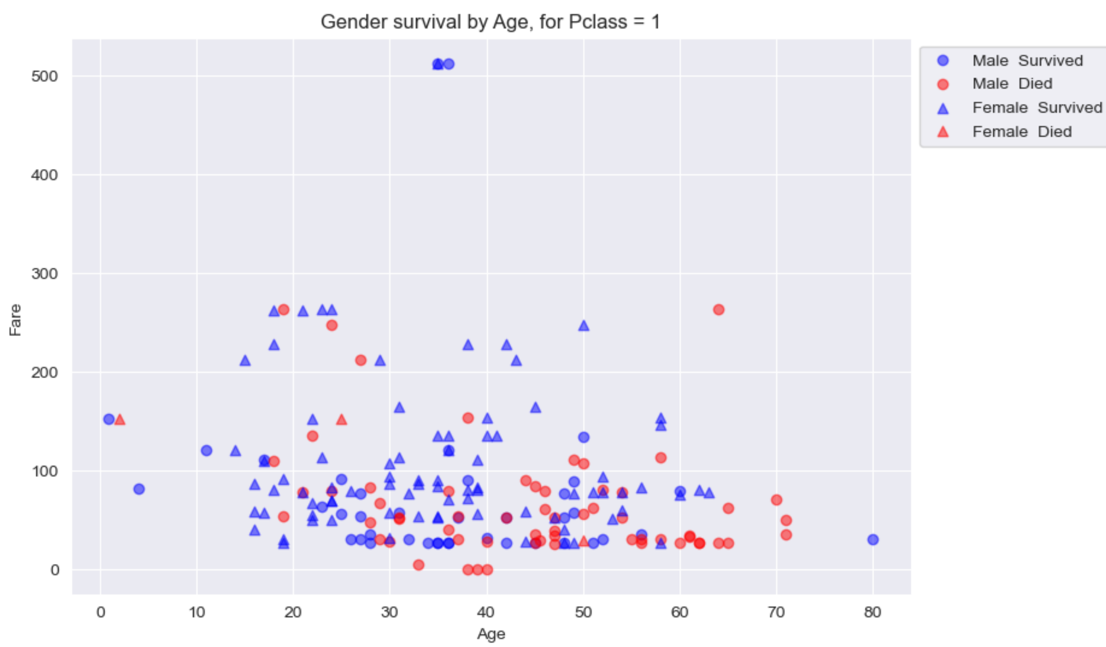
The highest average age of males was in the 1st class. However, this plot only provides insight into the age distribution of males and females within each class.

1.3.1 Male and Female Survival Per Pclass and by Age

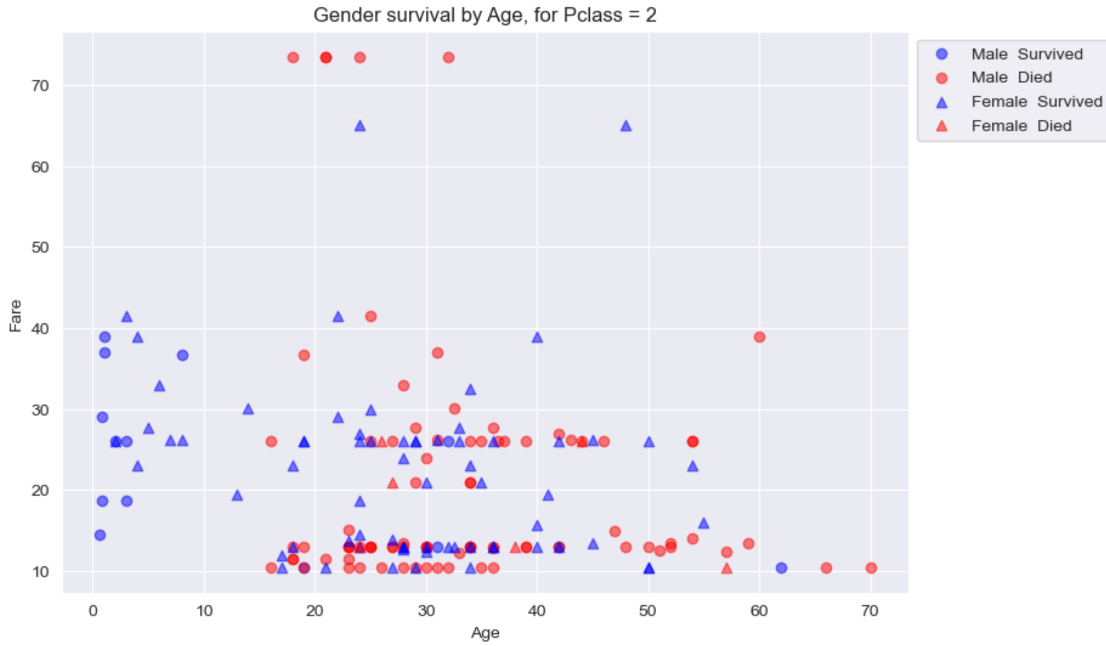
[155]:
```
def scatter(passengers, marker, legend_prefix):
    survived = passengers[passengers.Survived == 1]
    died = passengers[passengers.Survived == 0]

    x = survived.Age
    y = survived.Fare
    plt.scatter(x, y, c='blue', alpha=0.5, marker=marker, label=legend_prefix +␣
 ↪' Survived')


    x = died.Age
    y = died.Fare
    plt.scatter(x, y, c='red', alpha=0.5, marker=marker, label=legend_prefix +␣
 ↪' Died')
```

```
def scatter_by_class(pclass):
    class_passengers = train_df[train_df.Pclass == pclass]

    male_passengers = class_passengers[class_passengers.Sex == 'male']
    female_passengers = class_passengers[class_passengers.Sex == 'female']

    scatter(male_passengers, marker='o', legend_prefix='Male ')
    scatter(female_passengers, marker='^', legend_prefix='Female ')

    plt.legend(bbox_to_anchor=(1, 1), loc='upper left')  # bbox_to_anchor moves␣
 ↪the legend out of the plot
    plt.xlabel('Age')
    plt.ylabel('Fare')
    plt.title('Gender survival by Age, for Pclass = ' + str(pclass))
    plt.show()
```

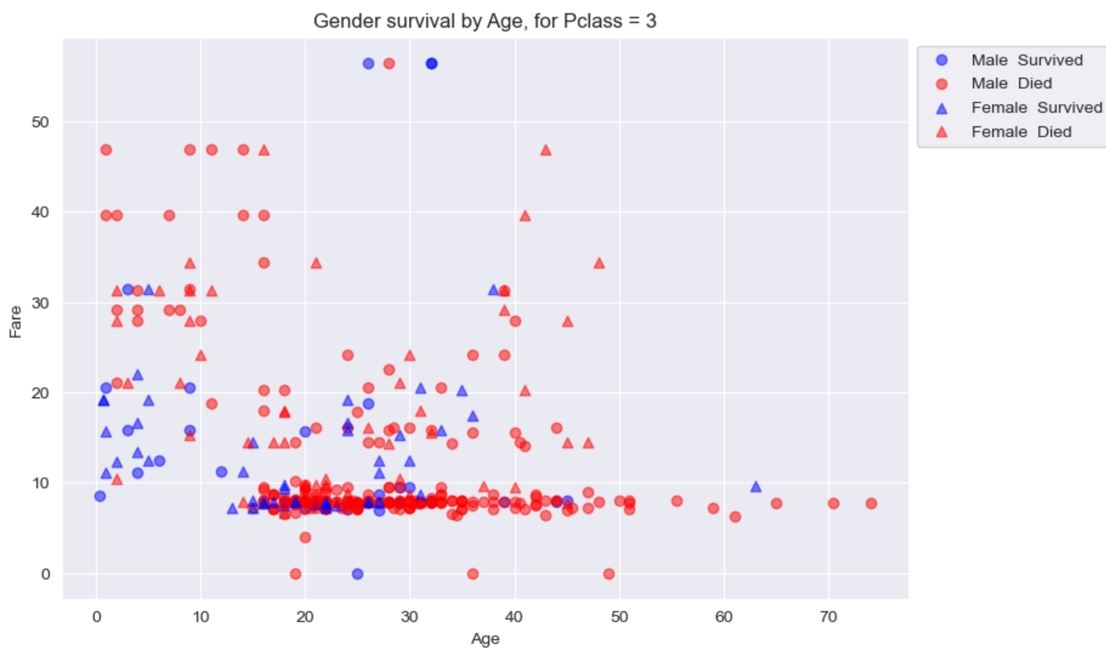
[157]:
```
scatter_by_class(1)
```



[159]:
```
scatter_by_class(2)
```



[164]:
```
scatter_by_class(3)
```



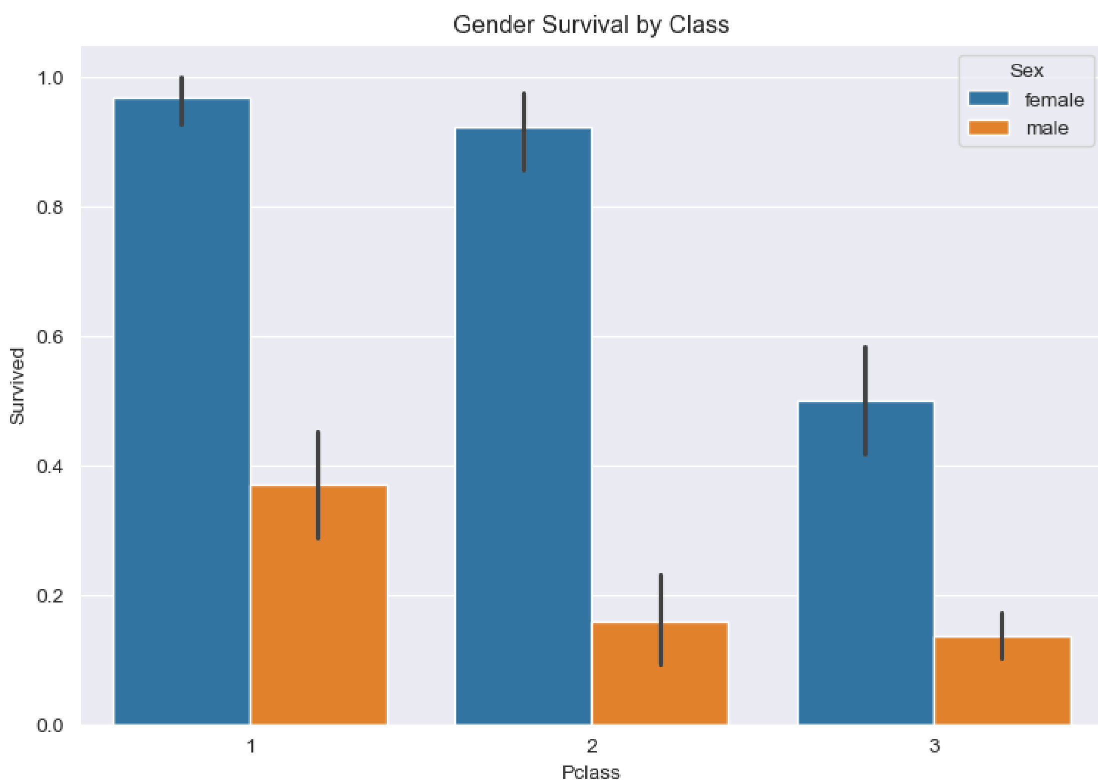
The three scatter plots above provide a visualization of the relationship between age, gender, and survival rate in each passenger class.

Conclusion From the scatter plots above, we can see a clear picture of the age spread and survival rates for males and females. Here's what we can observe: - Females in first and second class had a high survival rate. - In the first and second class, male and female children (aged 0-10) almost all survived. - In the third class, the survival rate for females was higher than for males, but it was lower compared to the survival rate of females in the first and second class.

We can confirm the observation mentioned above by creating a bar plot that shows the survival rate by class and sex.

[195]:
```
sns.barplot(x='Pclass', y='Survived', data=train_df, hue='Sex').
 ↪set_title("Gender Survival by Class")
```

[195]:
```
Text(0.5, 1.0, 'Gender Survival by Class')
```



1.4 Overall Conclusion

1.4.1 Findings

In the Titanic disaster, the survival rate for females was 74.3% while for males it was 18.9%, indicating that females were about four times more likely to survive than males. As a result, females and children were given priority in rescue operations and were likely saved by other male passengers.

Additionally, 62.96% of 1st class passengers survived, while only 24.24% of 3rd class passengers survived, which is about one-third of the survival rate of 1st class passengers. This suggests that first class passengers received preferential treatment due to their social status.

Furthermore, 50% of passengers travelling with family members survived, compared to a 30% survival rate for those travelling alone. This indicates that passengers travelling with family had a higher chance of survival than those travelling alone.

Lastly, it's worth noting that children had higher survival rates than adults.

1.4.2 Future Plans

Please take note of the following text:

Future work or potential areas to explore:

- The analysis only utilized 3 parameters - Age, Sex, and Passenger Class. Further analysis is possible.
- Additional questions that can be explored include:
  - Did individuals with higher fares have a better chance of survival?
  - Did the deck of the cabin affect the rate of survival?
  - Is there any correlation between survival and a person's title (e.g., Mr., Mrs., Miss, etc.)?

Thank You!

By: Ruth O. Ajagunna

```
[ ]:
```